Essays on Public Policy Outcomes Evaluation: Effectiveness and Cost-Effectiveness Analysis in Japan

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Abstract

This study, grounded in Japan's unique socio-economic context, explores the application of two analytical approaches in public policy evaluation: Effectiveness Analysis and Cost-Effectiveness Analysis. It presents three empirical case studies to illustrate their application.

The first case study applies Effectiveness Analysis to evaluate the impact of the 2017 expansion of the Special Spousal Exemption on women's labor supply. Using a counterfactual framework, the study estimates both the average treatment effect of the policy and its heterogeneous effects across different quantiles. The findings indicate that the policy significantly increased women's working hours, but this positive effect was limited to women in non-regular employment. Moreover, the effect was primarily concentrated among women with shorter working hours, driven by a combination of substitution and income effects. These results support the Japanese government's rationale for expanding Special Spousal Exemption coverage to encourage women to work longer hours.

The second case study employs Cost-Effectiveness Analysis to assess whether vaccine deployment during the early stages of the COVID-19 pandemic reduced regional disparities in local healthcare system efficiency (LHSE) caused by socio-economic inequalities. The results reveal that vaccination improved overall healthcare

efficiency disparities across regions. However, no evidence was found that efficiency gaps driven by socio-economic inequalities were alleviated. In fact, in regions with limited hospital bed resources, high occupancy rates of secured bed for severe cases significantly hindered improvements in healthcare system efficiency. These findings underscore the need for policymakers to prioritize the availability of secured bed for severe cases and the prevention of severe cases in resource-scarce regions to address regional disparities in healthcare efficiency, even in a post-pandemic era of widespread vaccine availability.

The third case study also utilizes Cost-Effectiveness Analysis but focuses on management efficiency while accounting for exogenous factors. The study evaluates the efficiency of suicide prevention and intervention programs across Japan's prefectures between 2010 and 2014, alongside their dynamic changes. The findings reveal significant disparities in suicide prevention and intervention efficiency across prefectures, although much of this variation can be attributed to exogenous factors such as environmental conditions and randomness. When accounting for these factors, actual disparities in management efficiency were relatively smaller. Additionally, while the of suicide prevention and intervention demonstrated an upward trend over time, marginal productivity gains declined. Most of the improvements were driven by technological advancements rather than by increases in managerial efficiency.

Taken together, these case studies provide actionable insights for policymakers, highlighting the importance of targeted, context-sensitive, and evidence-based public policy evaluation strategies to address Japan’s pressing policy challenges.

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Contents

List of Figures

List of Tables

Chapter 1: Introduction

1.1. Public Policy Evaluation and Analytical Frameworks

Public policy evaluation (PPE) systematically assesses the design, implementation, and outcomes of policies to determine their effectiveness and efficiency (Freund et al., 2019; Jensen, 2020). Among these approaches, outcome evaluation is critical for gauging whether policies achieve their intended goals. This involves comparing actual impacts to stated objectives, thereby providing a basis to judge a policy's success or failure. Particularly in evidence-based policymaking, an outcome-focused approach enables informed decision-making by relying on empirical evidence to optimize resource allocation and achieve desired results (Supardi et al., 2024).

Amid global challenges such as population aging and fiscal pressures, the role of PPE in resource allocation, emergency response, social equity, and socioeconomic development has become increasingly prominent. Population aging, for example, has led to higher government spending on social protection in developed countries, particularly in healthcare and pensions, often at the expense of growth-promoting sectors like education. This reallocation of resources may impede economic growth (Focacci, 2022; Temsumrit, 2023). Simultaneously, fiscal pressures constrain governments' capacity to address policy challenges, tax burdens, and economic priorities, forcing a focus on efficient resource use to maintain fiscal sustainability(ElsÄSser & Haffert, 2021; Oprisan & Dumitrache Serbanescu, 2023).

In Japan, the twin challenges of aging and fiscal strain underscore the importance of robust PPE to sustain social welfare and economic development. As of 2020, Japan's aging rate reached 28.9%, the highest globally and far exceeding the developed countries' average of 19.4%. This figure is projected to rise to 37.4% by 2060 (United Nations, 2024). Meanwhile, Japan's debt-to-GDP ratio stood at 257.2% in April 2020, the highest among developed nations (International Monetary Fund, 2024). Moreover, Japan’s unique socioeconomic characteristics—including traditional gender roles, effective central-local collaboration, and significant regional disparities—make it challenging to adopt foreign policy experiences or apply general analytical frameworks. Consequently, evaluating Japanese public policies requires a tailored approach that accounts for these distinct phenomena.

PPE on outcome often rely on two empirical measures: Effectiveness Analysis (EA) and Cost-Effectiveness Analysis (CEA). EA assesses the extent to which policies achieve their objectives, while CEA evaluates outcomes relative to the resources invested (Puett, 2019). In the other word, whereas EA focuses exclusively on outputs, CEA considers both inputs and outputs. These methods have different analytical purposes and scenarios, with neither being inherently superior.

EA is particularly advantageous in scenarios where inputs are secondary or when value judgments play a role in factual assessments. In cases involving ethical considerations, such as policies impacting vulnerable populations, EA helps circumvent ethical dilemmas tied to assigning monetary values to human life or welfare. For instance, in discussions surrounding potential discrimination against individuals with disabilities, CEA might face criticism for prioritizing cost savings over equitable outcomes (Bognar, 2010). Moreover, EA excels in evaluating non-monetary benefits when quantifying outcomes in financial terms is either impractical or unnecessary. It offers a clearer representation of policy impacts, such as the number of lives saved or crimes prevented (Basu et al., 2024). Finally, in situations where outcomes outweigh considerations of cost—such as emergency responses or addressing critical public health challenges—EA often proves more suitable, as the effectiveness of interventions becomes the primary focus (Basu et al., 2024).

CEA is a critical tool in public policy, particularly in resource-constrained settings where funding decisions must prioritize maximum impact. Unlike EA, which focuses solely on intervention outcomes, CEA evaluates both costs and outcomes, providing a more comprehensive understanding of policy value. This approach is especially valuable in budget-constrained environments, where ensuring that intervention benefits justify their costs is essential. Healthcare, where resources are scarce and demand is high, exemplifies this scenario (Greenhawt et al., 2021; Russell & Sinha, 2016). Furthermore, CEA is particularly effective when interventions yield multiple outcomes, including unexpected ones, as it offers a structured method for assessing these outcomes alongside their associated costs. Additionally, probabilistic methods in CEA allow decision-makers to incorporate preferences and thresholds for inputs and outputs, adding flexibility and precision to the decision-making process (Arsham et al., 2023).

These analytical tools—CEA and EA—are integral to factual evaluation, a technical approach to public policy assessment that emphasizes the alignment between policy outcomes and objectives. Factual evaluation contrasts with value evaluation, which assesses policies through the lenses of political fairness, justice, social responsiveness, and adaptability (Choi & Fox, 2022). Factual evaluations aim for value neutrality, avoiding partisan goals and conflicts while focusing on efficiency and effectiveness in achieving policy objectives. However, the possibility of conducting purely value-neutral factual evaluations has been widely debated (Elliott, 2006). Contemporary research increasingly advocates for the integration of factual and value-based analyses in PPE (Choi & Fox, 2022; Elliott, 2006; Pandey & Shukla, 2022). While empirical data and statistical models provide critical insights into policy impacts, ethical considerations and social values—such as economic interests, equity, and subjective well-being—remain central to informed decision-making.

1.2. EA and CEA in the Context of Japan's Socioeconomic Characteristics

In the subsequent sections, this study examines Japan’s recent tax reforms and healthcare policies as case studies to illustrate the application of EA and CEA in PPE on outcomes. Our objective is to present a framework for evidence-based PPE that is specifically adapted to Japan’s distinctive socioeconomic context. Furthermore, we integrate factual and value-evaluations to address and mitigate ethical and value conflicts, ensuring a more comprehensive and balanced approach to policy assessment.

Chapter 2 examines the effects of the 2017 reform of Japan's Special Spousal Exemption system on women's labor supply. While government agencies claimed the reform would unlock women's labor potential and encourage longer working hours (Ministry of Finance, 2017), robust empirical evidence supporting this claim remains scarce. Using a quasi-experimental framework, this study estimated both the average treatment effect of the policy change and its heterogeneous impacts across labor supply quantiles.

The results reveal that the 2017 Special Spousal Exemption reform significantly increased women’s average working hours. Even after excluding individuals who were entirely unemployed during the study period, the positive treatment effect remained statistically significant. However, the effect varied by employment type, being significant for informal workers but not for formal employees. Quantile analysis further demonstrated that the reform's labor supply-promoting effects were concentrated among women working shorter hours.

A theoretical model explains these findings: for short-hour workers, the reform's negative substitution effect—where leisure is replaced by consumption—outweighed the positive income effect, prompting an increase in working hours. Conversely, for mid- and long-hour workers, while substitution and income effects theoretically suggested a reduction in working hours, the limited household income changes induced by the policy were insufficient to alter their labor supply decisions.

Chapter 3 investigates the early stages of the COVID-19 pandemic, focusing on how vaccination influenced the relationship between regional socioeconomic disparities and local healthcare system efficiency (LHSE). During the initial phase of the pandemic, Japan experienced the "Japanese paradox": a relatively low mortality rate despite lenient restrictions—a phenomenon attributed to the efficient allocation and coordination of healthcare resources by local governments (Inoue, 2020; Karako et al., 2022a; Su et al., 2021).

Despite this success, socioeconomic disparities across prefectures posed varying challenges in pandemic control. Vaccination was expected to enhance antibody coverage, reduce healthcare pressures, and mitigate the influence of socioeconomic factors on LHSE. However, our study found that while vaccination significantly reduced overall regional disparities in LHSE, it did not alleviate disparities stemming from socioeconomic gaps. On the contrary, vaccination exacerbated the adverse impact of high occupancy rates of secured beds for severe cases on healthcare efficiency, particularly in regions facing bed shortages.

These findings highlight important considerations for policymakers in the post-pandemic era. Specifically, as vaccination coverage continues to expand, efforts to improve LHSE should prioritize ensuring sufficient medical resources to support the prevention and treatment of critically ill patients.

Building on the analytical approaches of Chapter 3, Chapter 4 employs CEA with a focus on the role of exogenous factors—such as environmental and luck variables—in influencing managerial efficiency. The chapter investigates the efficiency and dynamic evolution of local governments' suicide prevention and intervention (SPI) programs in Japan.

Since the early 1990s, Japan has faced rising suicide rates. In response, the government has implemented various SPI measures, encouraging local governments to take proactive roles with financial support from central authorities. Scholars have linked the decline in suicide rates since 2009 to collaborative efforts by local governments (Kato & Okada, 2019; Okada et al., 2020; Takeshima et al., 2015).

However, the cost-effectiveness of these efforts and regional disparities in SPI efficiency remain underexplored.

To address this gap, this study evaluates SPI efficiency across local governments, adjusting for environmental and chance factors, and constructs productivity indices to analyze efficiency changes over time. Results indicate significant disparities in SPI efficiency, partly driven by environmental and chance factors, which amplify differences in managerial capability. Furthermore, while SPI productivity has improved over time, marginal gains have diminished. Productivity improvements have disproportionately relied on technological advancements, with relatively little focus on enhancing efficiency. These findings highlight the need to balance technological innovation with improved managerial practices to ensure sustainable and cost-effective SPI programs.

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Chapter 2: Does Expanding the Coverage of the Special Spousal Exemption in the Japanese Tax System Encourage Women to Work More?

2.1. Introduction

In response to the challenges posed by Japan's declining birthrate and aging population, the government has actively sought to promote female labor supply. However, the existing spousal tax exemption system, including the Spousal Exemption (SE) and Special Spousal Exemption (SSE), has been criticized for suppressing women's labor supply. Specifically, these exemptions allow a portion of taxable income to be deducted from the income of taxpayer based on the taxpayer's and his/her spouse's income levels. Consequently, some women have adjusted their working hours to keep their income within certain thresholds, enabling their husbands to qualify for these exemptions. Supporting this, data from the Overview of the General Survey on Part-time Workers (Ministry of Health, 2017) revealed that 22.5% of married women had adjusted their employment in the past year, with 44.7% doing so to meet the eligibility criteria for SE or SSE.

The 2017 reform of the SE and SSE was regarded as a significant step toward promoting female labor supply. During the 193rd Session of the National Diet, Minister of Finance Asō argued that the reform "eliminates the need for concerns regarding working hour adjustments" (Ministry of Finance, 2017). This was achieved by raising the income threshold for the SSE, broadening its applicability and allowing women to increase their labor supply without reducing their husband's exemptions.

Although the 2017 SSE reform was expected to encourage female labor supply, empirical evidence supporting its effectiveness remains scarce. Previous studies indicate that while the SE and SSE suppress women's labor supply, their abolition or partial reform would lead to only modest increases. For example, Akabayashi (2006), Takahashi (2010), and Bessho and Hayashi (2014) estimated that abolishing the SE and SSE entirely would increase labor supply by approximately 5.6%, 0.7%, and 1.6%, respectively. These findings suggest that the optimistic expectations of policymakers regarding the SSE reform's impact on female labor supply may not fully materialize.

Moreover, the 2017 SSE reform raised the income threshold for spouses in households with husbands whose total income not exceeding ¥12.2 million (employment income only), increasing disposable income for most eligible households. Conversely, the partial abolition of the SSE in 2003 prevented low-income spouses from claiming both SE and SSE, reducing disposable income for these households. Studies by Mori and Urakawa (2009) and Yokoyama (2018) indicated that the 2003 reform led to an increase in female labor supply. In contrast, the 2017 reform, which reversed the 2003 changes, might decrease female labor supply. Drawing on Yokoyama's (2018) theoretical model, this study hypothesizes that while the reform's effects on part-time female workers remain uncertain, it could reduce working hours for women in medium- to long-hour employment.

The 2017 reform of the SSE raised the income threshold for spouses in households where the taxpayer's total employment income did not exceed ¥12.2 million, thereby increasing disposable income for households eligible for the SSE. In contrast, the 2003 reform partially abolished the SSE, preventing low-income spouses from simultaneously claiming both the SE and the SSE, which led to a reduction in disposable income for these households. This earlier reform was estimated to have positively influenced female labor supply (Mori & Urakawa, 2009; Yokoyama, 2018). Accordingly, it seems reasonable to hypothesize that the 2017 reform, which effectively reversed the changes introduced in 2003, might reduce female labor supply. Referring to Yokoyama (2018) theoretical model, this study examines the substitution and income effects resulting from the SSE reform. It hypothesizes that while the reform's effects on short-hour workers' labor supply remain uncertain, it may prompt medium- to long-hour workers to reduce their working hours.

To test these hypotheses, this study uses data from 2015 to 2019 to estimate the policy effects of the 2017 SSE reform on women's working hours. The findings confirm that the reform increased average weekly working hours of women. This effect remained significant even after excluding women who were completely unemployed during the study period. Furthermore, distinguishing between regular and non-regular employment revealed that the reform had little impact on women in regular employment, while it increased working hours among women in non-regular employment. The positive effects were particularly evident among workers with short working hours, while women in medium- to long-hour employment experienced limited effects.

Theoretical analysis attributes the increase in working hours among short-hour workers to the negative substitution effect (consumption vs. leisure) outweighing the positive income effect triggered by the policy change. In contrast, for medium- to long-hour workers, the theoretical model predicts a reduction in working hours, which contradicts the empirical findings. This discrepancy may stem from the theoretical model's inability to account for labor-hour bunching effects or established work habits. Moreover, as Kondo and Fukai (2023)point out, even when a wife's income falls below the full exemption threshold and her husband qualifies for the maximum SSE, the resulting increase in the household's real income is only about ¥6,000. Therefore, the reform's income effect appears minimal, offering limited incentives for medium- to long-hour workers to reduce their working hours in favor of leisure.

Empirical analysis and the theoretical model suggest that, given the limited income effect of the SSE reform, shifting backward or removing the kink in the budget constraint could amplify the substitution effect, favoring consumption over leisure. This, in turn, may lead to an increase in labor supply, particularly among married women engaged in short-hour work.

This study is structured as follows. Section 2.2 provides an overview of the SE, SSE, and the 2017 reform. Section 2.3 introduces the theoretical model illustrating the effects of the SSE reform on female working hours. Section 2.4 outlines the construction of the empirical model. Section 2.5 presents the empirical findings, followed by a discussion in Section 2.6. The study concludes with final remarks in Section 2.7.

2.2. Institutional Background

2.2.1. Spousal Exemption and Special Spousal Exemption

In Japan, taxpayers with spouses who reside in the same household may claim the SE or SSE. These exemptions allow a portion of the taxpayer's income to become non-taxable, depending on both the income of the taxpayers and their spouses. However, both the SE and SSE cannot be simultaneously claimed by the husband and his wife.

For simplicity, this study assumes that the wife is the "spouse" affected by the SSE reform, while the husband is the "taxpayer."

The SE and SSE were introduced in 1961 and 1987, respectively. Table 1 presents the schedules for the SE and SSE before and after the 2017 tax reform. Following the partial abolition of the SSE in 2003, claiming both the SE and SSE simultaneously became unavailable. Consequently, spouses may now claim either the SE, the SSE, or neither—but not both.

In recent years, these exemptions have faced criticism for violating the principle of tax neutrality. Specifically, they are argued to suppress labor supply among spouses and incentivize them to limit their income below specific thresholds to remain eligible for the exemptions (Sakata & McKenzie, 2005; Takahashi, 2010). In response to these criticisms, Japan implemented reforms to the SE and SSE in 2017. The key changes were as follows:

1) Beginning in 2018, the exemption amounts for both the SE and SSE gradually decrease as the taxpayer's total income increases. Taxpayers with an employment income exceeding ¥12.2 million became ineligible for these exemptions, regardless of the spouse's income.
2) For the SSE, the income thresholds for the spouse were raised. Specifically, if all income for both the taxpayer and spouse is employment income and the

taxpayer's total income is less than ¥12.2 million, the full exemption of ¥380,000 was previously available only when the spouse's income was below ¥1.05 million. Beyond this threshold, the exemption decreased incrementally and phased out entirely at ¥1.41 million. After the reform, the full exemption became available for spouses earning up to ¥1.5 million. For spouses earning between ¥1.5 million and ¥2.01 million, the exemption gradually decreases, with eligibility for the SSE ending when the spouse's income exceeds ¥2.01 million.

Table 2-1. Schedules of the SE and SSE.

		Taxpayer's total amount of income								
		¥11,200,000 or less		¥11,200,001 to ¥11,700,000		¥11,700,001 to ¥12,200,000		Over ¥12,200,000		
		Before 2018	After 2018	Before 2018	After 2018	Before 2018	After 2018	Before 2018	After 2018	
Spouse's total amount of income	¥1,030,000 or less	¥380,000	¥380,000	¥380,000	¥260,000	¥380,000	¥130,000	¥380,000		SE
	Elderly qualified spouses (Those older than 70 years old)	¥480,000	¥480,000	¥480,000	¥320,000	¥480,000	¥160,000	¥480,000		
	¥1,030,001 to ¥1,050,000	¥380,000		¥380,000		¥380,000				
	¥1,050,001 to ¥1,100,000	¥360,000		¥360,000		¥360,000				
	¥1,100,001 to ¥1,150,000	¥310,000		¥310,000		¥310,000				
	¥1,150,001 to ¥1,200,000	¥260,000		¥260,000		¥260,000			¥0	
	¥1,200,001 to ¥1,250,000	¥210,000	¥380,000	¥210,000	¥260,000	¥210,000	¥130,000	¥0		SSE
	¥1,250,001 to ¥1,300,000	¥160,000		¥160,000		¥160,000				
	¥1,300,001 to ¥1,350,000	¥110,000		¥110,000		¥110,000				
	¥1,350,001 to ¥1,400,000	¥60,000		¥60,000		¥60,000				
	¥1,400,001 to ¥1,410,000	¥30,000		¥30,000		¥30,000				

	¥1,410,001 to ¥1,500,000		¥380,000		¥260,000		¥130,000			
	¥1,500,001 to ¥1,550,000		¥360,000		¥240,000		¥120,000			
	¥1,550,001 to ¥1,600,000		¥310,000		¥210,000		¥110,000			
	¥1,600,001 to ¥1,670,000		¥260,000		¥180,000		¥90,000			
	¥1,670,001 to ¥1,750,000		¥210,000		¥140,000		¥70,000			
	¥1,750,001 to ¥1,830,000	¥0	¥160,000	¥0	¥110,000	¥0	¥60,000			
	¥1,830,001 to ¥1,900,000		¥110,000		¥80,000		¥40,000			
	¥1,900,001 to ¥1,970,000		¥60,000		¥40,000		¥20,000			
	¥1,970,001 to ¥2,010,000		¥30,000		¥20,000		¥10,000			
	over ¥2010,000		¥0		¥0		¥0			

Note: this is the schedule where both the taxpayer and the spouse have only employment income

2.2.2. Other Income Thresholds

In addition to the SE and SSE, Japan's tax and social security systems include several benefits tied to income thresholds around ¥1 million (Kondo & Fukai, 2023; Oishi, 2003). For individuals with employment income and no additional income sources, the following measures apply, considering employment income deduction and standard deduction:

In many prefectures, individuals with a total income below ¥1 million are exempt from paying partial resident tax.

1) Individuals with a total income of ¥1.03 million or less are exempt from personal income taxes.
2) Part-time workers who are not students and meet certain criteria—such as regular weekly working hours, duration of employment, and the size of their workplace—become eligible for social insurance if their monthly wages exceed ¥88,000 (approximately ¥1.06 million annually).
3) Furthermore, if a spouse's annual earning is below 1.3 million yen, her insurance premiums will be collectively covered by the employee's pension plan or mutual aid association to which her husband belongs, thereby relieving her of the individual obligation to pay them.

2.3. Theoretical Model

Although the 2017 tax reform introduced changes to both the SE and the SSE, the reform of the SE primarily affected high-income households where the husband's annual income exceeds ¥11.2 million. Data from the Japanese Panel Study of Employment Dynamics (JPSED) (2016–2020) indicate that only 3.91% of married women belong to households where the husband earns more than ¥11.2 million annually. Moreover, for these high-income households, the change in household income due to the reform constitutes only a small fraction of their total income. Therefore, even if the SE reform influences the labor supply of women in these households, such effects are likely minimal. In summary, we assume that the changes in women's labor supply resulting from the 2017 reform are primarily attributable to the reform of the SSE.

This section analyzes the impact of the SSE reform on women's working hours. To simplify the analysis, it is assumed that the husband's total annual income is below ¥11.2 million and that neither the husband nor the wife has any income other than employment wages. The analysis is further based on the following assumptions:

1) The husband's income is exogenously determined, reflecting the typical dynamic in Japanese households where husbands are the primary earners, and the wife's employment status has minimal influence on the husband's income (Akabayashi, 2006; Kuroda & Yamamoto, 2008).

2) Leisure is a normal good.

3) The wife's wage rate is exogenously determined.

The household's utility maximization problem is formulated as follows:

$$max_{C,H}\ U(C,H) \tag{2.1}$$

$$s.t.\ C = wH - t_w(wH - EID - 38) + Z_h - t_h(Z_h - SEs)$$

$$SEs = \begin{cases} 38, & if\ wH \le K_1 \\ 38 - \lambda wH, & if\ K_1 \le wH \le K_2 \\ 0, & if\ wH > K_2 \end{cases}$$

$$t_w = 0\ if\ wH - EID - 38 < 0$$

Here, the utility function $U(C,H)$ adheres to standard assumptions: it is increasing in consumption C and satisfies the usual convexity properties with respect to working hours H. C represents household consumption, and H denotes the wife's working hours (labor supply). The parameter w is the wife's hourly wage, Z_h represents the husband's total income, and t_w and t_h are the effective tax rates applied to the wife's and husband's incomes, respectively. The term $(wH - EID - 38)$ corresponds to the wife's total taxable income, where EID denotes the employment income deduction, and the standard deduction is assumed to be ¥ 0.38 million.

The term SEs represents the amount of spousal exemptions (either SE or SSE), which depend on the wife's income, wH. The spousal exemptions function, SEs, is non-increasing with respect to wH. Specifically, SEs is phased out incrementally as the wife's income increases beyond certain thresholds. The parameter λ represents the marginal reduction rate of the spousal exemptions as the wife's labor income increases in the phase-out region of the SSE. While the actual phase-out process is incremental, for simplicity, we assume a constant reduction rate and smooth the SEs function. The thresholds K_1 and K_2 denote key income limits. K_1 is the maximum income level at which the husband qualifies for the full SSE, and K_2 is the income level beyond which the husband is ineligible for the SSE.

Then, the budget constraint can be rewritten as follows:

$$C = \begin{cases} wH(1-t_w) + t_w(EID+38) + Z_h(1-t_h) - 38 \cdot t_h, & if\ wH \leq K_1 \\ wH(1-\lambda t_h - t_w) + t_w(EID+38) + Z_h(1-t_h) - 38 \cdot t_h, & if\ K_1 \leq wH \leq K_2 \\ wH(1-t_w) + t_w(EID+38) + Z_h(1-t_h), & if\ wH > K_2 \end{cases} . \quad (2.2)$$

This reformulation reflects the segmented nature of the budget constraint based on the wife's income and the corresponding phase-out or inapplicability of the spousal exemptions.

2.3.1. Case of the Special Spousal Exemption as the Sole Threshold

This simplified analysis assumes that all kink points on the household budget line are caused solely by the SSE. As illustrated in Figure 2-1, prior to the reform, if the wife's annual income was ¥1.05 million or less, the husband could claim the full exemption amount of ¥0.38 million through either the SE or the SSE. If the wife's annual income exceeded ¥1.05 million but was below ¥1.41 million, the exemption amount gradually decreased as her income rose. Once the wife's annual income exceeded ¥1.41 million, the husband became ineligible for the SSE.

After the reform, the full exemption amount applied to cases where the wife's income was ¥1.5 million or less. For incomes between ¥1.5 million and ¥2.01 million, the deduction amount decreased incrementally, and for incomes exceeding ¥2.01 million, the husband became ineligible for the SSE. As a result, the kink points on the budget line shifted from $K_1 = 1.05$ and $K_2 = 1.41$ (pre-reform) to $K_1 = 1.50$ and $K_2 = 2.01$ (post-reform).

The analysis then examines the impact of the SSE reform on the wife's labor supply. As shown in Figure 2-1, the choice of a point on the budget line depends on how individuals value consumption relative to leisure (or labor supply), represented by their indifference curves.

1) For wives with incomes $wH < 1.05$ or $wH > 2.01$, the reform did not alter the budget line, leaving these individuals unaffected.
2) For wives with incomes $1.50 < wH < 2.01$, the budget line shift induces both a positive income effect and a positive substitution effect of consumption for labor supply, leading to a reduction in labor supply. Optimal labor hours shift from H_3^0 to H_3^1.
3) For wives with incomes $1.41 < wH < 1.50$, there is no substitution effect, but the positive income effect reduces labor supply, with optimal labor hours

shifting from H_2^0 to H_2^1.

4) For wives with incomes $1.05 < wH < 1.41$, the income effect is positive while the substitution effect of consumption for labor supply is negative, making the direction of labor supply changes ambiguous. Optimal labor hours shift from H_1^0 to H_1^1, but the relationship between H_1^0 and H_1^1 depends on the relative strengths of the substitution and income effects.

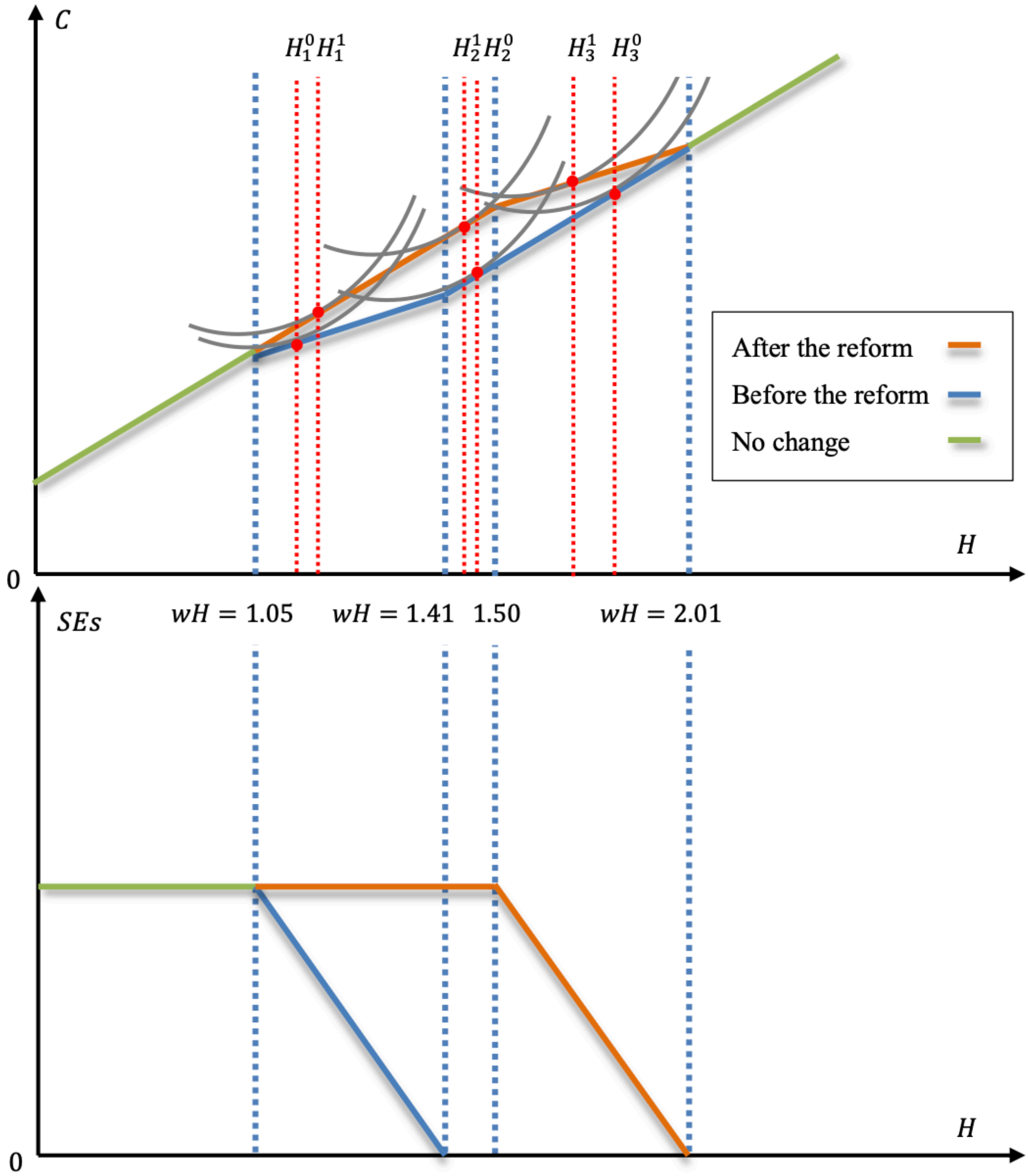

Figure 2-1. Household Budget Constraint and the Schedule of the SSE.

Note: Thresholds for resident tax, personal income tax, and national pension and health insurance premiums are not considered.

2.3.2 Effects of Other Thresholds

Figure 2-2 illustrates the household budget line, accounting for thresholds related to the wife's resident tax, personal income tax, national pension premium, and health insurance premium. In addition to the kinks caused by the SSE, the budget line features additional kinks at ¥1.0 million and ¥1.03 million. Furthermore, a notch appears around ¥1.3 million, reflecting a significant change in the marginal tax rate.

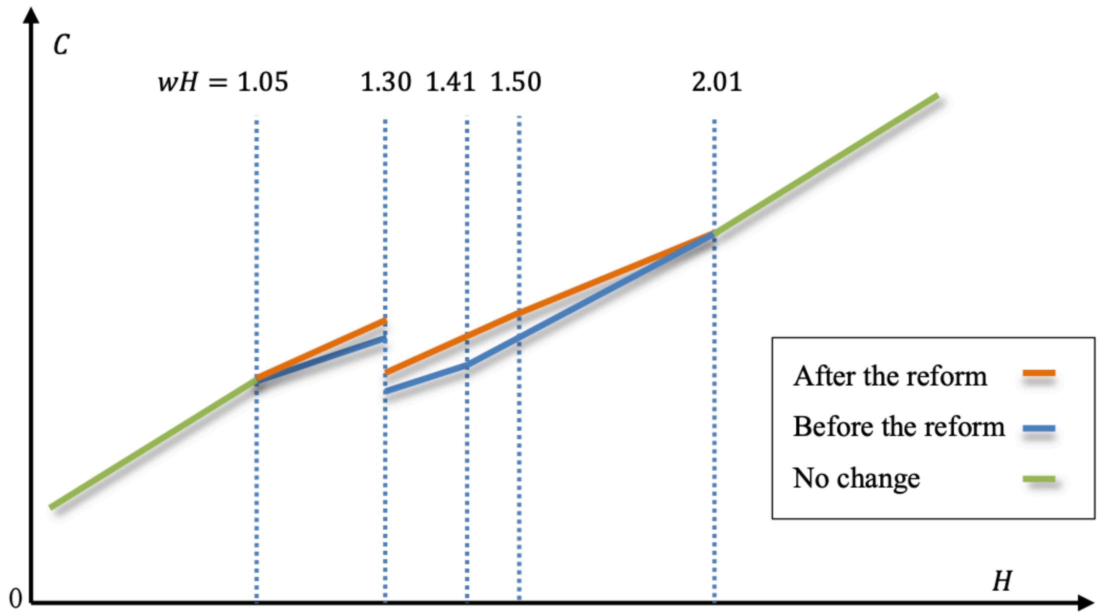

Figure 2-2. Household Budget Constraint.

Note:

1) Thresholds for resident tax, personal income tax, and national pension premium, and health insurance premium are considered.

2) The vertical lines for $wH = 1$ (resident tax) and $wH = 1.03$ (personal income tax) are not individually marked, as they are very close to the line for $wH = 1.05$, for better visibility.

Before and after the tax reform, the budget line at the kink points of ¥1.0 million and ¥1.03 million remains unchanged, suggesting that these thresholds have a limited effect on the SSE reform's impact. However, the notch at ¥1.3 million lies between the pre-reform upper threshold of ¥1.05 million for the full SSE and the post-reform threshold of ¥1.5 million. For spouses earning more than ¥1.3 million, an additional household burden of approximately ¥300,000 arises due to national pension and health insurance premiums (Kondo & Fukai, 2023).

Considering that even if the wife's earnings exceed the threshold for the full SSE, the actual increase in the household's tax burden is only approximately ¥6,000, we assume that for wives with incomes between ¥1.05 million and ¥1.41 million, the negative substitution effect induced by the reform outweighs the positive income effect, making them theoretically more inclined to increase their labor supply. However, for wives who had previously kept their employment income below ¥1.3 million, the policy effects of the SSE reform are insufficient to encourage them to surpass the ¥1.3 million income threshold.

For wives with incomes between ¥1.3 million and ¥1.41 million, rational workers, in the absence of frictional factors, would theoretically avoid supplying labor within this range. This is because reducing their labor income to below ¥1.3 million would simultaneously increase both their consumption and leisure. Nevertheless, due to the existence of frictional factors, some wives ultimately choose to supply labor within this range. Therefore, as long as these frictional factors persist and remain independent of elements associated with the SSE, it can be inferred that the policy effects of the SSE reform on wives earning between ¥1.3 million and ¥1.41 million are not influenced by the ¥1.3 million threshold.

2.4. Methodology

2.4.1. Synthetic Difference-In-Differences Estimation

In this empirical analysis, we employ a Difference-in-Differences (DID) model to estimate the average treatment effect of the Special Spousal Exemption (SSE) reform on women's working hours. The basic estimation model is specified as follows:

$$Hours_{it} = \beta_0 + \beta_1(Treat_i \times Post_t) + \beta_2 X_{it} + u_{it}. \qquad (2.3)$$

Here, $Treat_i = 1$ denotes the treatment group, and $Post_t = 1$ indicates observations from the post-reform period (2018–2019). The interaction term $(Treat_i \times Post_t)$ identifies treated individuals, and the coefficient β_1, representing the average treatment effect, is the primary focus of this analysis. $Hours_{it}$ measures the weekly average working hours of individual i in December of year t. X_{it} is a matrix of control variables capturing observable characteristics of individual i during period t, and u_{it} is the error term.

Considering the differences in workplace and household environments between married and unmarried women, married women may face additional barriers to increasing their working hours. As a result, the parallel trends assumption required for conventional DID estimation may not hold. To address this limitation, we adopt the Synthetic Difference-in-Differences (SDID) model proposed by Arkhangelsky et al. (2021). The SDID model assigns greater weights to control group individuals who closely resemble those in the treatment group (unit weighting) and places more emphasis on post-reform periods that are similar to pre-reform periods (time weighting). By relaxing the parallel trends assumption, the SDID approach enhances estimation accuracy, particularly in small samples, making it a robust alternative to traditional DID methods.

Giving a balanced panel with N sample individuals and T periods data, where the $1 \sim N_{co}$ individuals (control group) never experienced policy intervention, and the $N_{co} + 1 \sim N$ individuals (treated group) received policy intervention from period $T_{pre} + 1 \sim T$. Here, $N_{co} + N_{tr} = N$, and $T_{pre} + T_{post} = T$ hold. The indicator variable $(Treat_i \times Post_t)$ denotes whether an individual was subject to policy intervention, β_1 represents the policy effects. u_t and u_i represent the time-varying and unit-varying unobservable error, respectively. β_0 is the intercept, ω is the individual weight, λ is the time weight. The model is expressed as:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\beta, u_i, u_t, \tau}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} [Hours_{it}^{res} - \mu - \alpha_i - \beta_t - (Treat_i \times Post_t)\tau]^2 \, \widehat{\omega}_i^{sdid} \hat{\theta}_t^{sdid} \right\}, (2.4)$$

Where

$$Hours_{it}^{res} = Hours_{it} - \hat{\tau}X_{it}. \tag{2.5}$$

For control group individuals similar to the treated group, higher unit weights are assigned through the following optimization problem:

$$\left(\widehat{\omega}_0, \widehat{\omega}^{sdid}\right) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\arg\min}\, \ell_{unit}(\omega_0, \omega). \tag{2.6}$$

Here, $\ell_{unit}(\omega_0, \omega)$ is the unit-level loss function. Ω is the set of permissible unit weights. $\mathbb{R}$ denotes the positive real line. Where:

$$\ell_{unit}(\omega_0, \omega) = \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i\, Hours_{it}^{res} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Hours_{it}^{res} \right)^2 + \zeta^2 T_{pre} \|\omega\|_2^2, \tag{2.7}$$

$$\Omega = \left\{ \omega \in \mathbb{R}_+^N : \sum_{i=1}^{N_{co}} \omega_i = 1, \omega_i = N_{tr}^{-1}\ for\ all\ i = N_{co} + 1, \dots, N \right\}, \tag{2.8}$$

The regularization parameter ζ is computed as:

$$\zeta = \left(N_{tr} T_{post}\right)^{\frac{1}{4}} \hat{\sigma}. \tag{2.9}$$

Here,

$$\hat{\sigma}^2 = \frac{1}{N_{co}\left(T_{pre} - 1\right)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} (\Delta_{it} - \bar{\Delta})^2, \tag{2.10}$$

$$\Delta_{it} = Hours_{i(t+1)}^{res} - Hours_{it}^{res}, \tag{2.11}$$

$$\bar{\Delta} = \frac{1}{N_{co}\left(T_{pre} - 1\right)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} \Delta_{it}. \tag{2.12}$$

Similarly, for the time periods similar to pre-intervention after policy intervention, higher time weights are assigned through following optimization problem:

$$\left(\hat{\theta}_0, \hat{\theta}^{sdid}\right) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\arg\min}\, \ell_{time}(\omega_0, \omega). \tag{2.13}$$

Here, Λ is the set of permissible time weights. $\ell_{time}(\theta_0, \theta)$ and Λ are defined as:

$$\ell_{time}(\theta_0, \theta) = \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t \ Hours_{it}^{res} - \frac{1}{T_{post}} \sum_{i=T_{post}+1}^{T} Hours_{it}^{res} \right)^2 + \zeta^2 \, T_{pre} \|\omega\|_2^2, \quad (2.14)$$

$$\Lambda = \left\{ \theta \in \mathbb{R}_+^N : \sum_{t=1}^{T_{pre}} \theta_t = 1, \theta_t = T_{post}^{-1} \ for \ all \ t = T_{pre} + 1, \ldots, T \right\} \quad (2.15)$$

The SDID model requires a balanced panel, so sample dropouts during the longitudinal survey are excluded. To ensure robustness, a Two-Way Fixed Effects Difference-in-Differences (TWFE-DID) model, which does not require a balanced panel, is also employed following the frameworks of Yokoyama (2018) and Sakata and McKenzie (2005).

2.4.2. Quantile Difference-In-Differences Estimation

Following Yokoyama (2018), the Quantile Difference-in-Differences (QDID) method is employed to estimate the effects of the policy change across different quantiles of working hours. The basic estimation model is specified as follows:

$$Hours_{it}^{\tau} = \gamma_0^{\tau} + \gamma_1^{\tau}(Treat_i \times Post_t) + \gamma_2^{\tau} X_{it} + \varepsilon_{it}. \quad (2.16)$$

Here, τ denotes the τ_{th} quantile. Individual and time fixed effects are controlled for using the method proposed by Powell (2022), ensuring robust estimation across the quantiles of interest.

2.5. Results

2.5.1. Data and Preprocessing

The data used in this study is derived from JPSED, which tracks changes in respondents' employment, income, and working conditions. The first wave of the JPSED was conducted in January 2016, including a sample of 49,131 individuals from across Japan. During the 2016–2020 period, 42.2% of the respondents were successfully followed up. Respondents were instructed to answer based on their circumstances in December of the previous year, resulting in a one-year lag between data collection and publication. For instance, data labeled as 2016 reflects respondents' circumstances in 2015. To avoid confusion, the time series in this study is labeled using the year corresponding to the actual information.

This study uses data from 2016, 2017, 2018, and 2019. The 2016 and 2017 data represent the pre-reform period, while the 2018 and 2019 data reflect the post-reform period. Prior to analysis, several preprocessing steps were undertaken. Specifically, the sample was restricted to women aged 15–64 residing in Japan who were not students. To mitigate the influence of outliers, the top 0.1% of values for working hours were excluded.

Since only spouses as defined by the Civil Code are eligible for tax deductions, married women were designated as the treatment group and unmarried women as the control group (Sakata & McKenzie, 2005). To maintain consistency in the identification of treatment and control groups, samples with marital status changes before and after the reform were excluded.

The control variable matrix, X_{it}, includes the following variables: age, age squared, lagged household income, the number of preschool children, whether the respondent lives with parents, whether the respondent has a high school or higher education, and a dummy variable indicating whether the respondent qualified for Employee Pension Insurance (EPI) following the October 2016 expansion of social insurance coverage. Women's income is composed of three components: annual income from their primary job, annual income from secondary jobs, and annual income from non-work-related sources. Household income is defined as the average annual income of the woman and her husband; for unmarried women, household income is equal to their own income.

Following the October 2016 reform, EPI coverage was expanded to include part-time workers who met specific criteria: employment at companies with 501 or more employees, working 20 or more hours per week, earning at least ¥88,000 per month, and being employed for more than one year. This policy change may have influenced companies' employment strategies and workers' decisions regarding working hours. To capture the effect of the EPI reform on labor supply, a binary variable indicating whether a respondent met the EPI eligibility criteria after 2017 was included in the control variable matrix.

The details of the variables used in this analysis are provided in Table 2-2.

Table 2-2. Descriptive Statistics.

	Overall		Unmarried		Married	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Married dummy	.682	0.466	-	-	-	-
Working hours(hours/week)	24.241	18.811	36.188	14.731	18.664	17.889
Household's income (million yen/year)	331.365	218.168	298.452	234.192	346.728	208.507
Wife's income (million yen/year)	200.596	232.617	298.452	234.192	154.921	217.289
Husband's Income (million yen/year)	367.16	377.760	-	-	538.534	342.078
Age	47.932	10.289	44.377	11.035	49.591	9.476
Highschool dummy	.841	0.365	.828	0.378	.848	0.359
Living with parent dummy	.221	0.415	.457	0.498	.111	0.315
Number of preschool children	.139	0.451	.010	0.105	.199	0.531
EPI dummy	.072	0.259	.110	0.313	.054	0.227

2.5.2 Results of the SDID Model

After estimating the policy effects using the overall sample, several heterogeneity analyses were conducted. First, individuals who were never employed during the survey period—those who did not participate in the labor market at all—were excluded, and the policy effects were re-estimated using the remaining sample. This exclusion was based on the assumption that individuals outside the labor market would face greater challenges in adjusting their labor supply compared to those already participating.

Next, recognizing that non-regular workers, such as part-time employees, have more flexibility to adjust their working hours compared to regular employees, the policy effects were analyzed separately for women in regular and non-regular employment before the reform.

According to the SDID estimation results shown in Table 2-3, the reform of the SSE increased women's working hours by an average of 1.081 hours. When non-working women were excluded, the reform was shown to increase average working hours by 0.888 hours. Additionally, while the response among regular employees was not statistically significant, the weekly working hours of non-regular employees increased by an average of 0.934 hours as a result of the reform.

Since the SSE cannot be claimed by both spouses simultaneously, it was assumed that the household member with higher income is the "taxpayer," while the one with lower income is the "spouse." If the wife’s income is higher than the husband’s, the wife becomes the "taxpayer," and the husband is regarded as the "spouse." In such cases, the impact of the SSE reform would affect the labor supply of the husband rather than the wife. Therefore, women whose pre-reform income was higher than their husband’s were excluded, and the policy effects were re-estimated using the remaining sample. The results shown in the right-hand side of Table 2-3 indicate that the estimated coefficients for the full sample and employed women are 1.211 and 1.065, respectively, both significant at the 99% confidence level. Similarly, for women in non-regular employment, the policy effect coefficient was 1.024, which was also significant. However, for women in regular employment before the reform, the coefficient did not pass the hypothesis test.

The lower section of Table 2-3 presents the results of a robustness check using TWFE-DID. These results align with the SDID estimates and confirm that the policy effects of the reform are significant for the overall sample, employed women, and non-regularly employed women. Notably, the TWFE-DID estimated coefficients were larger than the SDID estimates, suggesting that the SDID results are relatively conservative and cautious.

Table 2-3. Results of SDID and TWFE-DID Model.

Estimation Method	Variables	Full Sample				Excluding Women Earning More than Their Husbands			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Overall	Excluding Fully Unemployed	Regular Employment	Non-Regular Employment	Overall	Excluding Fully Unemployed	Regular Employment	Non-Regular Employment
SDID	$Treat_i \times Post_t$	1.081***	0.888***	-0.021	0.934**	1.211***	1.065***	0.052	1.024***
		(3.974)	(2.602)	(-0.044)	(2.277)	(4.618)	(3.322)	(0.109)	(2.580)
	N	25,592	20,240	6,952	12,388	23,924	18,704	6,184	11,712
TWFE-DID	$Treat_i \times Post_t$	1.411***	1.403***	-0.281	1.820***	1.569***	1.600***	-0.312	1.946***
		(4.832)	(4.294)	(-0.666)	(3.760)	(5.089)	(4.619)	(-0.642)	(3.908)
	N	45,878	36,327	12,391	22,302	42,857	33,649	11,106	21,052
	R-squared	0.865	0.766	0.560	0.743	0.866	0.766	0.562	0.740

Note:

1) z-statistics and t-statistics: *** p<0.01, ** p<0.05, * p<0.1.

2) In the SDID estimation, the values in parentheses represent z-statistics, and the standard errors were estimated using the bootstrap method.

3) In the TWFE-DID estimation, the values in parentheses represent robust t-statistics, and the standard errors were estimated using a sandwich estimator clustered at the prefecture level.

2.5.3. Results of the Quantile DID

The variation in the coefficients of $Treat_i \times Post_t$ across the 1st to 99th quantiles was analyzed, and the values of these coefficients is presented in Figure 2-3. The red dots represent the estimated policy effect coefficients at each quantile, while the white dots denote the 95% confidence intervals. The upper figure is based on a sample that excludes individuals who were never employed during the survey period. The lower figure further excludes women whose income exceeded their husband's income.

From the figure, it can be observed that, irrespective of whether women with higher incomes than their husbands are excluded, the policy change positively affects working hours in the 10th to 30th percentiles, while its impact on working hours at or above the median is minimal. This suggests that the reform offers stronger labor supply incentives for women with shorter working hours.

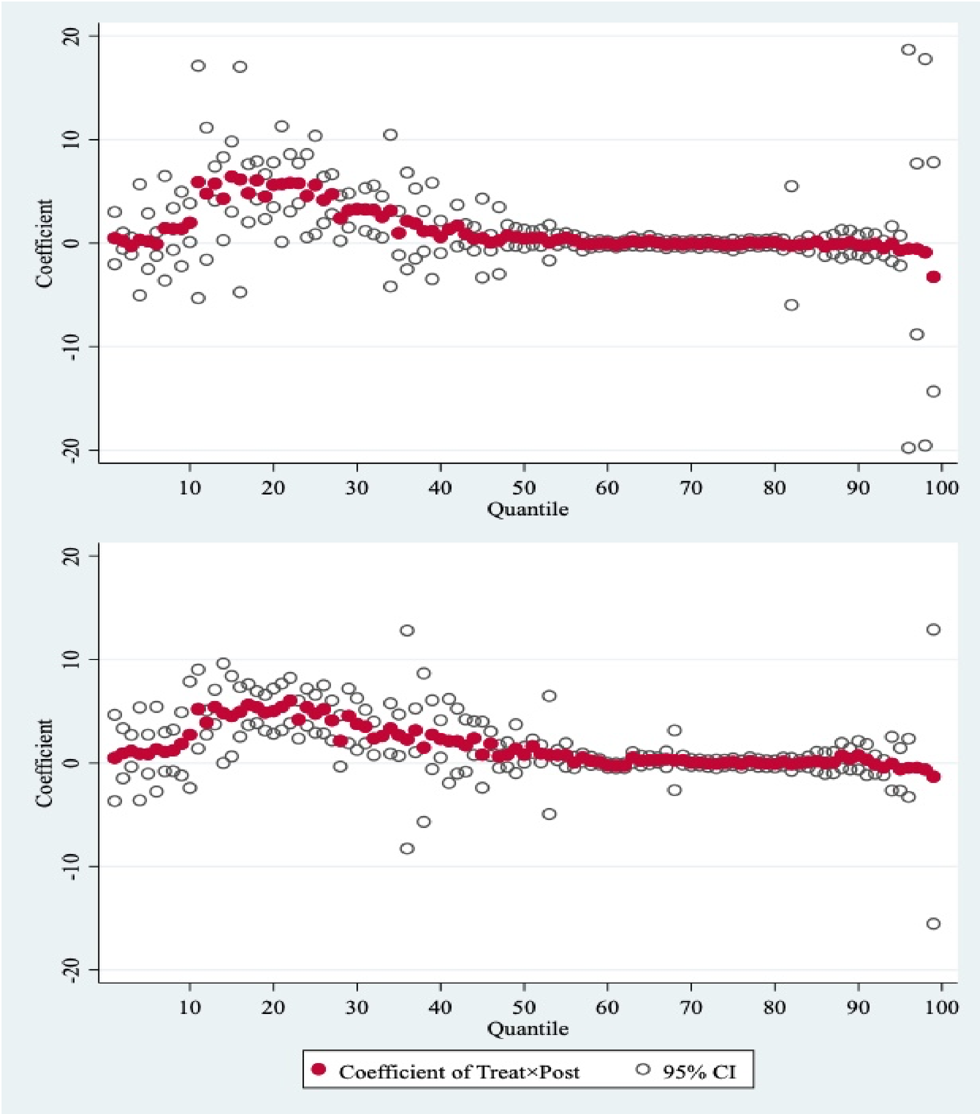

Figure 2-3. Estimated Coefficients and Confidence Intervals of the Quantile DID.

Note: The upper figure shows the estimation results after excluding women who were never employed during the survey period, while the lower figure shows the estimation results after excluding women who were unemployed during the survey period and those with higher incomes than their husbands.

2.6. Discussion

The estimation results indicate that the reform of the SSE led to an overall increase in women's labor supply. Notably, even after excluding individuals who were never employed during the survey period, the reform's positive effect on working hours was confirmed. However, the policy's impact exhibited heterogeneity, being particularly pronounced among non-regularly employed women, while no significant effects were observed for regularly employed women. Regarding the reform's impact on the distribution of working hours, the findings suggest that the labor supply incentives were concentrated primarily among women with shorter working hours, whereas the effects on women with medium- to long-working hours were relatively limited.

The empirical results partially align with the hypotheses proposed in the theoretical model. Assuming a fixed wage rate, the observed labor supply-promoting effect among women with shorter working hours (i.e., those earning between ¥1.05 million and ¥1.41 million before the reform) suggests that the positive income effect outweighed the negative substitution effect, leading to an increase in labor supply. Conversely, the theoretical model predicted that the reform would reduce the labor supply of women with medium- to long-working hours (i.e., those earning between ¥1.41 million and ¥2.01 million before the reform). However, the empirical analysis did not find significant evidence to support this hypothesis.

This discrepancy may be attributed to several factors. First, the theoretical model relies on substitution and income effects under a linear budget constraint and does not account for variations in bunching effects caused by changes in kink points. Second, persistent work habits may limit the extent to which policy changes influence labor supply decisions. Third, as noted by Kondo and Fukai (2023), even if a wife's income exceeds the deduction threshold, rendering the husband ineligible for the full SSE, the resulting increase in household tax burden is only approximately ¥6,000. This minimal income effect provides limited incentive for leisure, particularly for women with medium- to long-working hours.

2.7. Conclusion

The SE and SSE in Japan's tax system provide income tax exemptions to taxpayers whose spouses meet specific conditions and whose incomes fall below a designated threshold. To qualify for these exemptions, some wives may reduce their working hours to keep their income under the thresholds, potentially suppressing female labor supply. The 2017 SSE reform raised the income threshold for spouses, expanding eligibility and aiming to encourage greater labor supply. However, prior research on the policy effects of the 2017 SSE reform on women's labor supply remains limited.

To address this gap, this study estimated the impact of the SSE reform on women's working hours using the SDID model proposed by Arkhangelsky et al. (2021). The findings revealed that the reform increased women's working hours. Heterogeneity analysis confirmed that the positive effect of the reform remained significant even after excluding women who were unemployed during the study period. Notably, the reform led to a significant increase in the working hours of non-regularly employed women, while its effects on regularly employed women were not statistically significant. Furthermore, applying the panel QDID model proposed by Powell (2022), the study analyzed the policy effects across different quantiles of working hours. The results indicated that the SSE reform had particularly pronounced effects on women with shorter working hours, while its effects on women with medium- to long-working hours were relatively limited.

This study provides evidence that the 2017 SSE reform effectively promoted labor supply among women, particularly those engaged in short-time work. Based on theoretical model analysis, and assuming that the income effect of the full exemption under the SSE is limited, shifting backwards or eliminating the kink point of the full exemption could ensure that an increase in a wife's working hours does not reduce household consumption. Such adjustments to the tax system could further enhance labor supply among married women, especially those in part-time employment.

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Chapter 3: Socioeconomic Inequalities in Healthcare System Efficiency in Japan in COVID-19 Pandemic: An Analysis of the Moderating Role of Vaccination

3.1. Introduction

Approximately four years after the World Health Organization declared coronavirus disease 2019 (COVID-19) a Public Health Emergency of International Concern on January 30, 2020, Japan continues to grapple with the pandemic. The Japanese paradox, denoting limited fatalities despite relaxed restrictions (Inoue, 2020; Su et al., 2021), has garnered global attention in the fight against COVID-19. Despite Japan's avoidance of strict lockdowns, which are prevalent in many parts of Europe and the United States, it remarkably maintains the lowest mortality rate among all OECD countries (World Health Organization, 2023). In addition to the distinctive lifestyle habits of the Japanese (Yasuda et al., 2022) and effective government policies for disease prevention (Z. Chen et al., 2021; Takahashi & Kawachi, 2021; Tanaka et al., 2020), some studies attribute this phenomenon to the efficient allocation and coordination of medical resources by local authorities (Inoue, 2020; Karako et al., 2022a; Su et al., 2021).

During the pandemic, almost all Japanese prefectures faced challenges due to insufficient medical resources and healthcare system disruptions. Prefectures can request cooperation from hospitals, and while this request is essentially a directive for public hospitals, it remains a request for private hospitals. It is important to note that the majority of healthcare institutions in Japan are privately operated, constituting approximately 80% of the total facilities. Shin et al. (2020) found that in April and May of 2020, hospitals in Japan experienced reduced hospital charges compared to the same period in 2019. Notably, for hospitals admitting COVID-19 patients, longer hospitalization periods for these patients, including suspected cases, led to greater reductions in hospital charges. The average additional cost reduction per COVID-19 patient was estimated at 5.5 million Japanese yen. Therefore, from a hospital management perspective, admitting COVID-19 patients may not be financially advantageous.

To enhance the healthcare system's resilience to shocks and crises, it is crucial for the government to invest in the core functions of the healthcare system. Funding for public health services, encompassing infection prevention, control, surveillance, and information systems, is considered fundamental for ensuring preparedness and response to health emergencies (Kwon & Kim, 2021). Various policies have been implemented to secure hospital resources and improve the healthcare delivery system since April 2020. Two key initiatives have been introduced as economic support measures: an additional hospital charge for severely ill COVID-19 patients and the provision of subsidies (referred to as the "COVID-19 Emergency Comprehensive Support Grant - Medical Portion" or ECSG) for healthcare system development projects established by each prefecture (Ibuka, 2021). The ECSG, established in the First Supplementary Budget for the fiscal year 2020, is intended for prefectures and is designed to support expenses related to projects conducted by prefectures, municipalities, private organizations, and others deemed appropriate by the prefecture (Ministry of Health, Labor and Welfare, 2020). Therefore, the ECSG has given local governments discretionary authority to undertake urgently needed measures related to the response to COVID-19 to some extent.

In this study, local governments receive transfer payments, referred to as ECSG, from the central government to bolster and invest in the local healthcare system, aiming to mitigate the loss of human resources caused directly or indirectly by the COVID-19 pandemic. This input-output ratio is defined as the local healthcare system efficiency (LHSE) and is estimated using the Data Envelopment Analysis (DEA) with Slack-Based Measure (SBM). Additionally, in the context of DEA, the Decision-Making Units (DMUs) refer to the prefectures in this study.

The primary objective of this study is to investigate the moderating effect of vaccine usage on the socioeconomic inequalities in LHSE. The moderating effect refers to the influence of a third variable on the relationship between the first and second variables (Stevany et al., 2022). Then in the other word, this research is to examine the impact of vaccine introduction on the relationship between socioeconomic factors and LHSE. The motivation for this study arises from two key observations: firstly, during the COVID-19 pandemic, improvements in the LHSE exhibited socioeconomic inequality (Kocisova et al., 2019; Lupu & Tiganasu, 2022; Mourad et al., 2021). For example, Lupu and Tiganasu (2022) found that during the initial wave of the pandemic in Europe, factors like population density and the elderly population negatively impacted LHSE improvement.. Secondly, the COVID-19 vaccination proves to have reduced the inequality in mortality (Oroszi et al., 2022; Sa, 2022) and infection (Roel et al., 2022). The question at hand is whether the deployment of vaccines can reduce these socioeconomic inequalities in LHSE. A straightforward intuition is that vaccines, by increasing the recovery rate of COVID-19 patients per unit input, thus reducing the pressure on healthcare resources faced by DMUs with relatively unfavorable socioeconomic characteristics and endowments, may decrease the dependence of LHSE on socioeconomic factors. However, on the other hand, if DMUs do not timely adjust their healthcare system operational strategies post-vaccine deployment, there is a possibility of increased resource wastage, leading to a tighter connection between certain socioeconomic factors and LHSE.

The necessity of studying healthcare efficiency arises from the rapid changes in healthcare service supply and demand, especially in the context of limited fiscal resources (Andrews, 2021). Japan is one of the most rapidly aging countries globally, and it boasts a relatively efficient and comprehensive healthcare system. However, during the early stages of the pandemic, most prefectures experienced significant healthcare system disruptions due to the surge in cases, leading them to implement non-medical measures to control the virus's spread while ensuring the availability of healthcare resources, such as hospital beds and healthcare personnel (Ibuka, 2021). The introduction of vaccines is expected to bring regions closer to herd immunity by increasing antibody coverage, thereby reducing the pressure on both healthcare demand and supply. This alleviates the situation of supply shortages and eases the obstacles to healthcare system efficiency improvement posed by socioeconomic factors. However, as of mid-2023, there is still little research that can confirm this prediction.

This study examined whether vaccine administration could reduce the disparities in improving healthcare efficiency among regions with different healthcare demand environments. The results indicate that, on one hand, the introduction of vaccines did indeed overall reduce the regional disparities in LHSE. On the other hand, there's no evidence to support that vaccine introduction moderated socioeconomic inequalities in LHSE. Instead, the introduction of vaccines intensified the negative impact of high occupancy rates of secured beds for severe cases on LHSE improvements in regions with insufficient bed resources. It also established a positive correlation between the proportion of elderly individuals in the population and LHSE improvements in regions with sufficient bed resources during the initial phase of vaccine deployment. These findings prompt policymakers that in the post-pandemic era with continuously expanding vaccine coverage, efforts to enhance LHSE should particularly focus on ensuring the supply of medical resources required for the treatment of severe cases and the prevention of severe cases.

This study makes two significant contributions: first, it focuses on LHSE in Japan and provides a visual representation of LHSE spatial distribution during different stages of the COVID-19 pandemic. Second, it goes beyond the perspective in existing literature that mainly considers mortality rates and infection rates as outcome indicators, by studying the impact of vaccination on socioeconomic inequality within LHSE for the first time.

The remainder of this study is structured as follows: Section 3.2 gives a brief introduction to prior studies on the assessment of LHSE and the effects of COVID-19 vaccination; Section 3.3 and Section 3.4 describe the research design and methodology, respectively, providing a detailed description of model construction, variable selection, and so on. Section 3.5 presents the results of the empirical analysis, explains their implications, and discusses the limitations of this study. Finally, Section 3.6 draws conclusions.

3.2. Materials and Methods

This study aims to investigate the changes in socioeconomic inequalities in LHSE before and after the administration of COVID-19 vaccines in Japan's prefectures. To accomplish this objective, the research design process, as depicted in Figure 1, comprises (i) a cross-sectional evaluation of LHSE across prefectures for each wave using the SBM-DEA method, (ii) the identification of socioeconomic determinants of LHSE in each prefecture through the OLS and Tobit models, and (iii) the utilization of the Seemingly Unrelated Estimation (SUE) t-test to explore the moderating influence of vaccination on LHSE. The SBM-DEA is performed by MaxDEA X, and the OLS, Tobit regression, and the SUE t-test are carried out using Stata 16.

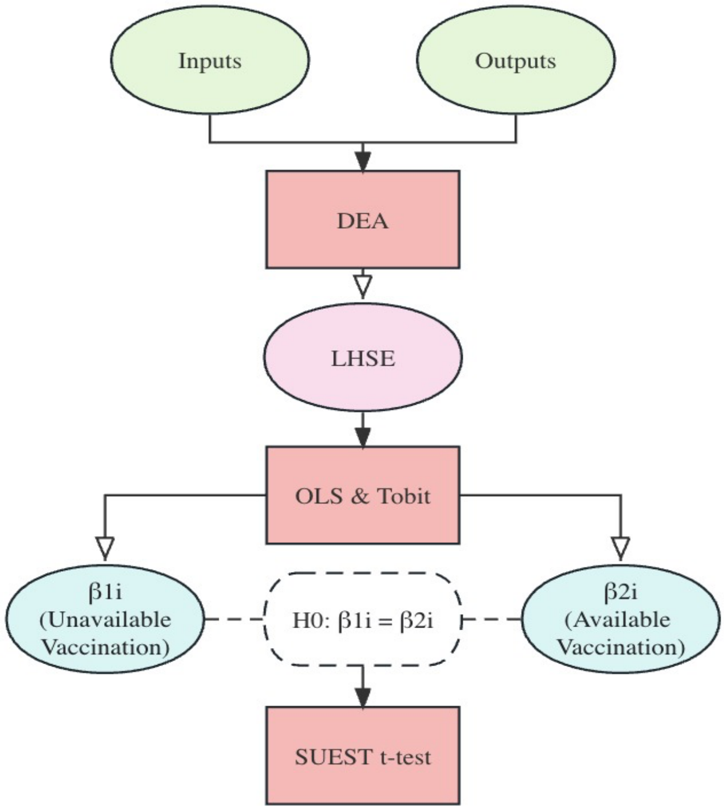

Figure 3-1. Research Flow.

It is essential to clarify that this study concentrates on the healthcare efficiency of COVID-19. Consequently, economic consequences stemming from the pandemic, such as economic downturns and increases in unemployment, are not taken into account. Additionally, the study's focus is on efficiency itself, rather than proposing methods to enhance it.

With reference to Paxson and Shen (2022)'s research, I define an epidemic wave as the temporal evolution of dead persons with an isolated peak and tails. The study period spans from the second wave to the fifth wave of the COVID-19 pandemic in Japan, from August 1, 2020, to December 31, 2021. As of April 2023, Japan has experienced eight significant COVID-19 outbreaks, each associated with a notable surge in new infections and fatalities. To ensure consistency, the study excludes the initial outbreak, considering that different regions were affected at varying times during the first outbreak. For instance, the first confirmed COVID-19 case in Japan was reported on January 16, 2020, while no confirmed cases were recorded in Iwate prefecture as of August 7, 2020 (Takahashi & Kawachi, 2021).

Furthermore, according to the Japan Variant Report (Gangavarapu et al., 2023; Tsueng et al., 2023), the Omicron variant became dominant in Japan in early 2022, replacing the Delta variant. Several studies suggested that the Omicron variant had high transmission (Brandal et al., 2021; Wang et al., 2022) but low pathogenicity (Halfmann et al., 2022; Shuai et al., 2022; Yang & Qi, 2022) compared to previous variants. This led to the Japanese government and local authorities adopting a coexistence strategy with COVID-19 and gradually easing containment measures (Kamegai & Hayakawa, 2022; Karako et al., 2022b). Consequently, the situation post-2022 significantly differs from the preceding circumstances. Therefore, data analysis is based exclusively on data up to December 31, 2021.

Due to the absence of official definitions for the start and end times of each pandemic wave in Japan, this study defines each wave of major COVID-19 outbreaks based on peaks and troughs in the trend of new deaths in the COVID-19 pandemic, and specific definitions are provided in Table 3-1. To simplify the analysis, the beginning and end of each wave are set on the first and last day of a month, respectively.

It is important to note that COVID-19 vaccination became available in Japan on

February 14, 2021. Initially, the vaccine was authorized only for use by healthcare workers and the elderly due to limited availability. According to statistics from the Prime Minister's Office of Japan (2022), the count of fully vaccinated individuals began on May 3, 2021, during the fourth wave of the pandemic.

Table 3-1. Time periods of each wave.

Wave	Time period	Availability of vaccination
wave 2	2020.8.1-2020.10.31	unavailable
wave 3	2020.11.1-2021.3.31	unavailable
wave 4	2021.4.1-2021.7.31	available
wave 5	2021.8.1-2021.12.31	available

3.2.1. Estimation of local healthcare system efficiency scores

- ***Data Enveloped Analysis***

The foundation of the DEA method dates back to Farrell (1957). Building upon Farrell's work, Charnes et al. (1979) introduced the DEA with constant returns to scale (CRS), known as the CCR model. Banker et al. (1984) extended the DEA to accommodate variable returns to scale (VRS), called the BCC model. Tone (2002) proposed the classic SBM model as an improvement upon the traditional DEA model. This model incorporates slack variables to enhance the assessment of input-output relationships, allowing for non-proportional measures in different inputs or outputs based on distinct proportions.

In this section, I employ the SBM-DEA model with CRS assumption to estimate the efficiency scores of healthcare systems, because the CRS assumption aligns with the goal of evaluating efficiency rather than resource management or cost control within healthcare units, which is consistent with the purpose of DEA in this study (Cantor & Poh, 2017). In SBM-DEA model, efficient DMUs are assigned a value of 1, while inefficient DMUs receive scores between 0 and 1.

Assuming there are *n* DMUs to be evaluated with *m* input indicators and *q* output indicators, we can determine the LHSE score of DMU_0, denoted as $\boldsymbol{\theta_0}$, using the following constraints:

$$
\begin{aligned}
&\theta_0 = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{r0}}} \\
&\text{s.t.} \sum_{j=1,\neq 0}^{n} x_{ij}\,\lambda_j + s_i^- = x_{i0} \\
&\sum_{j=1,\neq 0}^{n} y_{rj}\,\lambda_j - s_r^+ = y_{r0} \\
&\lambda_j, s_i^-, s_r^+ \geq 0 \\
&i = 1, \dots, m \\
&r = 1, \dots, q \\
&j = 1, \dots, n,
\end{aligned}
\tag{3.1}
$$

where x_{ij} and y_{rj} indicate the inputs and outputs of DMU_j, respectively; $\boldsymbol{\theta_0}$ is the target value; s_i^- and s_r^+ are the slack variable and the residual variable, indicating the amount of inputs that need to be reduced and the amount of outputs that need to be increased to reach the optimal allocation, respectively.

- ***Indicators of Input and Output***

This study employs several input indicators, including the primary projects of the ECSG, the number of PCR tests conducted, the number of COVID-19 vaccine shots administered, and the proportion of days the state of emergency declaration (DSE) was in effect relative to the total days of each pandemic wave. The primary activities of the ECSG encompass the projects for priority medical institution system development, hospital bed securing project and accommodation treatment facility securing, equipment improvement project of inpatient medical institution and priority medical, and facilities improvement project for returnees/contact persons outpatient facilities. Moreover, a cure rate is defined as the ratio of the number of new discharges or releases from isolation to the number of newly positive cases, serving as an output indicator. The specific definitions of each indicator are provided in Table 3-2.

Table 3-2. Notation and definition of inputs and outputs.

Indicator	Definition
Inputs	
ECSG_MIS	ECSG for priority medical institution system development project (Unit: thousand yen per 1,000,000 population)
ECSG_BA	ECSG for hospital bed securing project and accommodation treatment facility securing project (Unit: thousand yen per 1,000,000 population)
ECSG_FD	ECSG for equipment improvement project of inpatient medical institution and priority medical institution (Unit: thousand yen per 1,000,000 population)
ECSG_RCP	ECSG for facilities improvement project for returnees/contact persons outpatient facilities, etc. (Unit: thousand yen per 1,000,000 population)
PCR	Number of PCR tests in the period (Unit: cases per 1,000,000 population)
Vaccination	Number of COVID-19 vaccine doses1 in the period (Unit: cases per 100 population)
DSE	$\mathrm{DSE} = \frac{Number\ of\ days\ the\ DSE\ was\ in\ force}{Total\ number\ of\ days}$
Output	

[1] All does are counted except for the first does, considering that two doses of any WHO Emergency Use Listing vaccine to be a complete primary series.

Cure rate	$\text{Cure rate} = \frac{Number\ of\ the\ cases\ discharged\ from\ hospital\ or\ released\ from\ treatment}{Number\ of\ the\ newly\ confirmed\ cases\ with\ a\ 10{-}day\ lag}$

Note: The number of vaccine doses administered is based on data published by the Prime Minister of Japan and His Cabinet, while all other variables are derived from data provided by the Ministry of Health, Labor and Welfare of Japan.

It's important to note that the ECSG covers the primary labor-related, capital-related, and consumable resources-related inputs, which are considered as three main input categories in the framework of the DEA assessing the efficiency of primary care and healthcare organizations (Cantor & Poh, 2017). According to the Guidelines for the Fiscal Year 2020 COVID-19 Emergency Comprehensive Support Grant (Medical Portion) (Ministry of Health, Labor and Welfare, 2020), all pertaining to activities aimed at preventing the spread of infection and enhancing the medical infrastructure are eligible for payment under the ECSG, such as the expenses related to staff wages, compensation, rewards, and the purchase of supplies and necessary expenses.

In addition to the above-mentioned input indicators, I argue that the influence of quarantine policy and ad hoc measures should be considered. NHK of Japan (2020) reports that from April 7 to April 16, 2020 (the end of the first wave), the first DSE was issued throughout Japan, requesting residents of each prefecture to reduce their outings and gatherings, issuing restrictions on the operation of public facilities and places where people gather, and deploying medical resources in response to the expansion of the outbreak of COVID-19. The effective periods and coverage of each DSE are available in the supplementary material. During the research period of this study, the second, third, and fourth DSE were in effect. Despite some studies suggest that they were not as effective in strengthened the regional containment of the infection risk as the first DSE (Z. Chen et al., 2021; Kumagai, 2021; Okamoto, 2022), it's deemed important to consider their impact. Furthermore, the study acknowledges the changes in the social environment and the utility loss experienced by residents due to the implementation of these measures, which are considered as part of the cost of COVID-19 prevention and control. Therefore, including these aspects as input indicators is considered reasonable.

Regarding the output indicator, the recovery rate is expected to reflect the effectiveness of the healthcare system and medical institutions in the treatment and management of COVID-19 patients. The denominator of this indicator reflects the combined pressure on the healthcare system from the pandemic itself and the demographic characteristics of the region, and the numerator reflects the actual output of the healthcare system under this pressure. It's worth noting that in Japan, severe COVID-19 patients typically require hospitalization, while those with moderate and mild symptoms are usually advised to undergo accommodation-based or home-based care until they are no longer considered a public health threat. Consequently, the denominator, in fact, represents the total number of patients who achieved discharge or release from treatment during the given period. Furthermore, considering that the average number of days of hospitalization is approximately 10 (Osaka Prefectural Health and Medical Care Department, 2022), a lag of 10 days was set for the number of infected patients requiring inpatient care, since recovery at time point t should be attributed to infections and medical practices prior to time point t.

- ***Moderating Role of Vaccination: OLS model, Tobit model, and SUE t-test***

To explore the socioeconomic factors influencing LHSE scores assessed by the DEA, I employed Pooled Tobit models for cross-sectional data in my study. Additionally, I utilized the Pooled OLS model to ensure the robustness of my findings. Previous research often used Tobit models to identify the factors impacting LHSE scores, considering these scores as censored at 1 (Lupu & Tiganasu, 2022; Medarevic & Vukovic, 2021; Mourad et al., 2021). However, a study by McDonald (2009) demonstrated that LHSE scores are not generated through a censoring process, suggesting that Tobit estimates might be inconsistent. In contrast, OLS estimates are consistent. Therefore, to enhance the robustness of the research findings, I employ the OLS model in the main body of the article and subsequently conduct a robustness check using the Tobit model.

The LHSE determination models before and after vaccine introduction can be specified as follows:

For Model 1 (pre-vaccine introduction):

$$LHSE_{iw} = \alpha_0 + \alpha_1 X_{iw} + u_{iw}, w = 2, 3 \tag{3.2}$$

For Model 2 (post-vaccine introduction):

$$LHSE_{iw} = \beta_0 + \beta_1 X_{iw} + v_{iw}, w = 4, 5 \tag{3.3}$$

In these models, i represents different DMUs, w represents different waves of the pandemic, X_{iw} denotes socioeconomic factors. Considering the real-world scenario, it is assumed that $Cov(u_{iw}, v_{iw}) \neq 0$ implying a correlation between the error terms in the two models.

This research characterizes socioeconomic factors from multiple angles, including the role of local authorities (Guo et al., 2017; ZHOU, 2020), the stress on the healthcare system (Medarevic & Vukovic, 2021), demographic characteristics (Kocisova et al., 2019; Lupu & Tiganasu, 2022; Medarevic & Vukovic, 2021), and the viral characteristics. Specifically, the role of local authorities is represented by the financial index and the proportion of newly confirmed cases not linked to known transmission sources. A higher financial index indicates a surplus of financial resources. The unlinked proportion of newly confirmed cases reflects the local government's ability to control the spread of the virus. Healthcare system stress is gauged by the occupancy rates of total available beds and beds reserved for severe cases. Demographic characteristics, such as population density and the percentage of residents over 65 years old, are considered key factors affecting LHSE scores. Additionally, I examined the impact of SARS-CoV-2 and its variants on the LHSE score, focusing on the severity rate (indicative of pathogenicity) and the positivity rate (indicative of infectiousness). You can find detailed definitions for each variable in Table 3-3. Furthermore, regional dummies were included in the model to investigate spatial changes in LHSE scores.

Table 3-3. Notation and definition of explanatory variables and covariables for Tobit and OLS.

	Explanatory Variable		Additional Descriptions
Explanatory variables	Demographic characteristics	Population density	(Unit: people per 1000 m² of total area.)
		Old ratio	The proportion of the population aged 65 and older.
	Ability of local authority	Financial index	The average of the last three years of $\frac{\text{basic amount of financial receipt}}{\text{basic financial need}}$
		Unlinked proportion	Unlinked proportion of newly confirmed cases
	Healthcare system stress	Bed rate	Occupancy rate of total secured bed
		Bed rate for severe	Occupancy rate of secured bed for severe cases
	Characteristics of virus	Positive rate	Percentage of COVID-19 positives
		Severe rate	$\text{Severe rate} = \frac{\text{Number of severe cases}}{\text{Number of the newly confirmed cases with a } 10-\text{day lag}}$
	Region disparities	Hokkaido	Equals 1 for DMU = Hokkaido
		Tohoku	Equals 1 for DMU = Aomori, Iwate, Miyagi, Akita, Yamagata, and Fukushima
		Kanto	Equals 1 for DMU = Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa
		Chubu	Equals 1 for DMU = Niigata, Toyama, Ishikawa, Fukui, Yamanashi, Nagano, Gifu, Shizuoka, and Aichi
		Kinki	Equals 1 for DMU = Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama

	Kyushu	Equals 1 for DMU = Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima, and Okinawa

Note:

1) Considering that the current year's medical activity was actually more affected by the previous year's financial situation, I introduced a lag period to financial index. I.e., assuming that LHSE in year t is affected by the financial index in year t-1.

2) The population density, old ratio, and financial index are only available for annual data, so the data of these three variables for wave3 is defined across years as the weighted average of the 2019 data and 2020 data.

3) Population density, the proportion of the population aged 65 and older, and financial index data are sourced from the Statistics Bureau of Japan, while all other data is derived from data provided by the Ministry of Health, Labor and Welfare of Japan.

I confirm the moderating effect of the vaccine by examining the differences in estimated coefficients between Model 1 and Model 2. For this purpose, I propose the null hypothesis $H_0: \alpha_1 = \beta_1$. Due to the assumption that $Cov(u_{iw}, v_{iw}) \neq 0$, the traditional Hausman test is not applicable. Therefore, I am using the SUE t-test as an alternative. The SUE t-test offered several advantages compared to the Houseman test. First, it allowed us to estimate the covariance of coefficients and the entire model. Second, it facilitated the estimation of the covariance matrix across models and the testing of whether common coefficients were significantly equal or not (Ali & Irfan, 2020). It's important to note that for the SUE command in Stata 16, the estimator should be initially estimated without cluster or robust options, although cluster and robust options are permissible when SUE returns results.

In addition, apart from the analysis based on all DMUs, I conducted a heterogeneity analysis based on the per capita bed capacity of each DMU. I used the average per capita bed capacity of all DMUs as a benchmark, identifying DMUs with lower per capita bed capacity as those with insufficient bed resources and DMUs with higher per capita bed capacity as those with sufficient bed resources. Then, I separately conducted regressions and analyzed the moderating effect of vaccines on both DMUs with insufficient bed resources and those with sufficient bed resources. It's well-known that there is significant variation in per capita bed capacity among Japan's prefectures. With increasing infection numbers, the issue of insufficient bed capacity in local hospitals has at times pushed the healthcare system to the brink of collapse. For example, during the fourth wave of the pandemic, Okinawa Prefecture had bed utilization rates of 67.84% and intensive care bed utilization rates of 66.33%. Given that a higher per capita bed capacity may provide local healthcare institutions with more resilience in the face of medical resource shortages caused by a major COVID-19 outbreak, as a supplement to the analysis of all DMUs, I conducted a heterogeneous analysis of DMUs with both higher and lower per capita bed capacities.

3.3. Results

3.3.1. The Efficiency of Healthcare System

Table 3-4 presents descriptive statistics for the input and output indicators. It is important to note that the number of vaccine doses administered is not included in the input indicators for LHSE estimates during the second and third waves of the pandemic. Additionally, since no region declared a DSG during the second wave of the pandemic, the input indicators for the LHSE estimates of the second wave do not include the DSG input. Moreover, Japan is typically considered to have 47 prefectures, i.e., DMUs. However, due to the unavailability of some ECSG data for a portion of Gunma Prefecture, the actual sample includes only 46 prefectures.

Table 3-4. Descriptive statistics of inputs and outputs.

	wave 2			wave 3		
	N	Mean	SD	N	Mean	SD
ECSG_MIS	46	938107.380	1104064.470	46	6541031.200	2659120.537
ECSG_BA	46	397081.650	305367.742	46	1529229.800	997050.751
ECSG_FD	46	98820.097	340399.623	46	755761.960	341609.188
ECSG_RCP	46	9693.825	20513.025	46	111151.830	81244.769
DSE	-	-	-	46	0.083	0.158
PCR	46	9828.920	6628.207	46	40900.036	19461.983
Vaccine	-	-	-	-	-	-

	wave 4			wave 5		
	N	Mean	SD	N	Mean	SD
ECSG_MIS	46	726842.500	1117745.258	46	5947831.100	3041608.713
ECSG_BA	46	344237.890	290138.578	46	1528321.400	947704.983
ECSG_FD	46	39690.806	216108.418	46	305048.660	356603.132
ECSG_RCP	46	1238.880	5184.250	46	21755.318	29455.925
DSE	46	0.089	0.179	46	0.122	0.151
PCR	46	58762.116	28634.123	46	63814.889	31419.429
Vaccine	46	30.134	2.958	46	45.063	3.455

Table 3-5 reports the LHSE scores estimated by the DEA, with DMUs considered efficient receiving a score of 1 and marked in green. It's essential to understand that DMUs encounter different external conditions and possess varying technological capabilities during different stages of the pandemic (different waves). Therefore, the LHSE estimates for each wave of the pandemic are cross-sectional. In theory, the absolute values of LHSE for different DMUs in different waves are not directly comparable. However, based on the technical efficiency measurement method introduced by Farrell (1957), the LHSE estimated using the DEA method represents the gap between the evaluated DMU and perfectly efficient DMUs. For instance, in the 4th and 5th waves of the pandemic, Hokkaido has LHSE values of 0.859 and 0.842, respectively. I cannot conclude that Hokkaido's technical efficiency was higher in the 4th wave compared to the 5th wave, as I cannot assume that the external environment and technological capabilities were identical in both waves. However, it is evident that in the 4th wave, Hokkaido had a smaller gap with DMUs considered efficient compared to the 5th wave. Furthermore, the arithmetic mean of LHSE for each wave of the pandemic does not represent the average level of technical efficiency across DMUs in the time series. Instead, it signifies the overall gap between the inefficient DMUs and the efficient DMU within the same wave.

Table 3-5. Healthcare efficiency scores of the DMUs.

DMUs	Unavailable Vaccination		Available Vaccination	
	wave 2	wave 3	wave 4	wave 5
Hokkaido	0.248	0.319	0.392	0.334
Aomori	0.355	0.760	1.000	0.562
Iwate	1.000	0.505	1.000	1.000
Miyagi	0.315	1.000	0.785	0.369
Akita	0.443	1.000	1.000	0.654
Yamagata	0.175	1.000	0.704	0.919
Fukushima	0.207	0.380	0.675	0.455
Ibaraki	0.078	0.500	0.829	0.559
Tochigi	0.293	0.816	0.766	0.720
Saitama	0.118	0.460	0.584	0.657
Chiba	0.113	0.584	1.000	0.583
Tokyo	0.041	1.000	0.303	0.329
Kanagawa	0.104	0.286	1.000	0.511

Niigata	0.313	1.000	1.000	1.000
Toyama	0.159	0.544	0.847	0.591
Ishikawa	0.091	0.390	0.598	0.539
Fukui	0.227	1.000	0.838	1.000
Yamanashi	0.133	0.827	0.833	1.000
Nagano	1.000	0.549	0.827	0.735
Gifu	0.116	1.000	0.685	0.634
Shizuoka	0.570	0.709	1.000	1.000
Aichi	0.400	0.509	1.000	1.000
Mie	0.216	0.719	1.000	0.395
Shiga	0.276	1.000	1.000	1.000
Kyoto	0.097	0.388	0.574	0.408
Osaka	0.077	0.328	0.194	0.392
Hyogo	0.317	0.366	0.299	0.562
Nara	0.152	0.385	0.802	1.000
Wakayama	0.228	0.685	0.800	0.642
Tottori	0.118	1.000	0.316	1.000
Shimane	0.172	1.000	1.000	1.000
Okayama	0.115	0.658	0.683	0.342
Hiroshima	0.492	1.000	0.458	0.313
Yamaguchi	0.335	0.574	1.000	1.000
Tokushima	1.000	0.664	0.766	1.000
Kagawa	0.289	0.535	0.695	1.000
Ehime	1.000	1.000	1.000	1.000
Kochi	0.612	0.750	1.000	1.000
Fukuoka	0.264	0.362	0.471	1.000
Saga	0.384	0.626	0.945	0.350
Nagasaki	0.254	0.435	0.595	0.711
Kumamoto	0.360	0.439	1.000	1.000
Oita	0.142	0.677	0.638	0.778
Miyazaki	0.790	0.675	0.852	1.000
Kagoshima	0.371	0.804	0.868	0.611

Okinawa	0.134	0.419	0.334	0.251
Proportion of efficient DMUs	0.087	0.261	0.326	0.391
Mean	0.319	0.666	0.760	0.715

Concerning the distribution of LHSE scores across prefectures, several noteworthy findings have emerged. Firstly, during the 2nd to 5th waves of the pandemic, the lowest LHSE values were 0.041, 0.286, 0.194, and 0.251, respectively observed in Tokyo, Kanagawa, Osaka, and Okinawa. Secondly, only one DMU, Ehime Prefecture, has managed to maintain perfect efficiency across all four waves of the pandemic, indicating that most DMUs do not possess inherent advantages that make it easy for them to consistently achieve efficiency. Thirdly, overall, the proportion of efficient DMUs increased steadily from 8.7% during the 2nd wave of the pandemic to 39.1% in the 5th wave. Meanwhile, the average LHSE rose from 0.319 in the second wave to 0.760 in the fourth wave, then experienced a slight decline to 0.715 during the 5th wave of the pandemic.

3.3.2. The Moderating Role of Vaccination

Table 3-6 provides the descriptive statistics for the socioeconomic factors influencing LHSE. In Table 3-7, these factors are used as independent variables in an OLS regression, with LHSE estimated through DEA as the dependent variable. This identifies the contributions of various socioeconomic factors to LHSE before and after vaccine deployment.

Table 3-8 presents SUE t-tests based on the estimated coefficients from the pre-and post-vaccine deployment. These tests are used to demonstrate the moderating effect of vaccines on the socioeconomic inequality of LHSE. In order to present the analysis results more clearly, I have consolidated the simplified outcomes from Table 3-7 and Table 3-8 into Table 3-9. Furthermore, for a robustness test, Tobit model were used instead of OLS models, and the same procedures were conducted. The results are provided in the supplementary material. By contrasting the outcomes of the main regression and robustness tests, I observed consistency regarding the moderating effect of vaccinations on the association between socioeconomic factors, regional disparities, and the distribution of LHSE. This indicates a relative robustness in the findings of this study.

Table 3-6. Descriptive statistics of explanatory variables for Tobit and OLS.

	wave 2			wave 3		
	N	Mean	SD	N	Mean	SD
Population density	46	.665	1.235	46	.663	1.234
Old ratio	46	.307	0.032	46	.262	0.058
Financial index	46	.519	0.193	46	.520	0.190
Unlinked proportion	46	.328	0.160	46	.320	0.123
Bed rate	46	.123	0.107	46	.240	0.133
Bed rate for severe	46	.053	0.078	46	.131	0.132
Positive rate	46	.028	0.017	46	.042	0.021
Severe rate	46	.374	0.749	46	.300	0.160
	wave 4			wave 5		
	N	Mean	SD	N	Mean	SD
Population density	46	.662	1.233	46	.662	1.233
Old ratio	46	.311	0.032	46	.311	0.032
Financial index	46	.521	0.189	46	.521	0.189
Unlinked proportion	46	.373	0.128	46	.367	0.146
Bed rate	46	.285	0.111	46	.183	0.054
Bed rate for severe	46	.148	0.136	46	.098	0.089
Positive rate	46	.043	0.022	46	.070	0.038
Severe rate	46	.250	0.233	46	.100	0.068

Table 3-7. Results of Pooled OLS regression.

VARIABLES	All DMUs			DMUs with insufficient bed resources			DMUs with sufficient bed resources		
	Full sample	Unavailable vaccination	Available vaccination	Full sample	Unavailable vaccination	Available vaccination	Full sample	Unavailable vaccination	Available vaccination
Population density	0.008	-0.014	-0.013	-0.002	-0.010	-0.033	0.308	0.161	0.692**
	(0.284)	(-0.306)	(-0.394)	(-0.060)	(-0.198)	(-0.960)	(1.264)	(0.496)	(2.236)
Old ratio	-0.037	-1.647**	2.347	-1.695	-0.780	0.665	0.029	-1.620**	7.612*
	(-0.070)	(-2.363)	(1.470)	(-1.162)	(-0.363)	(0.211)	(0.049)	(-2.135)	(2.025)
Financial index	-0.481**	-0.403	0.143	-0.797**	-0.741	0.274	-1.426**	-0.648	-0.345
	(-2.052)	(-1.161)	(0.471)	(-2.276)	(-1.292)	(0.508)	(-2.583)	(-0.915)	(-0.463)
Unlinked proportion	-0.386*	-0.558**	-0.348	-0.360	-0.466	-0.261	-0.297	-0.278	-0.776
	(-1.868)	(-1.993)	(-1.174)	(-1.376)	(-1.212)	(-0.731)	(-0.843)	(-0.677)	(-1.388)
Bed rate	0.993***	-0.002	0.850*	1.229***	0.532	1.897**	0.073	-0.189	-0.862
	(3.028)	(-0.004)	(1.813)	(2.884)	(0.673)	(2.220)	(0.132)	(-0.200)	(-1.271)
Bed rate for severe	-0.898**	0.453	-1.198**	-0.425	0.762	-1.812**	0.666	-1.359	1.293
	(-2.228)	(0.688)	(-2.515)	(-0.836)	(0.908)	(-2.471)	(0.600)	(-0.679)	(1.034)
Positive rate	3.756***	2.884	2.244**	3.323***	2.523	1.232	5.116***	3.291	1.785
	(4.491)	(1.249)	(2.421)	(3.288)	(0.734)	(0.997)	(3.486)	(0.983)	(1.107)

Severe rate	-0.088*	-0.107*	0.119	-0.113**	-0.109*	-0.403	0.321	0.824**	0.335
	(-1.698)	(-1.845)	(0.805)	(-2.109)	(-1.747)	(-0.760)	(1.588)	(2.285)	(1.354)
Tohoku	0.056	0.142	0.006	0.048	-0.187	0.301*	0.144	0.400**	-0.295
	(0.765)	(1.260)	(0.074)	(0.305)	(-0.700)	(1.748)	(0.987)	(2.069)	(-1.365)
Kanto	0.004	-0.024	0.117	-0.023	-0.330	0.364**	-	-	-
	(0.046)	(-0.168)	(1.092)	(-0.150)	(-1.259)	(2.177)			
Chubu	0.056	0.077	0.093	0.113	-0.165	0.356**	-0.100	-0.232	0.017
	(0.816)	(0.722)	(1.169)	(0.748)	(-0.647)	(2.141)	(-0.851)	(-1.392)	(0.117)
Kinki	-0.176**	-0.161	-0.067	-0.257	-0.532**	0.230	-0.373*	-0.553**	-0.414
	(-2.332)	(-1.436)	(-0.719)	(-1.621)	(-2.047)	(1.211)	(-1.924)	(-2.271)	(-1.502)
Kyushu	-0.170**	-0.225**	-0.015	-0.945***	-1.154***	0.094	-0.110	-0.027	-0.010
	(-2.511)	(-2.279)	(-0.190)	(-3.386)	(-2.769)	(0.239)	(-1.475)	(-0.264)	(-0.100)
Constant	0.783***	1.289***	-0.152	1.404**	1.386*	-0.033	0.961***	1.063***	-1.580
	(3.790)	(5.037)	(-0.238)	(2.548)	(1.832)	(-0.025)	(3.372)	(2.896)	(-1.117)
R-squared	0.266	0.287	0.347	0.422	0.426	0.592	0.319	0.532	0.411
Observations	184	92	92	104	52	52	80	40	40
Number of DMU	46	46	46	26	26	26	20	20	20

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3-8. Results of SUE t-test based on OLS regression.

VARIABLES	All DMUs			DMUs with insufficient bed resources			DMUs with sufficient bed resources		
	Diff.	Chi2	Prob>chi2	Diff.	Chi2	Prob>chi2	Diff.	Chi2	Prob>chi2
Population density	0.001	0.00	0.980	-0.023	0.28	0.599	0.531	2.49	0.114
Old ratio	3.994**	6.25	0.012	1.445	0.31	0.580	9.232**	5.38	0.020
Financial index	0.546	1.67	0.196	1.015	2.49	0.114	0.303	0.10	0.758
Unlinked proportion	0.210	0.30	0.584	0.205	0.17	0.684	-0.498	0.87	0.351
Bed rate	0.852	1.47	0.226	1.365	2.16	0.142	-0.673	0.51	0.474
Bed rate for severe	-1.651*	3.51	0.061	-2.574**	6.04	0.014	2.652*	2.81	0.094
Positive rate	-0.640	0.09	0.764	-1.291	0.14	0.705	-1.506	0.24	0.627
Severe rate	0.226*	3.03	0.082	-0.294	0.56	0.456	-0.489	1.60	0.207
Tohoku	-0.136	0.95	0.329	0.488***	7.66	0.006	-0.695***	7.64	0.006
Kanto	0.141	1.00	0.317	0.694***	21.14	0.000	Omitted	Omitted	Omitted
Chubu	0.016	0.01	0.903	0.521***	10.53	0.001	0.249	1.61	0.205
Kinki	0.094	0.49	0.484	0.762***	16.86	0.000	0.139	0.30	0.584
Kyushu	0.210*	3.50	0.061	1.248***	10.88	0.001	0.017	0.02	0.879

Note:

1) "Coef." reported in this table is estimated based on standard errors

2) The SUE t-test statistics (Chi2) are estimated based on robust standard errors, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3) "Diff." indicates the difference in value between Coef. with vaccination and Coef. without vaccination.

Table 3-9. Summary of Pooled OLS and SUE t-test results.

	Explanatory variables	All DMUs			DMUs with insufficient bed resources			DMUs with sufficient bed resources		
		UV	AV	Changes in magnitude	UV	AV	Changes in magnitude	UV	AV	Changes in magnitude
Demographic characteristics	Population density	-	-	↓	-	-	↑	+	+**	↑
	Old ratio	-**	+	↑**	-	+	↓	-**	+*	↑**
Ability of local authority	Financial index	-	+	↓	-	+	↓	-	-	↓
	Unlinked proportion	-**	-	↓	-	-	↓	-	-	↑
Healthcare system stress	Bed rate	-	+*	↑	+	+**	↑	-	-	↑
	Bed rate for severe	+	-**	↑*	+	-**	↑**	-	+	↓*
Characteristics of virus	Positive rate	+	+**	↓	+	+	↓	+	+	↓
	Severe rate	-*	+	↑*	-*	-	↑	+**	+	↓
Region disparities	Tohoku	+	+	↓	-	+*	↑***	+**	-	↓***
	Kanto	-	+	↑	-	+**	↑***	Omitted	Omitted	Omitted
	Chubu	+	+	↑	-	+**	↑***	-	+	↓
	Kinki	-	-	↓	-**	+	↓***	-**	-	↓
	Kyushu	-**	-	↓*	-***	+	↓***	-	-	↓

Note:

(1) "UV" and "AV" respectively represent “Unavailable Vaccination” and “Available Vaccination”.

(2) "+" and "-" indicate the positive and negative signs of the estimated coefficients for each variable in the Pooled OLS regression. Subsequent "*" aligns with Table 3-7.

(3) "↑" and "↓" signify an increase or decrease in the absolute value of the estimated coefficients for each variable in the Pooled OLS regression following the introduction of vaccine deployment. Subsequent "*" corresponds to

- ***Demographic characteristics***

I utilized population density and the proportion of population aged 65 and older to depict the demographic impact on LHSE. Initially, the impact of population density on LHSE was found to be significant only for DMUs with sufficient bed resources post-vaccination, with higher-density DMUs exhibiting higher LHSE scores. Secondly, concerning the proportion of population aged 65 and older, before vaccine deployment, a higher proportion led to lower LHSE. However, vaccination shifted this influence from negative to positive, although this effect couldn't be statistically proven. Nevertheless, the moderating effect of vaccination on the relationship between the proportion of individuals aged 65 and older and LHSE was significant. Additionally, in regions with sufficient bed resources, the moderating effect of vaccines was more pronounced. Furthermore, even after vaccination, the positive correlation between the proportion of population aged 65 and older and LHSE remained statistically significant at a 90% confidence level in DMUs with sufficient bed resources.

- ***Ability of local authority***

Overall, the financial index of DMUs was negatively associated with LHSE, although this relationship wasn't individually confirmed in the pre- and post-vaccination datasets. Moreover, the unlinked proportion was negatively correlated with LHSE pre-vaccination. The vaccination's impact on the moderating effect of local authorities' ability on LHSE was not significant, regardless of the full sample, DMUs with abundant bed resources, or those with scarce resources.

- ***Healthcare system stress***

Overall, the overall bed occupancy rate is positively correlated with LHSE, while the intensive care bed occupancy rate is negatively correlated. For DMUs with insufficient bed resources, post-vaccination, LHSE became more dependent on both these occupancy rates. However, the vaccine's usage doesn't significantly moderate the relationship between total bed occupancy rate and LHSE. Nevertheless, the vaccine's usage significantly strengthened the contribution of intensive care bed occupancy rates to LHSE for DMUs with limited bed resources, amplifying it by a factor of 2.37 and transforming their positive correlation into a negative one.

- ***Characteristics of virus***

Regardless of whether DMUs had sufficient or insufficient bed resources, there was a significant positive correlation between Positive rate and LHSE. Although severe rate was generally negatively correlated with LHSE, in regions with more available bed resources, higher severe case rates led to higher LHSE pre-vaccination. Additionally, there was no evidence indicating that the advent of vaccines regulated the relationship between positive rate, severe rate, and LHSE.

- ***Region disparities***

Based on the estimated coefficients of regional dummy variables, the introduction of vaccines primarily regulated regional disparities in LHSE in areas with insufficient bed resources. Specifically, for DMUs with scarce bed resources, the vaccine's moderating effect on regional disparities was significant. After vaccine deployment, the

Tohoku, Kanto, and Chubu regions significantly outperformed others in LHSE. However, the Kinki and Kyushu regions were significantly disadvantaged pre-vaccination, and post-vaccination, this difference was no longer significant. For DMUs with abundant bed resources, the introduction of vaccines was found to weaken the relative advantage of the Tohoku region in LHSE.

3.4. Discussion

LHSE estimation results offer evidence to evaluate the overall performance of all DMUs. Firstly, except for Ehime Prefecture, no other prefectures managed to sustain efficient across the 4 waves of the pandemic. This indicates that achieving high LHSE solely through exogenous factors like socioeconomics and luck is challenging for most DMUs. Moreover, the rising trend in average LHSE and the percentage of efficient DMUs among all DMUs indicates a continuous narrowing of the gap between DMUs and the efficiency frontier during each pandemic wave, suggesting an overall reduction in efficiency disparities among DMUs. Compared to the vaccine-unavailable 2nd and 3rd waves, there was a notable improvement in the overall performance of DMUs during the 4th and 5th waves post-vaccination. Furthermore, analyses using OLS and SUE t-tests on regional dummies indicate that the usage of vaccines indeed impacted the uneven distribution of LHSE, primarily focusing on regions with insufficient bed resources. After vaccine deployment in regions with insufficient bed resources, the Tohoku, Kanto, and Chubu regions transformed from LHSE underperformers to overperformers, while the relative disadvantage of the Kinki and Kyushu regions pre-vaccination became insignificant post-vaccination.

The analysis of demographic characteristics reveals that before vaccine deployment, DMUs with a higher proportion of elderly population susceptible to COVID-19 faced greater resistance in improving LHSE. However, post-vaccination, DMUs with a higher proportion of elderly individuals, particularly those with ample bed resources, found it easier to improve LHSE. This might be due to Japan's early policy of prioritizing vaccination for the elderly. Even after vaccinating the general population, the vaccination rate among the elderly remained higher than other age groups. Thus, improving LHSE became relatively easier in DMUs with a larger proportion of elderly individuals.

Regarding the analysis of local government ability and LHSE, vaccine deployment didn't mitigate LHSE disparities caused by differences in local government capabilities. Nevertheless, the negative correlation between the financial coefficient and LHSE indicates that DMUs with better financial conditions found it harder to improve LHSE. Strong financial conditions usually reflect a better economy and complex demographics. Therefore, regions with better financial conditions faced more challenges in accurately controlling the pandemic's direction during a sudden public health crisis, leading to lower input-output efficiency.

The analysis on virus characteristics' relationship with LHSE shows that the impact of virus characteristics on LHSE isn't significantly regulated by vaccine usage.

The relationship between healthcare system stress and LHSE, and the moderating effect of vaccine deployment on this relationship, were proven. High total secured bed occupancy rates led to higher LHSE, representing a combination of two causal chains: higher bed occupancy rates indicate a severe COVID-19 situation, increased demand for medical resources, and stress on the healthcare system, risking a decrease in LHSE scores. Simultaneously, it implies that existing medical resources are actively used in medical activities, preventing a surge in mortality rates, hence boosting LHSE scores. Moreover, Inoue (2020) suggests that Japan effectively controlled the pandemic early on by coordinating optimal use of hospital beds at the community level, irrespective of low or high occupancy rates. Additionally, post-vaccination, LHSE improvement became more reliant on reducing the occupancy rate of beds for severe cases, especially for DMUs with inadequate bed resources. This suggests that, in the post-vaccine era, focusing on measures like ensuring supply of intensive care beds and treatment for severe patients could be crucial for improving LHSE.

Additionally, strengthening the review and oversight of the ECSG funds would contribute to an overall enhancement of LHSE. A report published by the Japan's audit watchdog indicates that 66 ECSG projects where funds were wasted or misused, totaling 10.23 billion yen from the 2019 fiscal year to the 2021 fiscal year. This included overpayments of around 5.5 billion yen to 32 hospitals with aside beds for treating COVID-19 patients. The ECSG is designed to pay for the cost of beds reserved specifically for COVID-19 patients that were never used or for bed costs that could not be used due to the need for space to treat COVID-19 patients. However, all 32 hospitals applied for funds, even during periods when beds were occupied. Another case is that four hospitals classified regular beds as advanced care units and received an extra payment totaling about 3.1 billion yen. A senior official from the Board Audit said "Many hospitals had an inadequate understanding of the program. The prefectural governments handling the payments were also lax in their initial evaluation." A senior official from the Board Audit attributed part of this problem to the lax initial assessments conducted by the prefectural governments (Yamamoto, 2022).

3.5. Conclusion

This study examined whether the use of vaccines during Japan's COVID-19 waves two through five mitigated inequalities in the spatial distribution and socioeconomic factors of LHSE. The findings indicate an overall reduction in LHSE disparities across regions due to vaccine utilization. However, this change varied concerning the availability of hospital bed resources in prefectures. In prefectures facing bed shortages, vaccine usage notably improved LHSE in most areas. Conversely, in prefectures with ample bed resources, vaccine deployment only significantly decreased the advantage of the Tohoku region, resulting in a more even overall performance among prefectures.

Nevertheless, the study's outcomes did not provide evidence supporting vaccines as a leveling factor in reducing socioeconomic LHSE disparities. On one hand, vaccine deployment increased the contribution of the population aged 65 and above to LHSE, particularly accentuated in regions with sufficient bed resources. On the other hand, the improvement in LHSE in prefectures, especially those with insufficient bed resources, relied more on reducing the occupancy rate of secured beds for severe cases due to vaccine deployment.

These results suggest that policymakers and implementers, in the post-COVID-19 era with rising vaccine coverage, should prioritize bolstering and supplying medical resources conducive to treating severe cases, such as secured beds for severe cases, especially in regions with limited bed resources. Additionally, I posit that the positive impact of the elderly population on LHSE due to initial vaccine prioritization might change as vaccination coverage among younger demographics increases.

Given the frequent alterations in preventive policies, it's impossible to encompass all potential influencing factors in the model determining medical efficiency. Consequently, any overlooked influencing factors would be included in the model's residual term, leading to endogeneity issues. For instance, during the second wave of COVID-19, the "Go To Travel" tourism promotion policy implemented from July 22, 2020, to December 28, 2020, was proven to significantly increase infection rates (Anzai et al., 2022; Tamura et al., 2022). Moreover, the hosting of the Tokyo Olympics and Paralympics exacerbated the pandemic's spread (Sapkota et al., 2022; Yamada & Shi, 2022). Therefore, validation of research findings is imperative upon acquiring more data and statistical information related to COVID-19.

Supplementary Material

Supplementary Table 3-1. The beginning and end of the declaration of the state of emergency

DMUs	the first DSE		the second DSE		the third DSE		the fourth DSE	
	start	end	start	end	start	end	start	end
Hokkaido	2020/4/16	2020/5/25			2021/5/16	2021/6/20	2021/8/25	2021/9/30
Aomori	2020/4/16	2020/5/14						
Iwate	2020/4/16	2020/5/14						
Miyagi	2020/4/16	2020/5/14					2021/8/25	2021/9/13
Akita	2020/4/16	2020/5/14						
Yamagata	2020/4/16	2020/5/14						
Fukushima	2020/4/16	2020/5/14						
Ibaraki	2020/4/16	2020/5/14					2021/8/20	2021/9/30
Tochigi	2020/4/16	2020/5/14	2021/1/14	2021/2/7			2021/8/20	2021/9/30
Gunma	2020/4/16	2020/5/14					2021/8/20	2021/9/30
Saitama	2020/4/7	2020/5/25	2021/1/8	2021/3/21			2021/8/2	2021/9/30
Chiba	2020/4/7	2020/5/25	2021/1/8	2021/3/21			2021/8/2	2021/9/30

Tokyo	2020/4/7	2020/5/25	2021/1/8	2021/3/21	2021/4/25	2021/6/20	2021/7/12	2021/9/30
Kanagawa	2020/4/7	2020/5/25	2021/1/8	2021/3/21			2021/8/2	2021/9/30
Niigata	2020/4/16	2020/5/14						
Toyama	2020/4/16	2020/5/14						
Ishikawa	2020/4/16	2020/5/14						
Fukui	2020/4/16	2020/5/14						
Yamanashi	2020/4/16	2020/5/14						
Nagano	2020/4/16	2020/5/14						
Gifu	2020/4/16	2020/5/14	2021/1/14	2021/2/26			2021/8/25	2021/9/30
Shizuoka	2020/4/16	2020/5/14					2021/8/20	2021/9/30
Aichi	2020/4/16	2020/5/14	2021/1/14	2021/2/26	2021/5/12	2021/6/20	2021/8/25	2021/9/30
Mie	2020/4/16	2020/5/14					2021/8/25	2021/9/30
Shiga	2020/4/16	2020/5/14					2021/8/25	2021/9/30
Kyoto	2020/4/16	2020/5/21	2021/1/14	2021/2/26	2021/4/25	2021/6/20	2021/8/20	2021/9/30
Osaka	2020/4/7	2020/5/21	2021/1/14	2021/2/26	2021/4/25	2021/6/20	2021/8/2	2021/9/30
Hyogo	2020/4/7	2020/5/21	2021/1/14	2021/2/26	2021/4/25	2021/6/20	2021/8/20	2021/9/30
Nara	2020/4/16	2020/5/14						
Wakayama	2020/4/16	2020/5/14						

Tottori	2020/4/16	2020/5/14						
Shimane	2020/4/16	2020/5/14						
Okayama	2020/4/16	2020/5/14			2021/5/16	2021/6/20	2021/8/25	2021/9/13
Hiroshima	2020/4/16	2020/5/14			2021/5/16	2021/6/20	2021/8/25	2021/9/30
Yamaguchi	2020/4/16	2020/5/14						
Tokushima	2020/4/16	2020/5/14						
Kagawa	2020/4/16	2020/5/14						
Ehime	2020/4/16	2020/5/14						
Kochi	2020/4/16	2020/5/14						
Fukuoka	2020/4/7	2020/5/14	2021/1/14	2021/2/26	2021/5/12	2021/6/20	2021/8/20	2021/9/30
Saga	2020/4/16	2020/5/14						
Nagasaki	2020/4/16	2020/5/14						
Kumamoto	2020/4/16	2020/5/14						
Oita	2020/4/16	2020/5/14						
Miyazaki	2020/4/16	2020/5/14						
Kagoshima	2020/4/16	2020/5/14						
Okinawa	2020/4/16	2020/5/14			2021/5/23	-	-	2021/9/30

Supplementary Table 3-2. Results of Pooled Tobit regression.

VARIABLES	All DMUs			DMUs with insufficient bed resources			DMUs with sufficient bed resources		
	Full sample	Unavailable vaccination	Available vaccination	Full sample	Unavailable vaccination	Available vaccination	Full sample	Unavailable vaccination	Available vaccination
Population density	0.024	-0.010	-0.001	0.012	-0.001	-0.035	0.493	0.226	1.038**
	(0.657)	(-0.197)	(-0.012)	(0.314)	(-0.010)	(-0.829)	(1.663)	(0.734)	(2.556)
Old ratio	0.062	-1.851**	2.740	-2.487	-1.508	0.432	0.250	-1.725**	10.795**
	(0.092)	(-2.390)	(1.217)	(-1.335)	(-0.640)	(0.104)	(0.340)	(-2.370)	(2.122)
Financial index	-0.590*	-0.465	0.188	-0.984**	-0.955	0.448	-1.934***	-0.762	-0.686
	(-1.940)	(-1.213)	(0.427)	(-2.236)	(-1.580)	(0.635)	(-2.779)	(-1.124)	(-0.647)
Unlinked proportion	-0.479*	-0.618**	-0.562	-0.448	-0.542	-0.358	-0.350	-0.296	-1.092
	(-1.803)	(-1.998)	(-1.319)	(-1.391)	(-1.343)	(-0.786)	(-0.800)	(-0.749)	(-1.322)
Bed rate	1.166***	-0.102	1.137*	1.487***	0.533	2.593**	-0.262	-0.356	-1.410
	(2.771)	(-0.158)	(1.731)	(2.815)	(0.645)	(2.402)	(-0.380)	(-0.388)	(-1.517)
Bed rate for severe	-1.181**	0.583	-1.577**	-0.717	0.894	-2.470**	1.108	-1.322	2.086
	(-2.280)	(0.801)	(-2.345)	(-1.137)	(1.005)	(-2.647)	(0.795)	(-0.698)	(1.169)
Positive rate	5.131***	3.312	3.635***	4.188***	2.891	1.590	7.905***	3.920	4.210*
	(4.602)	(1.271)	(2.703)	(3.303)	(0.811)	(1.041)	(3.865)	(1.162)	(1.788)

Severe rate	-0.102	-0.123*	0.096	-0.127*	-0.123*	-0.703	0.424*	0.915**	0.432
	(-1.573)	(-1.927)	(0.476)	(-1.955)	(-1.904)	(-1.065)	(1.736)	(2.671)	(1.400)
Tohoku	0.049	0.166	-0.030	0.058	-0.242	0.365*	0.161	0.462**	-0.498
	(0.512)	(1.307)	(-0.256)	(0.303)	(-0.853)	(1.767)	(0.861)	(2.374)	(-1.686)
Kanto	-0.055	-0.042	0.034	-0.056	-0.410	0.381*	-	-	-
	(-0.459)	(-0.276)	(0.227)	(-0.300)	(-1.473)	(1.906)			
Chubu	0.044	0.080	0.057	0.144	-0.215	0.406*	-0.156	-0.261	-0.041
	(0.488)	(0.675)	(0.500)	(0.785)	(-0.794)	(2.019)	(-1.112)	(-1.657)	(-0.231)
Kinki	-0.248**	-0.194	-0.150	-0.299	-0.641**	0.288	-0.538**	-0.631**	-0.657*
	(-2.542)	(-1.569)	(-1.132)	(-1.547)	(-2.289)	(1.258)	(-2.297)	(-2.712)	(-1.889)
Kyushu	-0.256***	-0.283**	-0.106	-1.108***	-1.430***	0.146	-0.203**	-0.054	-0.139
	(-2.922)	(-2.582)	(-0.915)	(-3.139)	(-2.999)	(0.291)	(-2.161)	(-0.555)	(-1.068)
Constant	0.860***	1.433***	-0.197	1.775**	1.829**	-0.070	1.075***	1.136***	-2.401
	(3.245)	(5.023)	(-0.219)	(2.492)	(2.123)	(-0.041)	(3.079)	(3.231)	(-1.255)
Observations	184	92	92	104	52	52	80	40	40
Number of DMU	46	46	46	26	26	26	20	20	20

Note: t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Supplementary Table 3-3. Results of SUE t-test based on Tobit regression

VARIABLES	All DMUs			DMUs with insufficient bed resources			DMUs with sufficient bed resources		
	Diff.	Chi2	Prob>chi2	Diff.	Chi2	Prob>chi2	Diff.	Chi2	Prob>chi2
Population density	0.009	0.03	0.865	-0.034	0.39	0.532	0.812*	3.23	0.072
Old ratio	4.591**	3.98	0.046	1.940	0.18	0.670	12.520**	4.29	0.038
Financial index	0.653	1.22	0.270	1.403	2.17	0.141	0.076	0.00	0.956
Unlinked proportion	0.056	0.01	0.919	0.184	0.07	0.793	-0.796	0.80	0.372
Bed rate	1.239	1.72	0.189	2.060	2.55	0.110	-1.054	0.60	0.437
Bed rate for severe	-2.160*	3.67	0.055	-3.364**	5.57	0.018	3.408	2.52	0.112
Positive rate	0.323	0.01	0.912	-1.301	0.10	0.752	0.290	0.00	0.950
Severe rate	0.219	1.47	0.226	-0.580	1.00	0.318	-0.483	1.09	0.296
Tohoku	-0.196	1.01	0.314	0.607**	5.86	0.016	-0.960**	5.60	0.018
Kanto	0.076	0.17	0.678	0.791***	13.23	0.000	-	-	-
Chubu	-0.023	0.02	0.899	0.621***	6.93	0.009	0.220	0.80	0.371
Kinki	0.044	0.05	0.815	0.929***	12.11	0.001	-0.026	0.01	0.940
Kyushu	0.177	1.22	0.270	1.576	6.71	0.010	-0.085	0.30	0.587

Note:

1) “Coef.” reported in this table is estimated based on standard errors

2) The SUE t-test statistics (Chi2) are estimated based on robust standard errors, *** p<0.01, ** p<0.05, * p<0.1.

3) "Diff." indicates the difference in value between Coef. with vaccination and Coef. without vaccination.

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Chapter 4: Regional Disparities and Dynamic Evolution of Suicide Prevention and Intervention Efficiency in Japan

4.1. Introduction

Although suicide prevention is a complex challenge, it is preventable through the formulation of effective public policies and the implementation of targeted interventions. (World Health Organization, 2014) In 2019, the Seventy-second World Health Assembly passed the World Health Organization's (WHO) first Mental Health Action Plan. Suicide prevention is a critical component of this plan, with the goal of reducing suicide rates by one-third by 2030 (World Health Organization, 2021). The plan's development was inspired, in part, by Japan's success in suicide prevention efforts. Since the early 1990s, Japan's suicide rate has increased, reaching its peak in 1998, and has since remained around 30,000 individuals annually (Cabinet Office, 2014). To alleviate the ongoing rise in the suicide rate, the Japanese government has implemented a series of suicide prevention and intervention (SPI) measures, including encouraging local governments and municipalities to play an active role in SPI while providing financial support for related activities.

Many scholars attribute the sustained decrease in suicide rates, particularly among males, after 2009 to the allocation of funds from the Regional Comprehensive Suicide Prevention Emergency Strengthening Fund, or Regional Fund (RF) (Kato & Okada, 2019; Okada et al., 2020; Takeshima et al., 2015). Between 2009 and 2014, local prefectural governments received 18.35 billion Japanese yen from the RF to support SPI activities among local public organizations[2] (Ministry of Health, 2012). This allocation effectively granted prefectural governments discretion in fund utilization. Specifically, based on SPI implementation plans and declared amounts submitted by municipal governments under their jurisdiction, prefectural governments formulated SPI implementation plans and applied for funds from the RF. As per the RF management guidelines, prefectural governments were responsible for fund allocation and oversight of fund utilization by subordinate public entities(Ministry of Health, 2009).

However, the severe financial burden and imperfect policy effectiveness have raised doubts regarding the cost-effectiveness of RF. They advocate for government efforts to improve regional SPI plans for greater cost-effectiveness (Nakano et al., 2021) and propose the need for more detailed observations to establish an evidence-based and cost-effective fiscal budget structure for SPI (Okada et al., 2020). Therefore, assessing the policy effectiveness and cost-effectiveness of local governments in SPI would aid Japan's central government in overseeing local government policy execution efficiency and providing references for future policy formulation.

As such, this study aims to analyze the cost-effectiveness of RF in local Japanese governments to understand the dynamic evolution of local SPI efficiency. The primary

[2]. The RF was allocated 10 billion yen in the supplementary budget for the 2009 fiscal year, 3.7 billion yen in the third supplementary budget for the 2021 fiscal year, 30.2 billion yen in the first supplementary budget for the 2022 fiscal year, and 16.3 billion yen in the first supplementary budget for the 2023 fiscal year.

contributions are as follows: Firstly, surpassing existing research that overly emphasizes government outcomes in SPI while overlooking cost-effectiveness, this study utilizes input-output efficiency measurement models to assess the efficiency of SPI by local governments. It takes into account environmental and luck factors' influence on the efficiency of local government policy implementation, filtering out relatively objective SPI efficiency using the three-stage Super Efficiency (SE) and Modified Slacks-Based Measure (MSBM) model framework (In the following text, it is abbreviated as SE-MSBM). The analysis demonstrates significant differences in SPI efficiency among local governments, where these disparities are partially attributed to environmental and luck factors, and the efficiency differences resulting from differences in local government management are exaggerated. Secondly, this paper dynamically decomposes the factors contributing to the evolution of SPI efficiency from the perspectives of productivity changes, which can be decomposed into efficiency changes and technological changes. Over time, the study confirms an overall improvement in SPI productivity, but with a declining marginal improvement, resulting from joint progress in efficiency and technological changes. Moreover, there is a tendency for productivity improvement to excessively rely on technological progress while relatively neglecting efficiency improvement, particularly in pure efficiency. As a policy recommendation, based on the research findings, we advocate for recognizing the positive role of external environmental improvements in the cost-effectiveness of SPI. Furthermore, local governments should reduce reliance on technological progress and strive to promote SPI productivity through efficiency improvement, especially in pure efficiency.

The rest of this paper is structured as follows: Section 4.2 reviews the literature related to SPI and the efficiency measurement of public sector. Section 4.3 outlines the model-building process. Section 4.4 introduces the data sources and the analytical results of the model. Section 4.5 discusses the model analysis results from section 4.4 and provides relevant policy recommendations. The final section draws conclusions based on the entire discourse presented in the paper.

4.2. Literature Review

The decline in Japan's suicide rates post-2009 owes significantly to proactive interventions at national, local government, and community levels. At the national level, policies such as the 2006 Basic Act for Suicide Prevention, the 2007 General Principles of Suicide Prevention Policy, and a series of fiscal support policies (including RF) have been proven effective in some studies (Kato & Okada, 2019; Nakanishi et al., 2015; Takeshima et al., 2015). However, some studies suggest its actual policy impact has been notably limited (Nakanishi et al., 2020). Regarding central fiscal support and SPI, research falls into two categories. One focuses on government investment in public health and welfare, along with redistribution policies and their correlation with suicide behavior (Inoue et al., 2014; Shiroyama et al., 2021). For instance, Shiroyama et al. (2021) demonstrated a correlation between reduced suicide death rates and expenditure in "public health," "police," "ambulance/firefighting," "welfare," and "education" sectors in Japan from 2009 to 2018. The second category emphasizes the significance of central fiscal support for local SPI efforts (Kato & Okada, 2019; Nakanishi et al., 2015; Okada et al., 2020; Yonemoto et al., 2019). Nakanishi et al. (2015) highlighted that national fund facilitated the establishment of community SPI systems, streamlining the implementation of local SPI projects.

The WHO noted that besides evidence on the effect or impact of suicide prevention strategies, health planners and policymakers also need to understand the expected costs and cost-effectiveness to ensure that these strategies are economically viable. However, there is still a global shortage of robust economic research on the cost-effectiveness of suicide prevention (World Health Organization, 2014). In the case of Japan, the focus on the cost-effectiveness of local government suicide intervention policies (SPI) stems partly from strained fiscal conditions (Kato & Okada, 2019; Okada et al., 2020) and partly from the unstable and variable effectiveness of SPI measures. Yonemoto et al. (2019) found that although almost all local governments offered gatekeeper training programs, there was a lack of assessment of policy outcomes. Kato and Okada (2019), analyzing prefectural data, noted variations in the policy impact of RF on male and female suicide rates. Yet, scarce objective studies have quantitatively evaluated the cost-effectiveness of national or local government executions of SPI policies in Japan.

The WHO categorizes the risk factors influencing suicide rates into several levels: health system, society, community, relationships, and individual, and provides corresponding intervention measures (although these are not exhaustive) (World Health Organization, 2014). Similarly, Stack (2021) categorizes influences on suicide into political, social, cultural, and economic dimensions.. From a political perspective, increased social welfare and public assistance often correlate with reduced suicide rates (Flavin & Radcliff, 2008; Stack, 2021). Socially, marital and parental social institutions remain protective factors against suicide, albeit with gender disparities in their protective effects (Fujimoto & Yokoyama, 2016; Fukuchi et al., 2013). Additionally, most articles support the view that social isolation causally relates to suicide, while social support serves a protective function against suicide (Motillon-Toudic et al., 2022). Some studies indicate a correlation between alcohol consumption issues and suicide rates (Brady, 2006; Nakanishi & Endo, 2017; Stack, 2021). Culturally, religious beliefs often negatively correlate with suicide rates, but mediating factors require further exploration (Stack, 2021). Moreover, Japan's traditional notion of honorable suicide and modern conservative attitudes toward suicide are considered reasons for high suicide rates (Russell et al., 2017). Lastly, economically, a sluggish economic environment correlates with high suicide rates. Specifically, high unemployment rates and low job availability elevate suicide rates, especially among middle-aged men (Kuroki, 2010; Russell et al., 2017). However, some research contests the direct causality between unemployment rates and suicide rates, at least concerning Japan (Huang & Ho, 2016). Additionally, macroeconomic indicators like regional GDP and CPI are believed to influence suicide rates (Erdem & DİNÇ, 2022; Yosano, 2023). Therefore, to derive relatively objective management efficiency in evaluating local government efficiency, environmental factors influencing the implementation of local government policies need consideration.

Assessing public sector policy efficiency has been a widely debated topic in academia. However, scarcely any studies have delved into efficiency assessments of SPI policies. With respect to the possible reasons, on one hand, efficiency analyses in healthcare sectors primarily focus on healthcare facility (hospitals, primary healthcare facilities) efficiency, with few studies exploring system-level (national or sub-national) efficiency (Mbau et al., 2023). On the other hand, some studies suggest inconsistencies in the effectiveness of SPI policies across countries, with limited evidence supporting their impact on reducing suicide rates (Dunlap et al., 2019; Linskens et al., 2023; Nakanishi et al., 2020). Nevertheless, in Japan, there's a prevalent belief in academia that the implementation of RF is causally linked to the decline in suicide rates, particularly among males (Kato & Okada, 2019; Nakanishi et al., 2015; Okada et al., 2020).

4.3. Material and Methods

This study can be divided into two parts. The first part involves estimating the SPI efficiency of each prefecture using a three-stage SE-MSBM model. The second part calculates the Luenberger total factor productivity (LTFP) index based on the estimated SPI efficiency to reflect the dynamic evolution of this efficiency.

4.3.1. Three-Stage SE-MSBM Model

The Slacks-Based Measure is a type of Data Envelopment Analysis (DEA). It uses slack variables to evaluate the efficiency of decision-making units (DMUs). This method was proposed by Tone (2002), who also introduced a way to assess the SE of these units. However, traditional Slacks-Based Measure struggles with translation invariance. This can cause distortions when assessing DMUs with negative inputs or outputs. To resolve this, Sharp et al. (2017) developed the MSBM. This method is tailored for systems that naturally include negative values.

The three-stage SE-MSBM model builds on the existing three-stage DEA framework. It replaces the traditional DEA model with the SE-MSBM. This model, proposed by Fried and Lovell, improves on earlier DEA versions. The three-stage DEA method proposed by Fried et al. (2002). It overcomes the limitations of the one-stage DEA method, which cannot measure factors affecting efficiency, and the two-stage DEA method, which assumes a given form of influencing factor functions and cannot eliminate environmental impact factors. The main goal of this model is to filter out environmental effects and statistical noise from managerial inefficiency. This makes the efficiency assessments of DMUs more precise. For a detailed methodological explanation, refer to Figure 4-1. It provides a comprehensive framework for the three-stage SE-MSBM model.

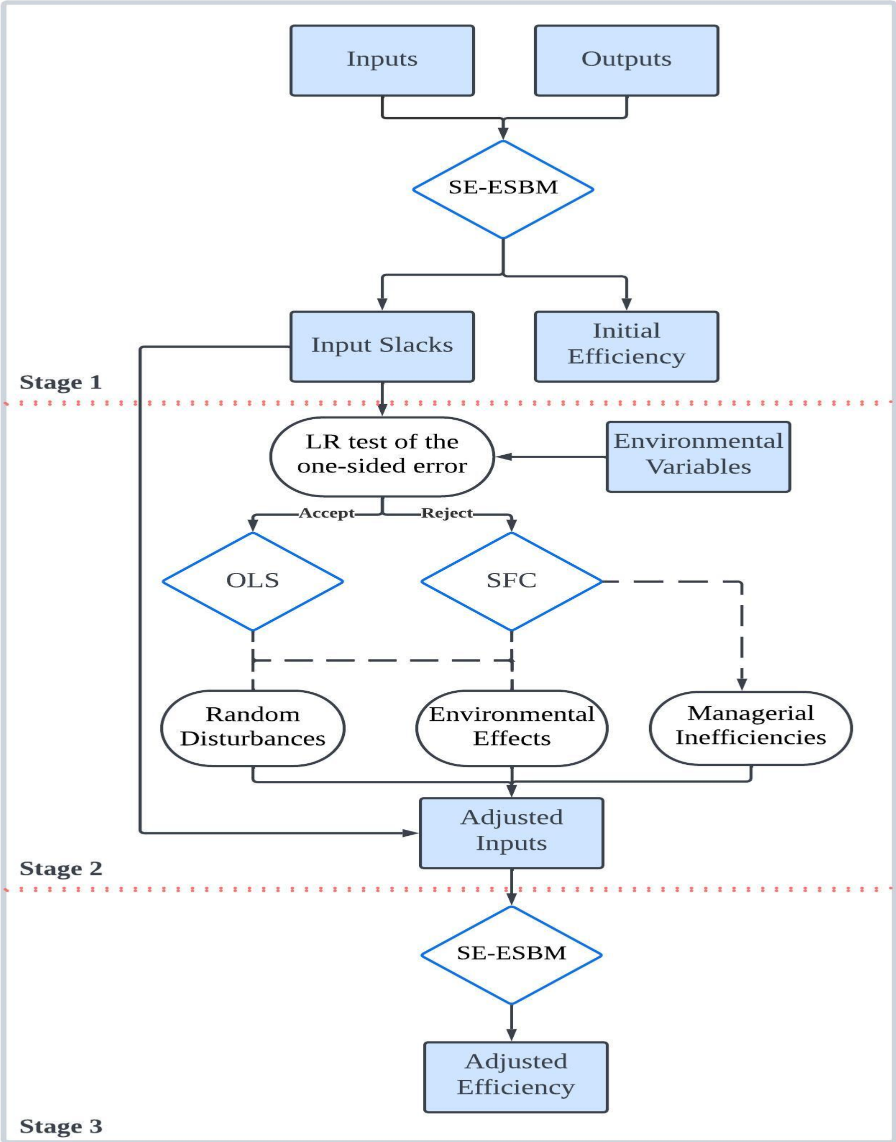

Figure 4-1. Methodological framework of the three-stage SE-MSBM Model.

- ***Stage 1: Initial MSBM Evaluation of DMUs Performance***

The standard form of efficiency score evaluated by MSBM is given as follows:

$$min\, \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{R_{i0}^-}}{1 + \frac{1}{q}\sum_{r=1}^{q} \frac{s_r^+}{R_{r0}^+}}$$

$$s.t. \sum_{j=1, \neq 0}^{n} x_{ij}\, \lambda_j + s_i^- = x_{i0}$$

$$\sum_{j=1,\neq 0}^{n} y_{rj}\,\lambda_j - s_r^+ = y_{r0} \tag{4.1}$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j = 1$$

$$R_{i0}^- = x_{i0} - min(x_i)$$

$$R_{r0}^+ = max(y_r) - y_{r0}$$

$$\lambda_j, s_i^-, s_r^+ \geq 0$$

Here,

j indicates the j^{th} DMU in n DMUs.

x_i and y_r represent the i^{th} input variable in m input variables and the r^{th} output variable in q variables, respectively.

R_{i0} and R_{r0} represent the range of possible improvement for the corresponding inputs and outputs. λ denotes the weight vector. Additionally, if $R_{i0}^- = 0$, the respective $\frac{s_i^-}{R_{i0}^-}$ term is removed from the objective function, and if $R_{r0}^+ = 0$, the corresponding $\frac{s_i^+}{R_{r0}^+}$ term is removed from the objective function.

For the $\text{DMU}(x_0, y_0)$ that is efficient under the SBM, we define its super-efficiency as the optimal objective function value ρ^* given by:

$$\rho^* = min\,\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{R_{i0}^-}}{\frac{1}{q}\sum_{r=1}^{q}\frac{\bar{y}_r}{R_{r0}^+}}$$

$$s.t.\,\bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j$$

$$\bar{y} \geq \sum_{j=1,\neq 0}^{n} \lambda_j y_j \tag{4.2}$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j = 1$$

$$R_{i0}^{-} = x_{i0} - min(x_i)$$

$$R_{r0}^{+} = max(y_r) - y_{r0}$$

$$\bar{x} \geq x_0, \bar{y} \leq y_0 \ and \ \lambda \geq 0.$$

In this stage, we conducted a simple SE-MSBM under the assumption of variable returns to scale (VRS) and obtained the efficiency values of each DMU without excluding environmental factors and the slack variables of each input variable. The former will be used for subsequent comparative analysis, while the latter will be included as dependent variables in the second stage.

- ***Stage 2: Filtering Out the Influence of Environmental Effects***

Based on the MSBM model from the first stage and input-output variable data, we can determine the slack values of each input and output, which represent the difference between the actual values and the optimal values. The slack value is influenced by environmental effects, statistical noise, and managerial inefficiency (Fried et al., 2002).

What we aim to do in the stage 2 is filter out the environmental effects and statistical noise, which are unrelated to managerial efficiency, from slacks. Subsequently, based on this, we adjust the original input and output indicators so that all DMUs face the same external environment and luck factors. According to Fried et al. (2002), it is acceptable to adjust either inputs or outputs, or to simultaneously adjust both inputs and outputs. In this study, we follow the approach adopted by most scholars, adjusting only the input indicators (Y. Chen et al., 2021; Chen et al., 2022; Guan et al., 2022).

To do this, we construct a Stochastic Frontier Analysis (SFA) model:

$$s_{ijt}^{-} = f\left(Z_{ijt}; \beta_{it}\right) + v_{ijt} + u_{ijt}, \quad (4.3)$$

$$i = 1,2 \ldots, m;\ r = 1,2 \ldots, q;\ j = 1,2 \ldots, n;\ t = 2010,2011 \ldots 2014,$$

where:

s_{ijt}^{-} is the slack value of the i^{th} input of the j^{th} DMU at time *t*.

$Z_{ijt} = \left[Z_{1jt}, Z_{2jt} \ldots, Z_{mjt}\right]$ represents the set of environmental variables.

β_{it} denotes the coefficients of environmental variables to be estimated in the secondary regression equation.

$f^{i}\left(Z_{ijt}; \beta_{it}\right)$ are deterministic feasible slack frontiers, which capture the impact of the environmental variables on the input slack value s_{ijt}^{-}.

$v_{ijt} + u_{ijt}$ represents the error structure, where v_{kit} denotes random disturbances and $v \sim N(0, \sigma_v^2)$. It is assumed that the managerial inefficiency term u_{ijt} follows a half-normal distribution $u \sim N(\mu, \sigma_u^2)$.

Before estimation, we need to specify the form of the error structure. According to Fried et al. (2002), if the LR test of the one-sided error results fail to reject the hypothesis $\sigma_u^2 = 0$, it indicates that the managerial inefficiency in that input does not affect the variation in the deterministic feasible slack frontiers, and the error term comprises only random disturbances. In such a scenario, this study will utilize Ordinary Least Squares (OLS) to estimate the influence of environmental factors and use their estimated coefficients to adjust the input indicators.

Moreover, assuming a parameter $\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$, which indicates the contribution of the managerial inefficiency in the variation of error. Additionally, considering whether the unit possesses time variability determines the use of either a time-invariant model or a time-varying decay model. In the time-invariant model, the v_{ijt} and u_{ijt} are independent of each other. The time-varying decay model features $u_{it} = u_i e^{-\eta(t-T_i)}$, where T_i is the last period for input i and η is the decay coefficient. Utilizing panel SFA estimation involves initially employing the time-varying decay model to estimate the equation and then conducting a test on the estimated decay parameter η. If rejecting the null hypothesis $\eta = 0$, a time-varying decay model should be used; otherwise, a time-invariant model is employed for estimation.

The estimation method for the random disturbance term is based on Jondrow et al. (1982)'s approach:

$$E\left(u_{ijt} \middle| v_{ijt} + u_{ijt}\right) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi\left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)}{\phi\left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)} + \frac{\varepsilon_{it}\lambda}{\sigma}\right]. \tag{4.4}$$

Where $\lambda = \frac{\sigma_u}{\sigma_v}, \varepsilon_{it} = v_{ijt} + u_{ijt}$. φ and ϕ respectively represent the probability density function and cumulative distribution function of the standard normal distribution.

Next, we use the estimation results of the SFA model to adjust the external environment of all DMUs to the same extent, aiming to eliminate the influence of heterogeneity. This adjustment ensures that the subsequent efficiency calculations are based on a homogeneous environment.

$$X_{ijt}^{*} = X_{ijt} + \left\{max\left[f\left(Z_{ijt}; \hat{\beta}_{it}\right)\right] - f\left(Z_{ijt}; \hat{\beta}_{it}\right)\right\} + \left[max\left(v_{ijt}\right) - v_{ijt}\right], \tag{4.5}$$

$$i = 1,2 \ldots, m;\ j = 1,2 \ldots, n;\ t = 2010,2011 \ldots 2014.$$

Where X_{ijt}^{*} represents the adjusted i^{th} input indicator of the j^{th} DMU at time t.

After adjusting for environmental factors and random error terms, all DMUs will face the same external environment and luck factors.

- ***Stage 3: Running MSBM Again After Adjusting Input Variables***

Using the adjusted input variables X_{ijt}^{*} obtained from the second stage to replace the original input data X_{ijt}, calculate the new efficiency values based on the SE-MSBM model performed in Stage 1. As the influence of environmental and random error factors has been eliminated, the efficiency scores obtained in the third stage more accurately reflect the managerial efficiency of each DMU.

4.3.2. SBM Based Adjacent Luenberger Productivity Index

At present, the Malmquist-Luenberger method stands as the most commonly used approach for measuring production indices, yet it harbors certain unavoidable limitations. On one hand, within the Malmquist-Luenberger productivity index measurement method, there's a need to select a measurement angle either under conditions of cost minimization or profit maximization (Fang et al., 2021). On the other hand, the multiplicative form of index construction renders it incapable of calculating the Malmquist-Luenberger index when negative efficiencies exist. Luenberger proposed an alternative, addressing these issues with the LTFP index. On one hand, it allows for profit maximization usage and reduces measurement inputs without selecting a measurement perspective, thereby enhancing output (Chambers et al., 2007; Fang et al., 2021). On the other hand, even in the presence of negative efficiencies, the additive structure of LTFP index make it possible to reflect real efficiency improvements. Hence, this study opts for the LTFP index to gauge improvements in efficiency over a time series.

During period t, assuming $D_0^t(x_0^t, y_0^t)$ represents the optimal solution for Problem (1); if $D_0^t(x_0^t, y_0^t)$ is deemed efficient, then $D_0^t(x_0^t, y_0^t)$ is the optimal solution for Problem (2). If $DMU(x_0^{t+1}, y_0^{t+1})$ is observable, similarly, assuming $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$ is the optimal solution for period $t+1$. Moreover, if we simply transfer inputs and outputs from period t to period $t+1$, the optimal solution under the reference set of DMUs in period $t+1$ can be denoted by the reciprocal efficiency $D_0^{t+1}(x_0^t, y_0^t)$. Similarly, $D_0^t(x_0^{t+1}, y_0^{t+1})$represents the optimal solution of transferring inputs and outputs from period $t+1$ to period t within the reference set of DMUs in period t. The optimal problem of $D_0^t(x_0^{t+1}, y_0^{t+1})$ is given as follow:

$$min\, D_0^t(x_0^{t+1}, y_0^{t+1}) = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{R_{i0t}^-}}{1 + \frac{1}{q}\sum_{r=1}^{q} \frac{s_r^+}{R_{r0t}^+}}$$

$$s.t. \sum_{j=1,\neq 0}^{n} x_{ijt}\, \lambda_j + s_i^- = x_{i0,t+1}$$

$$\sum_{j=1,\neq 0}^{n} y_{rjt}\, \lambda_j - s_r^+ = y_{r0,t+1} \tag{4.6}$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j = 1$$

$$R_{i0t}^- = x_{i0,t+1} - min(x_{it})$$

$$R_{r0t}^+ = max(y_{rt}) - y_{r0,t+1}$$

$$\lambda_j, s_i^-, s_r^+ \geq 0$$

For the efficient $DMU(x_0, y_0)$ under the SBM, its super-efficiency as the optimal objective function value given by:

$$D_0^t(x_0^{t+1}, y_0^{t+1})^* = min\, D_0^t(x_0^{t+1}, y_0^{t+1}) = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{R_{i0t}^-}}{\frac{1}{q}\sum_{r=1}^{q}\frac{\bar{y}_r}{R_{r0t}^+}}$$

$$s.t. \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j$$

$$\bar{y} \geq \sum_{j=1,\neq 0}^{n} \lambda_j y_j \tag{4.7}$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j = 1$$

$$R_{i0}^- = x_{i0} - min(x_i)$$

$$R_{r0}^+ = max(y_r) - y_{r0}$$

$$\bar{x} \geq x_0, \bar{y} \leq y_0 \; and \; \lambda \geq 0.$$

The aforementioned $D_0^t(x_0^t, y_0^t)$, $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, $D_0^t(x_0^{t+1}, y_0^{t+1})$, and $D_0^{t+1}(x_0^t, y_0^t)$ represent the optimal solutions under the VRS assumption, i.e., subject to the constraint $\sum_{j=1,\neq 0}^{n} \lambda_j = 1$. By removing this constraint, we obtain the optimal solutions under the assumption of constant returns to scale (CRS). For clarity, subscripts **v** and **c** are used to respectively indicate the optimal solutions under VRS and CRS assumptions. Additionally, it's important to note that under the CRS assumption, in the MSBM model, the maximum potential improvement R_{i0} of the evaluated DMU_0 might exceed s_i, implying $s_i > R_{i0}$, which could lead to a negative value for the objective function (Sharp et al., 2017). This is one of the reasons why we opt for the LTFP index to specify productivity changes.

Therefore, the LTFP index, which reflects the dynamic change of productivity in two adjacent periods can be expressed as:

$$LTFP_{t-1}^{t} = \frac{1}{2}[D_c^t(x^t, y^t) - D_c^t(x^{t-1}, y^{t-1})] + \frac{1}{2}[D_c^{t-1}(x^t, y^t) - D_c^{t-1}(x^{t-1}, y^{t-1})]. \quad (4.8)$$

The LTFP index can be broken down into two components: technical change (LTC) and efficiency change (LEC). Furthermore, TC and EC can be further decomposed into pure productivity technology changes (LPTP) and technology scale changes (LTPSC), pure efficiency changes (LPEC), and scale efficiency changes (LSEC). Their formulas are as follows (Fang et al., 2021; Grosskopf, 2003):

$$LEC_{t-1}^{t} = D_c^t(x^t, y^t) - D_c^{t-1}(x^{t-1}, y^{t-1}) \quad (4.9)$$

$$LTC_{t-1}^{t} = \frac{1}{2}[D_c^{t-1}(x^t, y^t) - D_c^t(x^t, y^t)] + \frac{1}{2}[D_c^{t-1}(x^{t-1}, y^{t-1}) - D_c^t(x^{t-1}, y^{t-1})] \quad (4.10)$$

$$LPEC_{t-1}^{t} = D_v^t(x^t, y^t) - D_v^{t-1}(x^{t-1}, y^{t-1}) \quad (4.11)$$

$$LSEC_{t-1}^{t} = [D_c^t(x^t, y^t) - D_v^t(x^t, y^t)] - [D_c^{t-1}(x^{t-1}, y^{t-1}) - D_v^{t-1}(x^{t-1}, y^{t-1})] \quad (4.12)$$

$$LPTP_{t-1}^{t} = \frac{1}{2}[D_v^{t-1}(x^t, y^t) - D_v^t(x^t, y^t)] + \frac{1}{2}[D_v^{t-1}(x^{t-1}, y^{t-1}) - D_v^t(x^{t-1}, y^{t-1})] \quad (4.13)$$

$$LTPSC_{t-1}^{t} = \frac{1}{2}\{[D_c^{t-1}(x^t, y^t) - D_v^{t-1}(x^t, y^t)] - [D_c^t(x^t, y^t) - D_v^t(x^t, y^t)]\}$$
$$+\frac{1}{2}\{[D_c^{t-1}(x^{t-1}, y^{t-1}) - D_v^{t-1}(x^{t-1}, y^{t-1})] - [D_c^t(x^{t-1}, y^{t-1}) - D_v^t(x^{t-1}, y^{t-1})]\}. \quad (4.14)$$

These indices satisfy the following relationship:

$$LTFP_{t-1}^{t} = LEC_{t-1}^{t} + LTC_{t-1}^{t}$$
$$= LPEC_{t-1}^{t} + LSEC_{t-1}^{t} + LPTP_{t-1}^{t} + LTPSC_{t-1}^{t}. \quad (4.15)$$

According to the definitions of the LTFP index and its decomposition, LEC reflects the change in relative efficiency of the DMU across different periods, known as the "catch-up effect." On the other hand, LTC represents the movement of the efficiency frontier between periods t and t-1, denoting the "frontier shift effect." Additionally, both LEC and LTC can be decomposed into two components: changes in pure efficiency and changes in scale efficiency.

The computation of the LTFP index requires estimation under CRS and VRS assumptions, where four are derived based on CRS and the remaining four are computed assuming VRS. In this context, LPEC, LPTP, LSEC, and LTPSC being greater than 0 (or less than 0) signify specific changes: pure technical productivity increases (or decreases), technological advancement (or regression), scale efficiency improvement (or decline), and deviation of technology from the optimal scale state of the DMU from period t to $t+1$.

4.4. Results

4.4.1. Variable and Data Selection

The study utilized data from various prefectures in Japan for a period spanning 2010 to 2014, encompassing a total of five years. Despite RF being established in 2009, the initial financial declaration data from each prefecture was incomplete at its inception. Therefore, we excluded the data for the year 2009. Additionally, due to the non-directional nature of the MSBM model, which does not support the efficiency calculation for DMUs with all inputs or outputs equal to zero, we omitted DMUs that had no reported RF declarations, resulting in the removal of a collective total of five observations.

- ***Stage 1 and Stage 3: Input and Output Indicators***

The per capita amounts allocated to the five programs funded by the RF[3]:

[3]. The RF data utilized in this study is the sum of the portion directly requested by prefectural governments from the central government and the portion representing funding usage plans submitted by municipalities within the jurisdiction of the prefectures

Development Program of Leaders and Listeners (DPLL), Personal Consultation Support Program (PCSP), Telephone Consultation Support Program (TCSP), Enlightenment Program (EP), Intervention Model Program (IMP) are included as input indicators in the SE-MSBM model. According to Cantor and Poh (2017), the evaluation framework for the efficiency of primary healthcare institutions in the DEA model requires the inclusion of primary inputs related to labor, capital-related inputs, and inputs related to consumable resources. As per the lines for the Management and Operation of the Regional Suicide Prevention Emergency Strengthening Fund , necessary expenses, wages, compensation, social insurance premiums, travel expenses, necessary expenses, service charges, usage fees, rental fees, equipment purchase costs, commission fees, subsidies, etc., can all be withdrawn from the RF. Therefore, utilizing RF as input indicators is justified (Ministry of Health, 2009). Additionally, the data for RF is sourced from publicly available data provided by the Japanese Ministry of Health, Labor, and Welfare.

Regarding the output indicators, I have selected the decrease in suicide rates for both men (DSRM) and women (DSRW) compared to 2008 as two separate output variables. The suicide rate is defined as the proportion of deaths by suicide to the total population of the DMUs for the current period, which is sourced from publicly available data provided by the Japan National Police Agency (2009-2014). This data is compiled based on the location where the individuals who died by suicide were discovered, rather than their registered residential address. Therefore, the decline in the suicide rate for males and females, as output variables, can be defined as follows:

$$DSRM_{jt} = \frac{Number\ of\ male\ suicides_{j2008}}{male\ population_{j2008}} - \frac{Number\ of\ male\ suicides_{jt}}{male\ population_{jt}} \quad (4.16)$$

$$DSRW_{jt} = \frac{Number\ of\ female\ suicides_{j2008}}{female\ population_{j2008}} - \frac{Number\ of\ female\ suicides_{jt}}{female\ population_{jt}}. \quad (4.17)$$

The reasons for designing output indicators in this manner is as follows:

Firstly, why differentiate between genders? According to the nationwide suicide rate statistics in Japan depicted in Figure 4-2, over the six years (2009-2014) within which the RF fund was available nationwide, there was a significant overall decrease in the national suicide rate. However, the contribution to the decline in the male suicide rate was notably greater than that in the female suicide rate (Ministry of Health, 2012). If a DMU's inputs from RF led to a decrease in male suicide rates but an increase in female suicide rates, using the total population's suicide rate as an output variable could potentially result in a calculated output of zero, which would evidently be unfair. Therefore, separating the output variables by gender would better aid in evaluating the actual efficiency of the DMU.

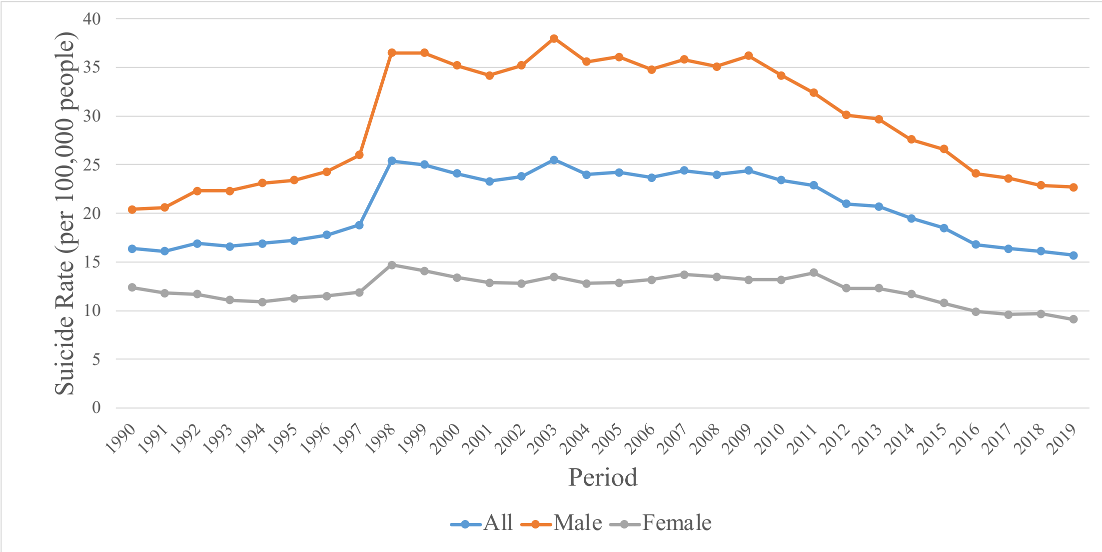

Figure 4-2. Trends in Suicide Rates in Japan (by Gender).

Secondly, why use the difference from the 2008 suicide rates as inputs rather than including the suicide rate of each year as undesirable outputs in the model? As per the Guidelines for the Management and Operation of the Regional Suicide Prevention Emergency Strengthening Fund , any SPI program funded or subsidized by the national treasury implemented by each DMU before the establishment of RF, as well as personnel expenses of permanent staff in relevant administrative agencies, are not covered within the scope of RF funding. Consequently, it is assumed that before 2009, some DMUs had already been implementing SPI projects, which continued post-RF establishment. Therefore, the variations in suicide rates from 2009 onwards can be regarded as the policy effects resulting from RF input.

The detailed information regarding input and output indicators is provided in Table 4-1.

Table 4-1. Descriptive Statistics of Input and Output Indicators.

Indicators	N	Mean	SD	Max	Min
Input					
PCSP	230	4197.617	4169.657	26502.622	0
TCSP	230	3156.205	2975.839	19492.743	0
DPLL	230	4653.228	3460.617	21484.079	0
EP	230	13855.281	9854.502	56547.962	0
IMP	230	7535.673	7265.083	44015.145	0
Output					
DSRM	230	6.774	5.365	24.607	-6.61
DSRW	230	1.454	2.615	11.331	-4.532

- ***Stage 2: Environmental Variable***

In the second phase of analysis, we designate an environmental variable matrix that includes stillbirth rates, alcohol consumption volume, year-on-year changes in the CPI (excluding owner-occupied rent), job availability ratio, unemployment rate, Prefectural Income per Capita[4] (unit: thousand yen), divorce rate, and marriage rate. These variables are considered factors capable of inducing input slacks, besides random disturbances and managerial inefficiencies. Their descriptive statistics are given in Table 4-2. Additionally, the data on alcohol consumption is sourced from the National Tax Agency of Japan and the Okinawa Regional Taxation Office, while the remaining data is obtained from publicly available information provided by the Ministry of Health, Labor, and Welfare.

4 Based on 2011 standard.

Table 4-2. Descriptive Statistics of Environmental Variables.

	N	Mean	SD	Max	Min
Marriage rate	230	4.921	0.551	7.1	3.7
Divorce rate	230	1.795	0.224	2.59	1.33
Unemployment rate	230	3.999	0.888	7.5	2.3
Job availability ratio	230	.801	0.255	1.57	.29
Year-on-year changes in the CPI	230	.512	1.479	4	-1.7
Alcohol consumption volume	230	79.591	10.764	127	60.2
Stillbirth rate	230	23.983	3.102	32.2	17.3
Prefectural Income per Capita	230	2694.174	489.635	5411	1972

4.4.2. Measurement and Correction of Efficiency Values

- ***Stage 1: Initial Efficiency Scores Based on Original Inputs***

This stage employed the SE-MSBM model in the MaxDEA software to evaluate the SPI efficiency across various prefectures in Japan from 2010 to 2014. The efficiency values calculated are presented in Table 4-3. DMUs with efficiency values less than 1 are considered inefficient in management; those with efficiency values equal to 1 are regarded as efficient and highlighted in yellow in the table; DMUs with efficiency values greater than 1 are considered supper-efficient and marked in red. The last row and column in Table 4-3 represent the average efficiency values across all DMUs for each year and the average efficiency values for each DMU across all periods, respectively. The evaluation was performed using original inputs and outputs, thus encompassing not only managerial efficiency but also the impact of environmental factors and random noise.

Table 4-3. The Initial Efficiency Score in the Stage 1.

DMUs	2010	2011	2012	2013	2014	Mean
Hokkaido	1.004	0.441	-	1.62	2.366	1.358
Aomori	1.147	1.288	-	1.436	1	1.218
Iwate	0.412	1.225	0.287	0.256	0.145	0.465
Miyagi	1.158	1.913	0.018	0.532	0.406	0.805
Akita	0.223	-	3.012	0.38	0.308	0.981
Yamagata	0.518	0.141	0.044	0.448	0.384	0.307
Fukushima	1.014	1	0.11	0.398	0.381	0.581
Ibaraki	1.008	0.078	0.026	0.592	0.538	0.448
Tochigi	0.678	0.046	0.258	1.171	1.008	0.632
Gunma	1	-	0.022	0.579	0.595	0.549
Saitama	1.018	0.138	0.025	1.018	1.194	0.679
Chiba	1.144	0.069	0.04	1.08	1.091	0.685
Tokyo	1	0.125	0.023	1.163	2.699	1.002
Kanagawa	1.288	0.199	0.069	1.594	1.362	0.903
Niigata	0.38	0.1	0.077	1.081	0.439	0.415
Toyama	1.196	0.098	0.21	0.41	1.077	0.598
Ishikawa	1.206	0.26	0.212	0.458	1.231	0.674
Fukui	0.408	1.206	0.045	0.604	0.599	0.572
Yamanashi	0.495	1	1	1	1.358	0.971
Nagano	0.615	0.172	1	0.552	0.354	0.539
Gifu	1.118	0.052	0.028	1.157	1.292	0.73
Shizuoka	0.603	0.023	1	0.397	1.011	0.607
Aichi	1.081	0.042	0.078	1.682	1.902	0.957
Mie	1.237	0.295	0.017	0.417	0.532	0.5
Shiga	0.463	0.042	1	0.41	0.492	0.481
Kyoto	1.169	0.115	0.037	0.273	0.358	0.391
Osaka	1.105	1.016	0.293	1.007	1	0.884
Hyogo	1.015	0.157	0.019	0.406	0.416	0.403
Nara	0.349	1.013	0.011	0.421	0.328	0.424
Wakayama	1	4.244	1.175	1	1	1.684

Tottori	1.71	1	1.689	4.298	7.458	3.231
Shimane	1.52	1.08	1.165	0.37	0.592	0.946
Okayama	1	0.067	0.044	1.685	0.519	0.663
Hiroshima	1.883	0.234	0.061	1.279	2.414	1.174
Yamaguchi	1.017	0.199	0.215	1.106	1	0.707
Tokushima	0.556	1.683	0.091	0.219	0.146	0.539
Kagawa	0.217	0.018	0.032	0.307	0.415	0.198
Ehime	1.955	0.181	0.085	1.219	1.162	0.92
Kochi	1.051	-	0.284	1	1	0.834
Fukuoka	1.261	0.015	0.038	1.044	0.759	0.623
Saga	0.221	0.063	0.013	0.31	0.33	0.187
Nagasaki	1.265	1.094	1.542	0.625	0.47	0.999
Kumamoto	0.281	0.076	0.058	1.151	1.743	0.662
Oita	0.219	1	0.028	1	1	0.649
Miyazaki	1.407	1.083	0.106	0.53	0.401	0.705
Kagoshima	1.475	0.239	1.043	1.053	1.275	1.017
Okinawa	0.222	0.148	14.067	0.549	0.251	3.047
Mean	0.922	0.561	0.682	0.878	1.017	0.816
S.D.	0.454	0.772	2.129	0.663	1.130	0.574

Note: "-" indicates that the observed values of the DMU for that period are excluded because all of its input indicators are zero, which does not meet the eligibility criteria for the SE-MSBM model.

Overall, the average efficiency across observed DMUs exhibits a U-shaped trend, which starts at 0.922 in 2010, declines rapidly to a minimum of 0.561 by 2011, then steadily rises, reaching a supper-efficient 1.017 by 2014. Moreover, the proportion of DMUs categorized as efficient or supper-efficient compared to all observed DMUs for each period also follows a U-shaped pattern, with percentages of 63.83%, 34.09%, 24.44%, 48.94%, and 48.94% for 2010 through 2014, respectively. This indicates an initial decrease followed by an increase in the overall average efficiency of DMUs. On the other hand, the standard deviation of DMU efficiency shows fluctuating trends across periods, reaching a peak of 2.129 in 2012, signifying significant regional disparities in SPI efficiency among prefectures.

A cross-sectional comparison of DMU efficiency over the five-year span reveals that only the average efficiency values of Hokkaido, Aomori, Tokyo, Wakayama, Tottori, Hiroshima, Kagoshima, and Okinawa achieved efficient or supper-efficient levels. Among these, only Wakayama and Tottori consistently achieved efficient or supper-efficient levels throughout the five years. This reflects that, even without considering non-managerial factors, hardly any prefecture has an environment or luck factor that readily leads to consistently high-efficiency values.

- ***Stage 2: SFA and OLS***

In this stage, the SFA or OLS models are employed to separate the environmental effects and random noise affecting DMU efficiency. Initially, a one-sided error LR test is conducted to test the null hypothesis $H_0: \sigma_u^2 = 0$. Rejecting this hypothesis indicates that the managerial inefficiency in the input leads to deterministic feasible slack frontiers variations, requiring the use of the SFA model to estimate environmental effects. Failing to reject the null hypothesis suggests that the managerial inefficiency in the input does not affect stochastic frontier variations, indicating that the error term is solely composed of random disturbances, allowing direct estimation using the OLS model. The SFA and OLS models are run using Frontier 2.0 and Stata software, respectively.

According to the results of the LR one-sided error test in Table 4-4, it's evident that, at a 95% significance level, we cannot reject the hypothesis of $\sigma_u^2 = 0$ for TCSP, EP, and IMP. Therefore, direct estimation using the OLS model is employed. However, for the slack variables of DPLL and PCSP, at a 95% significance level, the hypothesis of $\sigma_u^2 = 0$ is rejected, hence employing the SFA model for estimation. Moreover, the γ values indicate that managerial inefficiency in these two inputs contributes 43.2% and 56.9% to the error variance, respectively. Additionally, for these two input slacks, we cannot reject the hypothesis of η=0, thus the time invariant SFA model is employed to estimate environmental effects and random influences.

Table 4-4. The Results of SFA and OLS in Stage 2.

	SFA		OLS		
	Slack Variable of DPLL	Slack Variable of PCSP	Slack Variable of TCSP	Slack Variable of EP	Slack Variable of IMP
Marriage rate	566.348	1133.739***	-549.625	-388.885	-100.818
	(1.243)	(10.028)	(-0.796)	(-0.200)	(-0.068)
Divorce rate	-188.854	5501.821***	1,778.137	5,869.685	6,886.430**
	(-0.901)	(84.097)	(1.188)	(1.390)	(2.128)
Unemployment rate	320.415	-255.686	-726.406*	267.710	299.417
	(0.816)	(-0.769)	(-1.856)	(0.242)	(0.354)
Job availability ratio	-4324.645***	-3805.223***	-1,743.026	-3,725.113	-440.437
	(-21.275)	(-107.497)	(-1.340)	(-1.015)	(-0.157)
Year-on-year changes in the CPI	433.096*	96.232	-122.107	938.764**	463.961
	(2.232)	(0.478)	(-0.754)	(2.055)	(1.325)
Alcohol consumption volume	-7.699	-85.726**	-13.965	27.424	36.417
	(-0.302)	(-2.783)	(-0.699)	(0.487)	(0.843)
Stillbirth rate	-48.600	-63.606	18.746	-20.678	-347.203**
	(-0.628)	(-0.668)	(0.233)	(-0.091)	(-1.997)

Prefectural Income per Capita	0.789	0.705	0.710	2.286	-0.608
	(1.190)	(1.371)	(1.168)	(1.333)	(-0.462)
Constant	-4359.331***	-8,322.469	1,318.705	-18,840.891**	-10715.563***
	(-43.258)	(-1.370)	(0.470)	(-2.378)	(-3725.296)
σ^2	1.283E+07***	1.971E+07***	8.269E+06***	6.066E+07***	3.752E+07***
LR test of the one-sided error	16.561**	30.082***	6.951	2.631	4.970
γ	0.432***	0.569***	-	-	-
η	-0.091	-0.068	-	-	-

Note:

1) z-statistics and t-statistics: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In the SFA estimation, the values in parentheses represent z-statistics.

In the OLS estimation, the values in parentheses represent robust t-statistics.

As environmental variables affect input slacks inversely to their impact on efficiency values, assessing the influence of environmental variables on efficiency can be done through the sign of regression coefficients. (1) The estimated coefficient for marriage rate is positive, indicating that higher marriage rates tend to lead to slacks in PCSP. Similarly, the positive coefficient for divorce rate suggests that higher divorce rates are associated with slacks in PCSP and IMP. The connection between high divorce rates, high marriage rates, and low efficiency values implies a causal relationship between residents' marital life entanglements, and the decrease in SPI efficiency. (2) The job availability ratio to some extent reflects the social economic conditions; higher job availability rates correspond to lower slacks in DPLL and PCSP, which favor the improvement of SPI efficiency. (3) CPI positively impacts slacks in EP, suggesting that DMUs with higher CPI exhibit lower SPI efficiency. This reflects a negative correlation between rising living costs and the improvement in SPI efficiency. (4) Alcohol consumption shows a negative correlation with relaxation in PCSP, indicating that DMUs with higher alcohol consumption demonstrate higher SPI efficiency. (5) Stillbirth rates show a negative causal relationship with slacks in IMP, implying that DMUs with higher natural death rates are more likely to enhance SPI efficiency.

- ***Stage 3: Final Efficiency Scores Based on Adjusted Inputs***

In the third stage, adjustments were made to the original input indicators based on the regression results from the second stage. Subsequently, the SE-MSBM model was run again using the adjusted input indicators. Table 4-5 presents the efficiency values of each DMU in the third stage. DMUs with efficiency values greater than 1 are marked in red, while those with efficiency values equal to 1 are marked in yellow.

Table 4-5. The Adjusted Efficiency Score in the Stage 3.

DMUs	2010	2011	2012	2013	2014	Mean
Hokkaido	0.666	1.004	-	1.299	1.233	1.05
Aomori	1.106	1.174	-	2.064	1	1.336
Iwate	0.271	1.114	0.285	0.208	0.11	0.398
Miyagi	0.414	1.087	0.445	0.439	0.281	0.533
Akita	0.181	-	1.156	0.253	0.221	0.453
Yamagata	0.359	0.405	0.35	0.324	0.271	0.342
Fukushima	0.588	1.156	0.425	0.291	0.258	0.544
Ibaraki	0.658	0.392	0.461	0.507	0.431	0.49
Tochigi	0.499	0.436	0.576	0.673	0.461	0.529
Gunma	0.385	-	0.38	0.467	0.388	0.405
Saitama	0.537	0.461	0.521	1	1.061	0.716
Chiba	1.063	0.436	0.5	0.797	0.686	0.697
Tokyo	1	0.464	0.521	1.047	1.251	0.857
Kanagawa	1.488	0.504	0.617	1.005	1.342	0.991
Niigata	0.239	0.492	0.449	0.522	0.228	0.386
Toyama	1.139	0.381	0.486	0.367	0.417	0.558
Ishikawa	0.321	0.503	0.541	0.436	0.453	0.451
Fukui	0.344	1.042	0.364	0.439	0.364	0.511
Yamanashi	0.347	1	1	1	1.582	0.986
Nagano	0.426	0.453	1.075	0.415	0.241	0.522
Gifu	0.623	0.401	0.374	0.514	0.734	0.529
Shizuoka	0.376	0.376	1.025	0.367	0.671	0.563
Aichi	0.411	0.346	0.488	1.214	1.24	0.74
Mie	1.571	0.533	0.416	0.417	0.362	0.66
Shiga	0.207	0.345	1.022	0.4	0.334	0.461
Kyoto	0.497	0.446	0.422	0.311	0.342	0.404
Osaka	1.01	1.005	0.719	1	1	0.947

Hyogo	0.496	0.58	0.512	0.409	0.271	0.454
Nara	0.25	0.645	0.342	0.345	0.243	0.365
Wakayama	1	4.388	1.194	1	1	1.716
Tottori	1	1	1.231	4.434	2.097	1.952
Shimane	1.346	1.025	1.004	0.244	0.287	0.781
Okayama	1.386	0.496	0.534	0.593	0.383	0.678
Hiroshima	1.684	0.468	0.538	1.051	0.62	0.872
Yamaguchi	1	0.399	0.485	1	1	0.777
Tokushima	0.493	1.494	0.495	0.17	0.114	0.553
Kagawa	0.239	0.308	0.408	0.283	0.236	0.295
Ehime	2.05	0.469	0.478	1.038	0.489	0.905
Kochi	0.353	-	0.558	0.384	0.286	0.396
Fukuoka	1.533	0.446	0.575	0.655	0.51	0.744
Saga	0.181	0.32	0.322	0.295	0.248	0.273
Nagasaki	0.626	1.016	1.131	0.504	0.312	0.718
Kumamoto	0.224	0.405	0.463	0.575	1.036	0.54
Oita	0.22	0.56	0.487	0.529	0.3	0.419
Miyazaki	1.465	0.506	0.482	0.421	0.271	0.629
Kagoshima	1.165	0.545	0.658	0.65	1.027	0.809
Okinawa	0.182	0.34	1.183	0.336	0.179	0.444
Mean	0.715	0.713	0.616	0.696	0.593	0.666
S.D.	0.491	0.644	0.278	0.668	0.444	0.335

Note: "-" indicates that the observed values of the DMU for that period are excluded because all of its input indicators are zero, which does not meet the eligibility criteria for the SE-MSBM model.

The adjustments to the original input indicators in the second stage subjected all DMUs to the worst external environmental and luck-related factors, consequently leading to a decrease in efficiency values for most DMUs. Specifically, after removing the influences of external environment and luck-related factors, the number of DMUs with 5-year average efficiency values greater than or equal to 1 decreased from 8 in the first stage to 4, including Hokkaido, Aomori, Wakayama, and Tottori. Furthermore, compared to the first stage, 61.7% of DMUs experienced a decline in their average efficiency values over the 5-year period. However, despite the removal of external environmental and luck-related factors, Wakayama and Tottori continued to maintain efficient or super-efficient level over the 5-year period.

In contrast to the U-shaped average efficiency trend across all observed DMUs in the first stage, the average efficiency of DMUs displayed a fluctuating downward trend after the removal of external environmental and luck-related factors. Starting from its peak of 0.715 in 2010, the average efficiency demonstrated a steady decline, reaching 0.593 by 2014, with a minor uptick in 2013. This indicates that, at least during the ascending phase (2011 to 2014) of the U-shaped average efficiency trend observed in the first stage, favorable external environmental and luck-related factors masked the fact of low managerial efficiency among DMUs, resulting in a rebound trend in average efficiency. Additionally, compared to the first stage, the standard deviation of efficiency values for DMUs across periods tended to stabilize, indicating that external environmental and luck-related factors increased regional disparities in the efficiency of SPI among DMUs.

4.4.3. Dynamic Evolution of Suicide Prevention Efficiency

For the specific causes of SPI efficiency's variation, a further dynamic decomposition is necessary. Utilizing the MaxDEA software, this study employs the adjacent LTFP analysis to examine the relative shifts between prefectures and the production frontier, wherein LTFP, LPEC, LSEC, LPTP, and LTPSC respectively denote total factor productivity, pure efficiency changes, scale efficiency changes, pure productivity technology changes, and technology scale changes. It's important to note that in contrast to interpreting results from SE-MSBM, if LTFP and its decomposition are greater than 0, it signifies an improvement in productivity, efficiency, or technology compared to the base period; conversely, if it's less than 0, it indicates a decline.

Table 4-6 displays the average LTFP and its decomposition for all observed DMUs from 2010 to 2014. From Table 4-6, we observe that the national LTFP is positive from 2010 to 2013, indicating an overall increase in SPI productivity. However, the reasons for this productivity increase differ. The rise in LTFP from 2010 to 2011 is attributed to the enhancement of LSEC, leading to an improvement in LEC. Conversely, the regression in LTPSC diminished the magnitude of the productivity increase during that period. Improvements in productivity from 2011 to 2012 and 2012 to 2013 are credited to LTC. The former is due to improvements in LPTP, while the latter stems from the enhancement of LTPSC. Lastly, from 2013 to 2014, both LPTP and LTPSC exhibit notable improvements. However, the decline in LPEC and LSEC is greater, resulting in a slight regression in productivity.

Table 4-6. Luenberger Total Factor Productivity and Its Composition.

Period	LTFP	LEC			LTC		
			LPEC	LSEC		LPTP	LTPSC
2010-2011	0.903	2.084	-0.03	2.114	-1.18	0.204	-1.384
2011-2012	0.131	-0.042	-0.085	0.043	0.146	0.233	-0.087
2012-2013	0.170	-0.534	0.036	-0.570	0.704	-0.21	0.914
2013-2014	-0.052	-0.874	-0.103	-0.771	0.798	0.383	0.415
Mean	0.283	0.139	-0.046	0.185	0.123	0.149	-0.026

Overall, over the five-year period from 2010 to 2014, the average SPI productivity across Japan increased by 28.3%. Among this, 13.9% is attributed to the progress of LEC, while 12.3% is credited to LTC's advancements. Notably, the majority of LEC's progress comes from the enhancement of LSEC, while the advancements of LTC overall benefits from the progress of LPTP. Furthermore, in terms of developmental trends, LEC has exhibited a gradual decline since 2011, with the rate of decrease intensifying each year. This decline primarily stems from the overall regression of LSEC, which has shown a progressively increasing downward trend, while the contribution from changes in LPEC remains relatively limited. Conversely, although LTC displayed a significant decline from 2010 to 2011, it has since stabilized and shown a consistent upward trend, with the rate of increase intensifying each year. Both LPTP and LTPSC have made significant contributions to the changes observed in LTC from 2011 onward.

4.4.4. Robustness test

The concern regarding the robustness of this study originates from the insignificance of the OLS regression in the second stage SE-MSBM. Despite Fried et al. (2002)'s indication that under the circumstances where the LR one-sided error test fails to reject the null hypothesis $H_0: \sigma_u^2 = 0$, the stochastic frontier specification is rejected, hence obviating the need for the SFA model. However, the OLS regression in Table 4-4 demonstrates less significant estimation effects for environmental factor coefficients. As a robustness check, this study revisits the estimation of environmental factors' contribution on the slacks in TCSP, EP, and IMP in the second stage, using the SFA model to estimate the coefficients instead of the OLS, and subsequently adjusts the input indicators with the estimated coefficients from SFA. As shown in Table 4-7, compared to OLS, the results from SFA exhibit greater significance, indicating an enhanced explanatory power of environmental variables on the slacks of TCSP, EP, and IMP after accounting for managerial inefficiency's impact.

Table 4-7. The Results of SFA for Robustness Test.

	Slack Variable of TCSP	Slack Variable of EP	Slack Variable of IMP
Marriage rate	-540.976***	-382.821***	-60.352
	(-43.829)	(-25.485)	(-0.620)
Divorce rate	1777.163***	5872.930***	6889.457***
	(166.431)	(722.722)	(1003.856)
Unemployment rate	-683.387***	284.469***	407.418
	(-9.422)	(7.021)	(1.529)
Job availability ratio	-1756.093***	-3728.465***	-456.843***
	(-76.788)	(-476.787)	(-11.125)
Year-on-year changes in the CPI	-207.760	921.354***	408.200**
	(-1.555)	(22.935)	(2.930)
Alcohol consumption volume	-17.924	-1.732	11.519
	(-0.919)	(-0.031)	(0.266)
Stillbirth rate	29.615	37.096	-324.267**
	(0.565)	(0.258)	(-2.708)
Prefectural Income per Capita	0.734*	2.629**	-0.255
	(2.164)	(2.767)	(-0.383)
Constant	1,318.705	-21401.608***	-10715.563***
	(0.470)	(-5296.289)	(-3725.296)
σ^2	8.269E+06***	6.066E+07***	3.752E+07***
LR test of the one-sided error	6.951	2.631	4.970
γ	-	-	-
η	-0.114	-0.048	-0.028

Note: z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Following adjustments to the related input variables based on estimated coefficients, the third stage of the SE-MSBM model is rerun. The efficiency values estimated are then utilized for a subsequent adjacent LTFP analysis, as presented in

Table 4-8. Contrasting the results obtained from Table 4-6, the most notable change observed after considering managerial inefficiency in certain inputs is the shift of the 2013-2014 LTFP from negative to positive. This reversal is attributed to the absolute difference between positive LTC and negative LEC. Furthermore, for other periods and the overall productivity coefficients, the results of the robustness test exhibit minimal discrepancies from the primary analysis, signifying the robustness of the original analytical outcomes.

Table 4-8. Luenberger Total factor Productivity and Its Composition for Robustness Test.

Period	LTFP	LEC			LTC		
			LPEC	LSEC		LPTP	LTPSC
2010-2011	0.933	2.111	-0.034	2.145	-1.178	0.219	-1.397
2011-2012	0.132	-0.043	-0.085	0.042	0.148	0.245	-0.097
2012-2013	0.153	-0.565	0.054	-0.619	0.719	-0.224	0.943
2013-2014	0.157	-0.248	-0.112	-0.136	0.363	0.381	-0.018
Mean	0.342	0.303	-0.045	0.348	0.015	0.152	-0.137

4.5. Discussion

In the three-stage SE-MSBM model, the results from the first stage reflect the SPI efficiency of each prefecture under their respective environmental and stochastic influences. The outcomes from the third stage represent the relative actual managerial efficiency of each prefecture after removing the effects of environmental and stochastic factors. Comparing the results from the third stage with those from the first stage, it's observed that the differences in suicide prevention efficiency among prefectures are more pronounced in the first stage. This suggests that the uneven distribution of external environmental and stochastic factors amplifies regional disparities in SPI efficiency among prefectures. From another perspective, the differences in suicide prevention efficiency observed in reality, attributable solely to managerial efficiency across prefectures, only constitute a portion of the overall observed differences. Neglecting the influence of exogenous factors might potentially exaggerate spatial discrepancies in SPI efficiency.

The analysis concerning the impact of environmental factors on input slack in the second stage has revealed some intriguing findings. (1) Both marriage rates and divorce rates are positively correlated with input slack (negatively associated with efficiency values). Assuming that the societal institution of marriage has a protective effect on suicide prevention (Fujimoto & Yokoyama, 2016; Fukuchi et al., 2013), higher marriage rates and lower divorce rates should result in decreased suicide rates, thereby enhancing SPI efficiency. However, the negative correlation between marriage rates and efficiency values suggests that married life could potentially serve as a trigger for higher suicide rates. According to publicly available data from the Japan National Police Agency (2009-2014), family issues remained the second leading cause of female suicide after health issues during this period, and approximately 10% of male suicides were attributable to family issues. Thus, entering into marriage may offer some protection against suicide on one hand, while on the other hand, it may introduce additional stressors, thereby increasing suicide risk. Moreover, the impact of marriage rates on input slack via the PCSP underscores the significant role of "seeking help" in reducing the suicide rate among individuals facing marital and family problems. Inefficient management and utilization of funds in this sector might lead to an increase in suicides related to marital issues, consequently affecting the overall SPI efficiency of the DMUs. (2) The negative correlation between the job availability ratio and input slack implies that a robust economic environment is more conducive to improving SPI efficiency. Economic and livelihood issues were the second leading cause of male suicides in Japan between 2009 and 2014 (Japan National Police Agency, 2009-2014). Additionally, the surge in Japan's suicide rate in 1998 is believed to be causally linked to economic downturns (Nakanishi & Endo, 2017; Okamura et al., 2021). Therefore, in terms of enhancing SPI efficiency, prefectures facing poorer economic conditions encounter stronger resistance. (3) The negative correlation between CPI and efficiency suggests that increased pressure from higher prices may elevate the risk of suicide, consequently impeding improvements in the effectiveness of SPI. (4) Elevated alcohol consumption tends to decrease the slacks of PCSP, subsequently enhancing efficiency. Despite the common belief that high alcohol consumption increases the risk of suicide (Brady, 2006; Sher, 2006; Stack, 2021), considering the impact of alcohol consumption on PCSP slacks and its potential for alleviating tension and anxiety (Abrams et al., 2022), it is speculated that individuals may be more inclined to engage in conversations ('talk it out') post-alcohol consumption, thus paradoxically reducing the risk of suicide to some extent. However, conflicting evidence in prior studies necessitates further examination of the mediating effects between alcohol consumption and the effectiveness of SPI. (5) There exists a positive correlation between the stillbirth rate and efficiency. Previous studies commonly assert that the stillbirth rate increases the risk of female suicide, which contradicts the findings here. One plausible explanation for this outcome could be, according to the Guidelines for the Management and Operation of the Regional Suicide Prevention Emergency Strengthening Fund (2009), the IMP project serves as a safety net, wherein funds that cannot be allocated to other projects are designated to IMP. Therefore, the causal relationship between the stillbirth rate and the IMP slacks likely attributes to the funding division method of RF.

The analysis of the LTFP index indicates an overall upward trend in SPI productivity across Japan, despite a slight setback observed in 2013-2014. Additionally, there is a declining trend in the marginal improvement of productivity. Although the contributions of LEC and LTC to productivity improvement seem similar based on the outcomes, the developmental trends since 2011 reveal a gradual deterioration in LEC, contrasted with a gradual improvement in LTC. Moreover, the absolute values of the marginal change rates for both indicators have been steadily increasing. This indicates that post-2011, the overall improvement in SPI productivity of DMUs relied predominantly on technological enhancements, and technological advancements masked the deterioration in efficiency. Focusing on the causes of efficiency decline, it becomes evident that due to limited fluctuations in LPEC, the deteriorating trend in LSEC should primarily shoulder the responsibility.

We consider that the 2011 Great East Japan Earthquake has certain connections with the SPI efficiency across Japan. Occurring on March 11, 2011, this natural disaster is considered to have affected residents' psychological and mental health, increasing the risk of suicide (Nakanishi et al., 2020; Orui, 2022; Suzuki & Kim, 2012). According to nationwide studies, female suicide rates surged rapidly in the months following the earthquake, whereas male suicide rates, especially among middle-aged and elderly men, notably decreased in the months following the earthquake, although the declining trend weakened over time (Orui, 2022; Osaki et al., 2021). The contrasting trends in male and female suicide rates posed challenges for prefectural SPI efforts. Furthermore, in the two years following the earthquake, the proportion of female suicides attributed to "health issues" gradually increased (Inoue et al., 2015). According to the findings of Kato and Okada (2019), female suicide rates were inversely proportional to the amount of DPLL at the municipal level in the RF. Therefore, the post-2011 improvement in the management and utilization efficiency of DPLL might have contributed more to the efficiency enhancement. Lastly, the Great East Japan Earthquake might be an important exogenous environmental factor influencing SPI efficiency across prefectures. However, due to the inability to accurately delineate the effects of the natural disaster and its spillover effects on residents' suicide risk, this study could not precisely control for its impact on DMU efficiency, suggesting room for improvement in future research.

4.6. Conclusions

Existing studies on the decline in suicide rates in Japan from 2009 to 2014 have predominantly focused solely on the changes in suicide rates, overlooking the fiscal costs incurred by the government in controlling these rates. In the context of severe financial constraints, this outcome-oriented research approach has led to a lack of understanding regarding the cost-effectiveness of policies, consequently detaching the assessment of policy effectiveness from practical implications. Thus, this study concentrates on the cost-effectiveness of SPI by prefectural governments in Japan from 2009 to 2014, marking the first application of the DEA analysis framework to evaluate the government's efficiency in SPI.

Specifically, we employed the SE-MSBM model, using the declared amounts of RF as inputs and the reduction in male and female suicide rates as outputs to assess the efficiency of SPI across Japanese prefectures. Furthermore, to eliminate the influence of exogenous environmental factors and luck on efficiency, we utilized a three-stage analysis framework to derive a relatively objective managerial efficiency of SPI in these prefectures. Subsequently, to elucidate the dynamic changes in efficiency and their causes, we employed the LTFP index and its decomposition to analyze the productivity changes in SPI efficiency.

The analysis results indicate the following: Firstly, in the three-stage SE-MSBM analysis, the spatial differences in SPI efficiency reflected in the results of the third stage are relatively minor compared to those in the first stage. This suggests that efficiency values directly based on inputs and outputs are easily influenced by exogenous environmental and luck factors. However, after filtering out these exogenous factors, the differences in efficiency values resulting from the managerial efficiency disparities among prefectures are relatively limited. Secondly, the analysis in the second stage of the impact of environmental and luck factors on efficiency values reveals that high divorce rates, high marriage rates, high year-on-year changes in the CPI, low job availability ratio, and low alcohol consumption are likely to hinder the improvement of SPI efficiency. Finally, in the analysis of the LTFP index, we found that although the overall average productivity of SPI in prefectures maintains an upward trend, the marginal improvement demonstrates a diminishing trend. Additionally, productivity improvement comprises positive technical changes and negative efficiency changes, with the negative efficiency changes primarily attributable to the continuous deterioration of scale efficiency.

The results of this study provide some insights for policymakers: Firstly, in the process of enhancing the efficiency of SPI, efforts should not only focus on improving management efficiency but also consider improving the external environment. Secondly, an excessive reliance on technical advancements is observed in the improvement of SPI productivity, insufficiently supported by productivity enhancements arising from efficiency improvements. This highlights the need for further optimization of policy execution efficiency in each prefecture, ensuring that resources are used efficiently. Lastly, optimizing scale efficiency to promote positive efficiency changes, thereby enhancing SPI productivity, appears to be the most evident approach.

We must acknowledge several limitations in this study. Firstly, in the selection of environmental variables, our approach was to include external factors influencing input-output and factors affecting input-output conversion rates in the environmental variable matrix. However, the declaration rules of RF generally did not have specific limitations based on the external environment of each prefecture. Moreover, the input-output conversion rates mainly reflect the fund management and utilization efficiency of DMUs, which is precisely the efficiency that the three-stage SE-MSBM model aims to measure. Therefore, most variables eventually considered as environmental factors tend to exert exogenous influences on output variables, namely male and female suicide rates. The limitation of this variable selection approach lies in the possibility that if other exogenous environmental variables exist, the second stage's filtering effect on environmental and stochastic factors might be inadequate. Secondly, considering that RF does not subsidize SPI policies that had received other subsidies before 2009, we assumed that relevant policies implemented before 2009 continued unchanged during the study period. If this assumption does not hold, the reduction in suicide rates following RF implementation might contain confounding factors. Further examinations and analyses would rely on more precise data support.

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Chapter 5: Conclusion

This study is organized into five chapters. Excluding the introduction and conclusion, the three core chapters present case studies evaluating public policy outcomes within Japan’s unique socioeconomic context. Chapter 2 focuses on policy effectiveness using the Effectiveness Analysis method, while Chapter 3 and Chapter 4 evaluate policy efficiency through the Cost-Effectiveness Analysis method. Notably, the third chapter emphasizes management efficiency by isolating the influence of exogenous factors. Across these studies, evaluations are grounded in factual assessments, supplemented by value assessments where necessary, to mitigate political and ethical controversies.

Chapter 2 evaluates the 2017 reform of Japan's Special Spousal Exemption and its effect on women’s labor supply. The findings reveal that expanding Special Spousal Exemption coverage significantly increased women’s average working hours. This positive labor supply effect remained robust even after excluding individuals who were completely unemployed during the study period. However, the average treatment effect varied by employment type: non-regular female employees experienced significant increases in working hours, while no significant effects were observed for regular female employees. Furthermore, the policy’s impact was concentrated among women with shorter working hours, with no notable changes for women with medium or long working hours. These results can be explained by the substitution and income effects triggered by the reform. For women with shorter working hours, the substitution effect—where consumption goods replace leisure—outweighed the positive income effect, prompting an increase in labor supply. Conversely, for women with medium or long working hours, the limited household income change caused by the reform was insufficient to alter their labor supply preferences. This chapter focuses on whether the policy achieved its intended labor supply effects, without considering associated costs, such as reductions in personal income tax revenue. The findings support the expectation that expanding Special Spousal Exemption coverage encourages women to increase their labor supply.

Chapter 3 investigates whether the deployment of COVID-19 vaccines mitigated regional disparities in local healthcare system efficiency (LHSE) caused by socioeconomic inequality during the early stages of the pandemic. The results indicate that vaccines reduced LHSE disparities overall, particularly in regions with limited hospital bed resources. However, no evidence was found that vaccines weakened the influence of socioeconomic inequality on LHSE disparities. Interestingly, vaccine deployment showed a positive correlation between LHSE improvements and the proportion of elderly populations, but this effect was confined to regions with sufficient hospital bed availability. This phenomenon is attributed to Japan's prioritization of elderly populations during vaccine distribution in the early phases of scarcity. Conversely, in regions with hospital bed shortages, vaccine deployment exacerbated the relationship between the occupancy rate of secured beds for severe cases and LHSE, underscoring the need for sufficient secured beds for severe cases and effective prevention of severe cases in bed-scarce regions in the post-pandemic era.

Chapter 4 examines the efficiency of suicide prevention and intervention programs across Japan's prefectures from 2010 to 2014, with a focus on dynamic changes. Unlike the analysis in the previous chapter, this study isolates exogenous factors, such as environmental and random effects, to estimate the actual managerial efficiency of each prefecture. The findings reveal significant spatial disparities in observed efficiency values, much of which can be attributed to exogenous factors. In contrast, actual managerial efficiency exhibited smaller spatial disparities. Dynamic analysis showed a general upward trend in SPI productivity over the study period, primarily driven by technological advancements rather than improvements in individual efficiency. This highlights the need for policymakers to encourage competition and incentivize prefectures to optimize managerial practices and efficiency.

This study underscores the importance of evidence-based evaluations of public policy outcomes. To ensure accurate assessments, it is essential to define the focus—effectiveness or efficiency—before selecting an appropriate analytical framework. By applying tailored approaches, this research contributes to a deeper understanding of policy impacts in Japan's distinct socioeconomic environment and offers valuable insights for future policymaking.