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The economic burden of chronic diseases: A CGE model approach

Application to depression and Alzheimer's disease in Japan

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Alzheimer's disease (AD) and depression create substantial economic burdens on healthcare policy and resource distribution. A computable general equilibrium (CGE) model was used to quantify the direct and indirect macroeconomic effects of AD and depression in Japan, focusing on age-specific prevalence and sectoral impacts. The results demonstrate material outcomes of these diseases on productivity and gross domestic product (GDP) in an aging society.

The rising cost of long-term care, fueled by aging populations and the increasing prevalence of chronic illnesses, poses a major challenge for policymakers and insurers worldwide. However, it also brings new opportunities for innovation and the development of more effective care models, which has led to ongoing debate over the implementation of mandatory, long-term care insurance.

In Japan, where demographic shifts are particularly acute, accurately assessing the full economic burden of diseases such as AD and depression is essential for informing policy decisions. Traditional approaches, such as partial equilibrium (PE) models, which examine isolated sectors without accounting for interactions across the economy, often fail to precisely estimate indirect costs and broader economic ripple effects.

Recent policy discussions surrounding new AD treatments have further highlighted the importance of comprehensive economic evaluations. An investigation into Lecanemab (Leqembi), a humanized monoclonal antibody for early AD that slows cognitive decline, was launched in Japan in December 2023. During its cost-effectiveness evaluation by the Central Social Insurance Medical Council (Chuikyo), discussions focused on whether long-term care costs could be included alongside medical costs.[1] However, these evaluations were limited to costs affecting public long-term care insurance system benefits and excluded informal care and associated productivity losses (e.g., loss of productivity among family members providing care). The limited scope of the evaluations was partly due to the absence of established estimation methods, which underscores the critical need for scientifically grounded approaches to estimate broader economic impacts.

CGE models have emerged as valuable tools for evaluating the comprehensive economic impact of health conditions. Recent studies, such as Hafner et al.'s research on nocturia[2] and Yerushalmi et al.'s on malaria[3] illustrate how detailed age- and sector-specific prevalence data can be integrated to simulate the propagation of productivity losses and shifts in care demand across the economy. In their analysis, Hafner and colleagues measured productivity loss through absenteeism, thus capturing direct economic effects. Additionally, CGE models can quantify indirect consequences, such as sectoral interdependence and increased demand for professional care, which provides a more comprehensive perspective than more limited modeling approaches.

This study applies the CGE modeling framework developed by Lanz and Rutherford[4] to quantify the economic impact of depression and AD in Japan and address the methodological gap identified in recent policy evaluations. The analysis distinguishes between direct productivity losses and broader economic consequences, aiming to capture the full range of costs associated with these diseases. Disease-specific productivity shocks and alternative care scenarios are modeled to estimate total economic costs, which provide evidence to guide prevention strategies and policy design.

The findings indicate that the impact on GDP varies significantly across sectors, with some industries being affected more severely than others, depending on the health condition being addressed. Hypothetically eliminating new cases of depression would result in an estimated absolute GDP increase of $3.22 billion. For AD, shifting from informal care to professional caregivers could result in a $1.94 billion gain, with the largest economic benefit from an increased use of professional caregivers; this channel alone would contribute approximately $1.16 billion to Japan's GDP. Notably, the CGE model used here is linear, which facilitates estimation of the impact of a more limited and realistic health intervention on GDP.

It is important to note that CGE models have limitations, and their results should be interpreted with caution. They rely on structural assumptions and may not fully capture real-world complexities or adjustment delays. Nevertheless, unlike simpler methods such as PE models, CGE models provide more detailed insights into variables. A brief PE approach is presented later in this paper.

Future research should address additional comorbidities and chronic illnesses, assess intervention cost-effectiveness, and examine the long-term impact of an aging population on AD and related conditions. It would also be valuable to explore using dynamic models to determine whether they would better account for transition periods and labor market adjustments over time.

CGE model framework

CGE models are a class of economic models that use real-world data to simulate how an economy responds to changes in policy, technology, or external factors. Their structure enables them to capture complex interactions among households, firms, government, and other sectors.

Unlike traditional input–output models, CGEs account for changes in prices and substitution between inputs, reflecting cost-minimizing behavior by producers and optimizing decisions by households. Substitution between inputs refers to producers' ability to replace one input with another in response to changes in relative prices or availability. For example, if the price of labor increases, a manufacturer may choose to invest more capital into machinery and less into labor to minimize costs. This flexibility in production processes is captured in CGE models but not in traditional input–output models. CGE models can therefore estimate the indirect and economy-wide impacts of shocks or policy interventions, such as trade reforms, tax changes, or climate policies. Using them to measure the economic effects of health-related changes, however, is more recent and less widespread.

Key features of CGE models include the distinction between endogenous variables (determined within the model) and exogenous variables (set outside the model), with the choice of model closure impacting results. Comparative static CGE models show the change between two equilibrium states, whereas dynamic CGE models show adjustment paths over time.

The comparative static CGE model developed by Lanz and Rutherford was used in this report.[5] This model is considered particularly effective for capturing dependencies among economic variables. We have developed a Python model based on Lanz and Rutherford's model.

We have adapted the model to a small open economy (SOE) framework, which focuses on domestic shocks in Japan while keeping import prices fixed to isolate internal effects. In this framework, Japan is treated as a price-taker in international markets, meaning that domestic policy changes or productivity shocks do not affect world prices. It enables the isolation of the purely domestic effects of mental health interventions on the Japanese economy.

DATA

The primary data source is the 2017 **GTAP11 database**, which provides comprehensive macroeconomic and sectoral information, including trade flows, substitution elasticities, taxes and subsidies, and production factors for global economic modeling.[6] Notably, 2017 is the most recent data available in the database.

For this analysis, the data have been **aggregated into four key sectors** (agriculture, manufacturing, energy, and service) and **two regions** (Japan vs. Rest of the World).

DISEASE BURDEN ASSESSMENT

As in Hafner et al.,[7] the economic impact is measured here through changes in GDP. The analysis centers on **the relative difference in GDP between two model equilibria**: a reference scenario reflecting the current situation and a test scenario simulating the hypothetical elimination of the disease or the associated informal care.

The reported GDP variation thus represents the difference between these two scenarios rather than absolute GDP levels. Within this framework, eliminating the disease increases overall productivity, resulting in **higher GDP** in the test scenario compared to the reference scenario.

Methodology

LABOR PRODUCTIVITY SHOCK FROM DISEASE PREVALENCE

Our approach draws inspiration from Hafner et al.'s nocturia study,[8] in which the following labor productivity shock formula was used:

$$\boldsymbol{c^{labor} = \bar{c}^{labor}(1 + a\theta)}$$

where:

- $\boldsymbol{c^{labor}}$ (resp. $\boldsymbol{\bar{c}^{labor}}$) is the shocked (resp. baseline) **labor productivity**
- $\boldsymbol{a}$ is the **marginal change in productivity**
- $\boldsymbol{\theta}$ is the disease **prevalence**

Prevalence describes the proportion of individuals in a population who have a disease at a specific point in time or over a certain period.

This approach can be justified as follows:

- Let D represent the total number of working days in a year (245 in Japan, excluding paid holidays)
- Let d denote the average number of additional sick days taken annually by workers diagnosed with the disease, compared to those without the disease
- Let $c^{average}$ be the average labor productivity of healthy individuals, and $c^{diseased}$ be the labor productivity of individuals with the disease.

Baseline labor productivity can thus be decomposed into two components: the productivity of healthy workers and the productivity of those with the disease.

$$\bar{c}^{labor} = (1 - \theta)c^{average} + \theta c^{diseased}$$

It is assumed that the productivity of individuals with the disease is proportional to the average productivity of healthy workers based on the number of days worked. The corresponding productivity factor is calculated as the ratio of actual days worked by individuals with the disease (total working days minus sick leave due to illness) to the total number of working days.

$$c^{diseased} = \frac{D - d}{D} c^{average}$$

Thus:

$$\bar{c}^{labor} = (1 - \theta)c^{average} + \theta \frac{D - d}{D} c^{average}$$

$$\bar{c}^{labor} = c^{average}(1 - \theta \frac{d}{D})$$

The model is then adjusted by removing the disease to analyze the impact of its absence.

Let $a = \frac{d}{D}$ denote the marginal change in productivity. It follows that:

$$c^{labor} = c^{average} = \frac{\bar{c}^{labor}}{1 - \theta a} \approx \bar{c}^{labor}(1 + \theta a)$$

Hence, Hafner et al.'s formula is obtained,[9] as the product of a and $\boldsymbol{\theta}$ is much smaller than 1, justifying the use of a first-order approximation, which is more interpretable.

The objective of this study was to estimate the cost associated with the prevalence of a disease within the current population. In this analysis, the productivity shock is applied to **the value of labor**, which corresponds to the **total labor cost**. This refers to the total expenditure on workforce compensation in Japan and includes all labor-related expenses, such as wages, salaries, and other employment-related costs.

Labor productivity is directly linked to the total labor cost, as it measures the output per unit of labor input (e.g., per worker or per hour worked). Typically, increases in labor productivity lead to a rise in the value of labor, as more people working or longer working hours increase total wage expenditures.

By applying a productivity shock directly to the value of labor in the economic model, this study estimates the direct financial impact of reduced productivity on aggregate labor expenditure in each sector. This approach highlights the immediate effects of productivity changes on labor costs and underscores how these variations are reflected in overall GDP.

This variable is denoted as $\boldsymbol{c_{i,r}^{labor}}$ in this paper, where i denotes the sector and r represents the region—in this case, Japan.

ASSUMPTIONS

- **Productivity is assumed to be proportional to the actual number of days worked in relation to the total number of official working days** (245 per year in Japan)

  However, paid leave and vacation days, which vary across sectors, have not been excluded. As a result, the actual number of days worked among official working days is likely to be lower. Therefore, using 245 as the reference may, in fact, underestimate the true economic impact, as it does not fully account for the reduction in effective working days observed in real-world conditions.

- **An average, rather than perfect, productivity level is assumed for healthy individuals**

  For healthy individuals, all official working days are considered to be days actually worked. In contrast, for individuals with a disease, the number of days worked is reduced by the number of sick leave days taken due to illness.

- **Individuals transitioning from a depressive state to a healthy state under the alternative scenario are assumed to return to average productivity**

  This return is proportional to the number of days previously taken as sick leave due to depression, reflecting a recovery to typical productivity levels.

- **The SOE framework is assumed**

  This framework analyzes domestic shocks in Japan while keeping import prices fixed, treating Japan as a price-taker in international markets.

- **A distinction is assumed between direct and indirect effects in this study:**
  - **Direct effects:** Impact on active workers (e.g., depression leading to absenteeism)
  - **Indirect effects:** Impact mediated through informal caregivers (e.g., AD's effect on family members' productivity).

LABOR FORCE DATA

This analysis uses employment data from **Japan's official Labor Force Survey**, a monthly nationwide survey conducted by the Japanese government. For this report, we used data from July 2025, Table II-2-1.[10] This dataset provides detailed figures on employed individuals by age, sex, and industry.

For this study, the original industry categories are aggregated into four main sectors: agriculture, manufacturing, energy, and service. This harmonization aligns with the economic model's structure.

The official Labor Force Survey data is essential for both depression and AD scenarios. It is used to:

- **Weigh health prevalence rates** (by age, sex, and sector) when estimating the sectoral prevalence of a disease
- **Quantify and distribute the economic shocks** (productivity loss and caregiving costs) in line with Japan's actual workforce composition

Direct effect of depression

Depression (also known as major depressive disorder) is a common mental health condition characterized by persistent feelings of sadness, loss of interest or pleasure in activities, and a range of emotional and physical problems. Symptoms often include fatigue, difficulty concentrating, changes in appetite or sleep patterns, feelings of worthlessness or guilt, and, in severe cases, thoughts of self-harm or suicide.[11]

Depression is a leading cause of disability worldwide and significantly affects an individual's ability to function in daily life. Among the working-age population, depression is especially impactful, as it not only reduces quality of life but also leads to a substantial loss in productivity. This occurs through increased absenteeism (missing work due to illness) and reduced productivity while at work.[12]

SCENARIO DESIGN

The selected approach compares two model equilibria:

- **Reference scenario:** The current situation, reflecting the existing cases of depression in the workforce and its associated productivity losses. This scenario serves as the model's baseline equilibrium.
- **Shock scenario:** The hypothetical situation in which **no depression occurs in Japan**, effectively removing the direct productivity losses caused by depression. This scenario represents a counterfactual equilibrium.

The reported change in GDP reflects the difference between the baseline and counterfactual equilibria. This approach allows the economic impacts of depression on Japan's economy to be assessed, as the equilibrium model captures effects throughout the economy by comparing outcomes with and without the presence of depression.

LABOR SHOCK DESIGN

To estimate the direct economic impact of depression, the productivity shock is modeled as follows:

$$\boldsymbol{c_{i,r}^{labor}} = \boldsymbol{\bar{c}_{i,r}^{labor}}(\boldsymbol{1} + \boldsymbol{a\theta_i})$$

where:

- $\boldsymbol{c_{i,r}^{labor}}$ (resp. $\boldsymbol{\bar{c}_{i,r}^{labor}}$) is the shocked (resp. baseline) total cost of labor in sector i and region r (here Japan)
- $\boldsymbol{a}$ is the **marginal annual productivity variation** for individuals with depression if they no longer suffer from the condition
- $\boldsymbol{\theta_i}$ is the **prevalence of depression** in sector i

UNDERLYING ASSUMPTIONS

Marginal annual productivity gain $\boldsymbol{a}$

$\boldsymbol{a}$ is the ratio of average additional sick days taken by workers diagnosed with depression to the average number of working days per year:

$$\boldsymbol{a} = \frac{\boldsymbol{107}}{\boldsymbol{245}} \approx \boldsymbol{44}\%$$

where:

- 107 is the average number of additional sick days taken annually by workers diagnosed with depression, compared to the sick days taken by workers without depression.[13]
- In Japan, there are 104 weekend days, 16 public holidays, and 245 working days in 2025.[14]

This parameter reflects the hypothetical productivity gain if depression-related absenteeism is eliminated.

Prevalence of depression by sector $\boldsymbol{\theta_i}$

$\boldsymbol{\theta_i}$ is calculated as a weighted average prevalence rate, based on major depressive disorder rates by age group and sex for 2021 (Health Data Viz Hub[15]), and employment data by age, sex, and industry from Japan's Labor Force Survey (July 2025).[16] This approach captures sectoral heterogeneity in depression prevalence, adjusting for workforce composition.

FIGURE 1: PREVALENCE OF DEPRESSION IN EACH SECTOR

AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
3.53%	3.86%	3.13%	4.20%

Figure 1 presents the estimated prevalence rates of depression by sector in Japan. These sector-specific rates reflect the demographic composition and occupational characteristics captured in the Labor Force Survey, highlighting that depression prevalence varies moderately across sectors. Notably, the service sector appears to be the most affected, with the highest prevalence of depression among workers.

Applying the productivity shock to each sector yields the proportional increase in sectoral productivity. Figure 2 summarizes the resulting percentage change in the value of labor $\boldsymbol{c_{i,r}^{labor}}$ for each sector i.

FIGURE 2: CHANGE IN THE TOTAL COST OF LABOR $c_{i,r}^{labor}$

	AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
Variation	+ 1.54%	+ 1.68%	+ 1.37%	+ 1.83%

These results demonstrate that the service sector would experience the largest relative productivity gain if depression were eliminated, consistent with its higher depression prevalence. Conversely, the energy sector, with the lowest prevalence, would see the smallest improvement. This sectoral differentiation is crucial for understanding the uneven economic effects of mental health interventions across the Japanese economy.

Once these sectoral shocks are quantified, the aggregate impact on national productivity and GDP is estimated. Sector-specific changes are integrated into the CGE model to assess how alleviating depression among workers, by demonstrating the effect of hypothetically eliminating the disease, could translate into macroeconomic gains at the national level.

RESULTS

The analysis indicates that sectoral productivity improvements from addressing depression in the workforce could **increase Japan's GDP by approximately 0.080%.**

Based on Japan's 2024 GDP of approximately $4.03 trillion,[17] this translates to a **potential economic gain of around $3.22 billion**. This figure represents both the substantial economic benefits that could be achieved through effective mental health interventions and, when viewed from the opposite perspective, the **current economic burden that depression imposes on Japan's economy**.

The CGE model employed here is linear: for realism, the health intervention can therefore be limited, even though the objective of this paper is to provide a method for quantifying the overall cost of a disease. For example, it can be assumed that only 10% of individuals with depression can be treated effectively, in which case GDP would experience an increase of only 0.008%.

Treatment measures, such as free psychological consultations, could reduce absenteeism by addressing an individual's depression before it becomes severe,[18] thus mitigating the economic burden of the disease.

Indirect effect of AD

AD is a progressive neurodegenerative disorder that primarily affects older adults 65 and over. It is characterized by a gradual decline in cognitive functions such as memory, language, reasoning, and behavior, eventually leading to loss of independence. Patients with AD require increasing assistance with daily activities, such as eating, bathing, and temporal and spatial orientation.[19]

From an economic perspective, most individuals diagnosed with AD are no longer active in the workforce. However, the disease imposes a significant burden on informal caregivers, often family members, who provide daily support for free. These caregivers devote substantial time and energy to caring for their loved ones, which results in reduced work productivity, increased absenteeism, and deterioration of their own physical and mental health (including depression, anxiety, and burnout).[20]

SCENARIO DESIGN

- **Reference scenario:** The current situation, in which informal caregivers play a central role in supporting patients with AD.
- **Shock scenario:** The hypothetical removal of informal caregivers, replaced by professional workers, resulting in a productivity gain. The time previously devoted to informal caregiving is now provided by professional caregivers, thereby monetizing the formerly unpaid caregiving time.

It is important to note that, unlike the depression case study, this scenario does not consider the removal of AD itself, but rather the elimination of informal care as the primary support mechanism.

The change in GDP presented in the results corresponds to the difference in equilibrium GDP between these two scenarios. This approach allows for isolating and quantifying the measured impact on GDP by shifting from informal to professional care for patients with AD in Japan.

LABOR SHOCK DESIGN

The overall productivity shock is divided into three channels, each corresponding to a distinct manner in which caregiving affects labor productivity.

The three channels are:

- *j = 1*: Productivity gain for professional caregivers
- *j = 2*: Direct productivity gain among informal caregivers
- *j = 3*: Indirect productivity gain from alleviating depression among informal caregivers

Thus, the shock is calculated as follows:

$$\boldsymbol{c_{i,r}^{labor}} = \boldsymbol{\bar{c}_{i,r}^{labor}}(\mathbf{1} + \sum_{j=1}^{3} \boldsymbol{a_j \theta_j(i)})$$

where:

- $\boldsymbol{a_j}$ represents the annual marginal productivity change associated with each channel j
- $\boldsymbol{\theta_j(i)}$ denotes the share of affected workers in sector i for each channel j

UNDERLYING ASSUMPTIONS

1. Productivity gain for professional caregivers *(j = 1)*

Assumption

If informal caregivers are unavailable, professional caregivers (medical staff, home care aides) must assume all support responsibilities for patients with AD, leading to a substantial increase in their workload. Consequently, this channel pertains exclusively to the service sector.

Parameter values

$\boldsymbol{a_1} = \frac{\mathbf{86}}{\mathbf{245}} \times \frac{\boldsymbol{N_{inf}}}{\boldsymbol{N_{pro}}}$ is the **annual marginal increase in workload** where:

- 86 represents the average number of days per year that informal caregivers spend taking care of their ill loved ones [21]

In a study by Biasutti et al.,[22] informal caregivers were found to spend approximately 517 hours over a three-month period providing care. This amount of time is thus equivalent to approximately 86 days per year.

- In Japan, there are 245 working days[23]
- N_{inf} is the total number of informal caregivers and N_{pro} is the total number of professional caregivers in Japan

These values were calculated using the Labor Force Survey[24] and the data from Ohno et al.'s study of AD caregivers in Japan.[25]

Accordingly, Japan would require approximately $\frac{N_{inf}}{N_{pro}} \approx 1.89$ times more professional caregivers to compensate for the absence of informal caregivers.

An interpretation of $\boldsymbol{a_1}$ is as follows: the numerator $86N_{inf}$ reflects the total number of days that informal caregivers dedicate to supporting loved ones suffering from disease, whereas the denominator $245N_{pro}$ represents the total number of days worked by professional caregivers. If informal caregiving were to cease, the corresponding workload would need to be absorbed by professional caregivers, effectively redistributing the informal caregiving days into the professional workforce.

$\boldsymbol{\theta_1(i)}$ is the share of professional caregivers for each sector $\boldsymbol{i}$, calculated using the Labor Force Survey.[26]

FIGURE 3: SHARE OF PROFESSIONAL CAREGIVERS BY SECTOR

AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
0.0%	0.0%	0.0%	1.95%

Since health-related occupations are included in the service sector, only this sector contains professional caregivers. This group represents 1.95% of the service sector workforce (Figure 3).

Of note, due to the level of detail in the Labor Force Survey dataset,[27] only the total number of professional health workers is provided. As a result, the impact of this shock may be overestimated since only a portion of health workers are caregivers, and fewer still are specifically involved in caring for patients with AD. For reference, in France, approximately 20% of healthcare professionals are caregivers;[28] this proportion was therefore applied in this analysis.

2. Direct Productivity Gain Among Informal Caregivers *(j = 2)*

Assumption

Informal caregivers experience reduced productivity due to absenteeism associated with their caregiving duties.

Parameter values

$\boldsymbol{a_2} = \frac{\mathbf{16}}{\mathbf{245}}$ is the **marginal annual productivity gain** where:

- 16 represents the number of additional sick days taken annually by informal caregivers due to AD care compared to the annual sick days taken by non-AD caregiver workers[29]
- 245 is the average number of working days in Japan in 2025[30]

$\boldsymbol{\theta_2(i)}$ is the **share of informal caregivers for each sector $\boldsymbol{i}$**.

- θ_2 was calculated as a weighted average based on age, gender, and sectoral workforce composition, using the Labor Force Survey and the data from Ohno et al.'s study of AD caregivers in Japan[31][32].

Since the Ohno et al. study provides caregiver data disaggregated by age and gender but not by sector,[33] the sectoral distribution of informal caregivers was estimated by combining the age- and gender-specific shares from Ohno et al. with the sectoral workforce composition from the Labor Force Survey.[34]

FIGURE 4: SHARE OF INFORMAL CAREGIVERS BY SECTOR

AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
2.95%	2.75%	2.50%	2.72%

All sectors contain informal caregivers, with shares ranging from 2.50% to 2.95% (Figure 4).

3. **Indirect productivity gain** *(j = 3)*

Assumption

The emotional and physical stress of caregiving leads to a higher prevalence of depression among informal caregivers, further compounding productivity loss.

Parameter values

$\boldsymbol{a_3} = \frac{\mathbf{107}}{\mathbf{245}}$ is the **marginal annual productivity gain** if depression is alleviated (same method as in the depression case study). It represents an upper bound because informal caregivers may experience depression due to factors unrelated to caregiving.

$\boldsymbol{\theta_3(i) = 0.19 \times \theta_2(i)}$ is the share of informal caregivers with depression for each sector $\boldsymbol{i}$. Indeed, 19% of the informal caregivers are estimated to suffer from depression.[35]

FIGURE 5: SHARE OF INFORMAL CAREGIVERS WITH DEPRESSION BY SECTOR

AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
0.56 %	0.52 %	0.48%	0.52%

AGGREGATE PRODUCTIVITY SHOCK

By employing the equation for calculating shock (see the Labor Shock Design section above), the composite productivity shock can be derived and subsequently integrated into the model to obtain the following sectoral impacts:

FIGURE 6: CHANGE IN THE TOTAL COST OF LABOR $c_{i,r}^{labor}$

	AGRICULTURE	MANUFACTURING	ENERGY	SERVICE
Variation	+0.44 %	+0.41 %	+0.37%	+1.70%

The results indicate that the service sector experiences by far the largest relative increase (+1.70%). This pronounced effect is primarily due to the high concentration of healthcare professionals and caregiving activities within the service sector, making it particularly sensitive to changes in caregiving demands and the alleviation of productivity losses linked to AD.

RESULTS

The analysis reveals a change of **+0.048% in Japan's GDP** resulting from the aggregated direct and indirect economic effects associated with the three dementia caregiving channels examined. **This represents an increase of roughly $1.94 billion for the country.** This increase demonstrates that supporting dementia caregivers through professional care services can generate substantial economic benefits at the national level.

The largest economic effect comes from the increased reliance on professional caregivers (j=1), yielding a GDP variation of +0.029% when this channel is considered in isolation. This channel alone would contribute approximately $1.16 billion to Japan's GDP.

The results suggest that the economic burden of AD is driven primarily by the need for professional caregiving in the absence of informal caregivers. This raises important policy questions:

- **Access to private insurance or increased public support** may be necessary to cover the cost of professional care, as these expenses can exceed the financial capacity of many families.
- **Prevention of caregiver burnout and depression** is highly desirable from both an economic and social perspective. It can be promoted by offering training, support groups, and free counseling services.[36]

Using a PE model

PE models analyze specific markets in isolation, holding other factors constant. Unlike CGE models, which capture economy-wide interdependencies and cross-sectoral effects, PE models provide simpler calculations but may miss broader systemic impacts and general equilibrium adjustments.

Based on Hafner's approach,[37] the PE model here is based on the following formula:

$$c_{disease} = P_{disease} \times W \times a_{disease}$$

$$with: \ P_{disease} = POP \times \theta_{disease}$$

where:

- $c_{disease}$ is the cost of the disease
- $P_{disease}$ is the number of people suffering from the disease
- POP is the total active population
- $\theta_{disease}$ is the prevalence of the disease or the share of people with the disease in the total population
- W is the per capita GDP
- $a_{disease}$ is the marginal variation in productivity because of the disease

In Japan, POP is approximately 67 million and W is around $32,500.

APPLICATION TO DEPRESSION

For this disease, as before, only one channel is considered, which is the hypothetical elimination of depression.

The prevalence of depression is the average of disease prevalences by sector, weighted by the number of workers per sector. The marginal variation in productivity is the same as that used in the CGE model.

The cost of depression is then obtained: $c_{disease} \approx \$39$ billion, representing almost 1% of Japan's GDP.

It is essential to note that this relative variation is almost 10 times larger than that obtained with the CGE model.

APPLICATION TO AD

For AD, the total cost of caregiving will be the sum of the costs of each previous channel:

$$c_{caregiving} = W \times \sum_{j=1}^{3} (P_j \times a_j)$$

with $P_j = POP \times \theta_j$ for $j \in \{1;\ 2;\ 3\}$

For each channel, the share of the affected population is a weighted average using workers per sector as weights, and the marginal variation in productivity is that of the CGE model.

By adding the different intermediate costs, the total AD caregiving cost is approximately $30 billion, representing 0.7% of the national GDP. Here, the PE approach provides a variation almost two times higher than the CGE approach.

Channel 1, which represents the productivity gain for professional caregivers, remains the most impactful, with a cost of $21 billion, representing around 70% of the total cost or 0.5% of national GDP.

LINK THE PE AND CGE MODELS

Unlike Hafner's work, this article does not aim to compare PE and CGE models. However, the PE model yields GDP variations much larger than those obtained using the CGE model for both AD and depression studies, suggesting potential overestimation.

The CGE model's key advantage is its detailed breakdown of GDP components and its ability to capture complex economic effects. For instance, the CGE model reveals a significant capital-to-labor substitution effect: as labor becomes more productive and relatively cheaper, firms substitute it for capital. The PE model misses such inter-sectoral dynamics and feedback mechanisms.

Although useful for simple calculations, the PE model may not fully represent complex economic interactions captured by general equilibrium analysis.

Conclusion

This paper highlights the utility of CGE models for quantifying the macroeconomic impact of major diseases such as depression and AD in Japan. By capturing both the direct effects on the workforce and the indirect spillover effects through informal caregiving, this analysis demonstrates that chronic illnesses not only reduce individual well-being but also impose considerable economic burdens at the national level.

The findings, shown in Figure 7, demonstrate that hypothetically eliminating new cases of depression could lead to a GDP increase of 0.080%, whereas shifting AD care from informal to professional caregivers could yield a GDP gain of 0.048%. These results are consistent with previous research, such as Hafner et al.'s nocturia study,[38] which reported a GDP impact of +0.09% for severe cases, reinforcing the reliability of the CGE model for this paper and for the broader economic relevance of health-related productivity losses.

FIGURE 7: CHANGE IN JAPAN'S GDP

	DEPRESSION	AD
Relative change	+ 0.080%	+ 0.048%
Absolute change	+ $3.22 billion	+ $1.94 billion

Discussion

LIMITATIONS

Although CGE models are useful for assessing the economic impact of chronic diseases, they have important limitations. Their structure and calibration depend on several assumptions, such as the existence of a perfectly rational representative agent, zero-profit conditions, and market-clearing mechanisms. These assumptions, along with choices regarding parameter values, the representativeness of input data, and fixed variables, can significantly shape results. Because these elements are not always empirically grounded, they introduce uncertainty, reduce transparency, and may bias outcomes.

The static analysis assumes immediate labor reallocation after a shock, ignoring transition delays, adjustment costs, and institutional constraints. This leads to an estimation of maximum potential impacts but fails to capture short- and medium-term dynamics or broader social effects, such as team productivity losses or the role of unpaid work.

Applying CGE models to the health sector involves structural simplifications that may not reflect the sector's complexity. Modeling Japan as an SOE helps isolate domestic effects but overlooks potential international or systemic interactions. Moreover, aggregating the economy into only four sectors may miss important sub-sectoral variations.

Finally, focusing primarily on monetary indicators, such as changes in GDP, captures only a portion of the total value of health interventions. Social benefits, such as improved well-being, quality of life, and the contribution of unpaid care, remain unaccounted for.

FURTHER RESEARCH

These insights from this research are particularly relevant for Japan, where an aging population and rising dependency ratios are putting increasing pressure on the health and social care systems. Policy interventions aimed at prevention and formalized care could yield significant returns.

These results should be considered in the broader debate regarding the mandatory requirement for long-term care insurance.

Future research should incorporate other comorbidities for AD, such as anxiety; focus on other chronic illnesses to assess their economic burden; and evaluate the cost-effectiveness of specific interventions in the long term. Additionally, prospective studies could examine the future impact of population aging on the prevalence, economic burden, and management of AD and related comorbidities.

Finally, future research should consider more granular and dynamic modeling approaches, such as DSGE models or agent-based models, which can better account for the transition period and adjustment delays in labor markets, providing a more realistic assessment of the economic impacts over time.

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ENDNOTES

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