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INCOME INEQUALITY AND THE SUICIDE RATE IN JAPAN: EVIDENCE FROM COINTEGRATION AND LA-VAR

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Using time series techniques, this paper examines the relationship between the suicide rate and income inequality in Japan. Since both the suicide rate and income inequality (Gini coefficient) in Japan are integrated of order one for the sample period 1951–2007, the existence of cointegration is a prerequisite for the successful modeling of their relationship. The Durbin-Hausman test shows that the suicide rate is cointegrated with income inequality and the unemployment rate. The dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) methods demonstrate that income inequality and the unemployment rate are positively and significantly related to the suicide rate in Japan, and there is evidence supporting the parameter stability of our suicide model. Furthermore, the lag-augmented vector autoregression (LA-VAR) approach shows that there exists unidirectional Granger-causality from income inequality to the suicide rate. Hence, the fluctuations in Japan's suicide rate are partially explained by income inequality.

JEL classification codes: C22, I10
Key words: suicide, income inequality, time series, cointegration, LA-VAR

I. Introduction

Since the early 1990s, the suicide rate in Japan has increased remarkably, escalating from 16.1 (per 100,000 people) in 1991 to 25.4 in 1998—an approximate 60% rise within the short span of 8 years. Furthermore, in 2000, the suicide rate in Japan was the highest among the developed countries, excluding Russia and the central and eastern European countries. The World Health Organization (WHO) reported that the overall suicide rate in Japan was 24.1 in 2000; this figure was higher than those

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of most other developed countries such as Canada (11.7), France (18.4), Germany (13.5), Italy (7.1), the U.K. (7.2), and the U.S. (10.4). These facts have generated considerable concern among Japanese policy makers (e.g., Cabinet Office 2007). However, the determinants of suicide in Japan are still a matter of debate.

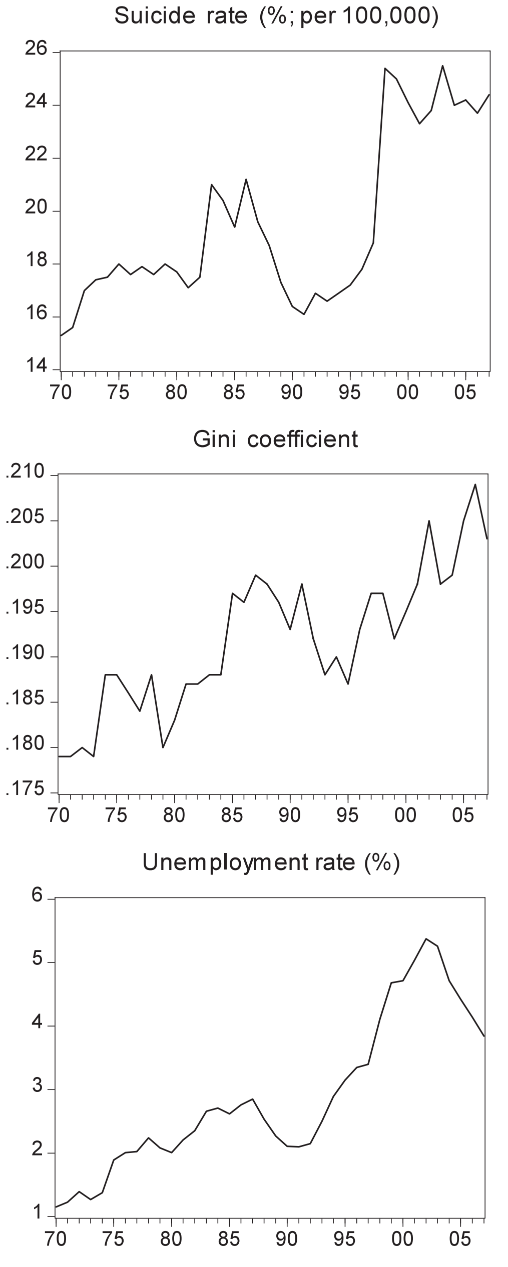
To illustrate the nature of the suicide problem in Japan, it is important to provide theoretical explanations of its determinants. In this regard, Daly, Wilson, and Johnson (2007) and Daly and Wilson (2009) point out the importance of interpersonal income comparisons. They argue that suicide data can be used as a direct measure to assess utility, and their theoretical model predicts that an individual commits suicide when his/her current and expected future utility is less than the perceived utility of committing suicide. If individuals compare themselves to others to determine their own utility, a deterioration of their relative position may lead to a decrease in their perceived utility and, consequently, to an increase in their suicide risk. In this respect, interpersonal income comparisons seem to be a useful measure for examining the determinants of suicide. Specifically, if an individual's utility does indeed depend on relative income as Daly, Wilson, and Johnson (2007) and Daly and Wilson (2009) demonstrate empirically, then an increase in the income of an individual has a negative impact on others since it deteriorates their relative positions. In other words, an increase in income inequality may lead to an increase in suicide risk for the less well-off individuals in the community.[1] Hence, from this perspective, it seems reasonable to suppose that income inequality is one of the determinants of suicide.

This paper addresses the question of whether income inequality in Japan affects the suicide rate. In the literature on the relationship between income inequality and suicide, little attention has been paid to the case of Japan. The prevention of suicide is an important issue in Japan, since it has one of the highest suicide rates in the world. In this light, an investigation of the relationship between income inequality and suicide in Japan seems significant; moreover, such an investigation could provide useful information to those responsible for formulating the Japanese policy on mental health care.

This paper examines the relationship between the suicide rate and income inequality in Japan by using time series techniques. As Figure 1 indicates, the suicide

[1] It is likely that individuals also take into consideration those who earn less than themselves. The existence of such downward-looking comparisons implies that an increase in income inequality improves the well-being of individuals at the top of the income distribution, which could offset, at least partially, the negative impact of income inequality on those at the bottom of the distribution. Hence, it seems more appropriate to regard the negative impact of income inequality on well-being as a net negative impact.

Figure 1. Suicide rate, Gini coefficient, and unemployment rate in Japan



Note: The Gini coefficient is calculated from data on the annual averages of monthly income per workers' household. Detailed explanations of the data are provided in Section IV.

rate in Japan has been on the rise since the 1970s. In the late 1990s, the suicide rate rose to its highest level since the 1970s, and it has remained at that level after 2000. The time series fluctuations in the suicide rate clearly describe the recent suicide conditions in Japan, and therefore, an investigation of the sources of these time series fluctuations may be beneficial. For example, the Gini coefficient and unemployment rate (a measure of economic conditions) appear to exhibit an upward trend similar to that of the suicide rate (Figure 1).[2] In particular, all three variables increased during the same period in the mid-1990s. These facts suggest the possibility that both income distribution and labor market conditions affect the time series fluctuations in the suicide rate. Therefore, the use of time series techniques could facilitate our understanding of the determinants of suicide in Japan.[3]

We examine the cointegration of the relationship between the suicide rate and income inequality in Japan. The cointegration property is important because it can provide greater insights into this relationship. For example, let us assume that the suicide rate and its determinants are integrated of order one. The existence of cointegration between them implies that they have common trends; in this case, we can estimate a regression equation for the suicide rate, which would be indicative of a long-run equilibrium relationship. However, if the suicide rate is not found to be cointegrated with its determinants, then the relationship can be regarded as a spurious regression, which gives rise to serious problems in terms of statistical inference (e.g., Granger and Newbold 1974). Therefore, to ensure that the regression results we obtain are not spurious, we need to test for the existence of cointegration. In other words, we can reasonably state that the existence of cointegration is a prerequisite for the successful modeling of the relationship between the suicide rate and income inequality in Japan, since both are likely to be integrated of order one.

This paper contributes to the literature on the relationship between suicide and income inequality in three respects. First, it uses the Durbin-Hausman test (Choi 1994), which is a residual-based test for cointegration, to examine the relationship. This test is more powerful in finite samples than the other residual-based tests for cointegration, such as the augmented Dickey-Fuller and Phillips-Perron tests (e.g.,

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[2] Detailed explanations of the data are provided in Section IV.

[3] The National Survey of Family Income and Expenditure reports income inequality data for each of the 47 prefectures in Japan; however, these data are available only for the years 1999 and 2004. Thus, since we are concerned with the time series fluctuations in the suicide rate in Japan after the 1970s, we do not use prefecture-level panel data.

Choi 1994). Hence, the Durbin-Hausman test can provide more accurate results for cointegration in cases with small samples as in the case of this study.

Second, we pay careful attention to the cointegration property of the suicide model that we estimate. More specifically, we use the fully modified ordinary least squares (FMOLS; Phillips and Hansen 1990) and dynamic ordinary least squares (DOLS; Stock and Watson 1993) methods. These methods correct for endogeneity and serial correlation in cointegrating regressions, thereby providing unbiased estimates of the cointegrating coefficients. In addition, we examine the parameter stability of the suicide model by using the SupF and MeanF tests (Hansen 1992), which can be applied to the FMOLS estimator.

Third, we apply the lag-augmented vector autoregression (LA-VAR) approach (Toda and Yamamoto 1995) to test for Granger-causality between the suicide rate and income inequality in Japan. The LA-VAR approach allows us to test for Granger-causality among time series variables in levels without taking their integration and cointegration properties into consideration. In this respect, it is more advantageous to use the LA-VAR approach rather than the standard VAR and vector error correction approaches when examining Granger-causality between the suicide rate and income inequality.

This paper is organized as follows. The next section briefly reviews the literature on the relationship between income inequality and suicide. Section III explains the methodologies used in the paper. Section IV describes the data. Section V reports the empirical results. Section VI presents the conclusion.

II. Overview of the literature

The literature on the relationship between income inequality and suicide can be classified into two groups.[4] The first group uses individual-level data, and the second group uses aggregate data such as cross-country or cross-state panel data.

[4] Many studies have been conducted on other determinants of suicide. For example, a number of studies have focused on economic and social factors such as income level, unemployment rates, economic growth, divorce rates, female labor force participation, urban environments, private and public health expenditure, mental health insurance, age, race, and gender (e.g., Andrés 2005; Brainerd 2001; Burr, McCall, and Powell-Griner 1997; Chen, Choi, and Sawada 2009; Chuang and Huang 1997; Daly, Wilson, and Johnson 2007; Daly and Wilson 2009; Klick and Markowiz 2006; Kowalski, Faupel, and Starr 1987; Minoiu and Andrés 2008; and Neumayer 2003, 2004). The epidemiologic literature has also examined suicide (e.g., Blakely, Collins, and Atkinson 2003).

The first group of studies tends to find that income inequality has a significant impact on suicide risk. We begin with key studies by Daly, Wilson, and Johnson (2007) and Daly and Wilson (2009), who examined the relationship between suicide risk and relative income to test for the existence of interpersonal income comparisons. They used individual-level data in the U.S. After controlling for own income and individual characteristics, Daly, Wilson, and Johnson (2007) found that the suicide risk of individuals in the U.S. was affected not only by their own income but also by the incomes of others residing in their local area. Daly and Wilson (2009) found similar results by using both suicide and subjective well-being (SWB) data, thus supporting the significance of interpersonal income comparisons.

Miller et al. (2005) examined the relationship between income inequality and suicide in New York City neighborhoods. They used accident victims as the control group in their multilevel case-control study. They reported that younger persons living in neighborhoods with greater income inequality were at a higher risk of suicide.

These analyses are connected with previous studies that focused on the relationship between income inequality and happiness. For example, Alesina et al. (2004) examined the effect of the level of income inequality on individual well-being. They used "happiness" data (i.e., SWB data) for the U.S. and Europe and applied an ordered logit regression model. Even after controlling for individual income, a large set of personal characteristics, and year and country, they found that individuals tend to report themselves as being happy less often when inequality is high.

Luttmer (2005) used individual-level data to examine the relationship between happiness and neighbors' earnings. After controlling for individuals' own income, he found that neighbors' earnings had the strongest negative effect on happiness for those individuals who socialized more in their neighborhood.

The second group of studies that uses aggregate data such as cross-country or cross-state panel data shows different results. For example, Neumayer (2004) employed panel data of German states for the period 1980–2000. Using static and dynamic panel data models, he found that the unemployment rate had a negative and significant impact on the suicide rate, while income inequality had a positive but insignificant impact on the suicide rate. These observations also applied to the other causes of mortality investigated in the study, such as the incidence of cardiovascular diseases.

Lynch et al. (2001) examined the relationship between income inequality and health, with focus on age-specific, sex-specific, and cause-specific mortality as well as on life expectancy. Their analyses were based on correlation coefficients calculated from cross-sectional data. They showed that the correlation between income inequality and suicide mortality was insignificant at the 5% level.

Andrés (2005) examined the determinants of suicide in 15 European countries for the period 1970–1997. He used panel data techniques and focused on age-specific suicide rates and overall suicide rates. He reported that economic growth, fertility rates, and alcohol consumption had a significant impact on suicide rates, while income inequality, GDP per capita, female labor participation rates, unemployment rates, and divorce rates did not have a significant impact on suicide rates.

Leigh and Jencks (2007) examined the relationship between income inequality and mortality. They used panel data of 12 countries (Australia, Canada, France, Germany, Ireland, New Zealand, Spain, Sweden, Switzerland, the Netherlands, the U.K., and the U.S.) for the period 1903–2003, and proposed the income share of the richest 10% of the population as a new measure of income inequality. They found little evidence in favor of a causal relationship between income inequality and suicide. This observation also applied to other mortality measures such as infant mortality, life expectancy at birth, and homicide.

Unlike the panel-data analyses of other studies, such as Leigh and Jencks (2007), Chen, Choi, and Sawada's (2009) study included Japanese data in their panel data analysis. They used panel data of all OECD countries for the period 1980–2003 and examined differences between Japan and the other OECD countries in terms of the determinants of suicide. They found that the parameter of the dummy variable for Japan's Gini coefficient was significant for all gender/age groups, excepting males in the age group 25–44 and females in the age group 65 and older.

III. Methodologies

A. Model specification

In the literature on the relationship between income inequality and health, it is common to include a measure for economic conditions as a key variable in the models. Along these lines, we include a variable for unemployment in our suicide model (e.g., Ruhm 2000) and adjust the basic bivariate specification with a variable for income inequality. We estimate the following suicide model:

$$\ln S_t = \beta_0 + \beta_1 \ln U_t + \beta_2 \ln G_t + u_t, \quad (1)$$

where $\ln S_t$ denotes the natural log of the suicide rate; $\ln U_t$, the natural log of the unemployment rate; $\ln G_t$, the natural log of the Gini coefficient; u_t, an error term; and β_0, β_1, and β_2, the coefficients to be estimated.[5]

In this paper, we use the Gini coefficient as a measure of income inequality. The discussion in Section I suggests that an increase in income inequality leads to an increase in suicides. Hence, the Gini coefficient is expected to be positively related to the suicide rate (i.e., $\beta_2 > 0$), since a higher Gini coefficient means greater income inequality.

The impact of unemployment on suicide allows two interpretations.[6] One is that suicide is countercyclical (e.g., Brainerd 2001; Chuang and Huang 1997). For example, Hamermesh and Soss (1974) suggested that an individual commits suicide when the discounted utility for the remainder of his/her life falls below a certain threshold. For example, an economic recession deteriorates the financial condition of unemployed persons and, consequently, decreases their future consumption. Hence, an individual might be more compelled to commit suicide during an economic recession. From this perspective, the unemployment rate is expected to be positively related to the suicide rate (i.e., $\beta_1 > 0$).

Another interpretation of the impact of unemployment on suicide is that suicide is procyclical (e.g., Neumayer 2004). For example, let us suppose that economic expansion decreases unemployment but increases individuals' working hours. An increase in an individual's working hours leads to a decrease in his/her leisure and utility. Hence, economic expansion increases job-related stress, which may lead to increased suicides. From this perspective, the unemployment rate is expected to be negatively related to the suicide rate (i.e., $\beta_1 < 0$).

According to Andrés (2005), the impact of unemployment on suicide is open to debate. Therefore, it is also important to focus on the sign and significance of β_1 in our empirical analysis.

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[5] To avoid multicolinearlity, in the model represented by equation (1), it seems better to include only unemployment as a measure indicating economic conditions. In Section V, we extend this three-variable model to a six-variable model. This six-variable model includes the following additional variables: (i) proportion of the population over the age of 65, (ii) divorce rate, and (iii) female labor force participation rate. The results showing the impact of income inequality remain robust even after these variables are incorporated into the basic three-variable model.

[6] These interpretations apply to the other health status indicators as well. For example, using U.S. panel data, Ruhm (2000) found that suicide is countercyclical but that most of the other causes of death are procyclical.

B. Durbin-Hausman test for cointegration

In this subsection, we briefly explain the Durbin-Hausman test for cointegration developed by Choi (1994). Let $z_t = (Y_t, X_{1t}, \ldots, X_{mt})'$ be an $(m+1)$-vector time series, and let us suppose that each element of the vector z_t is integrated of order one. Using the ordinary least squares (OLS) method, we estimate the following regression:

$$Y_t = \hat{\gamma}_0 + \hat{\gamma}_1 X_{1t} + \cdots + \hat{\gamma}_m X_{mt} + \hat{u}_t , \tag{2}$$

where $\hat{\gamma}_0, \ldots, \hat{\gamma}_m$ are the OLS estimates of the coefficients, and $\hat{u}_t$ is the OLS residual.

The residual $\hat{u}_t$ is regressed on its own lagged value $\hat{u}_{t-1}$ as follows:

$$\hat{u}_t = \alpha \hat{u}_{t-1} + e_t , \tag{3}$$

where e_t denotes an error term. Then, the null hypothesis of no cointegration is formulated as

$$\mathrm{H}_0 : \alpha = 1. \tag{4}$$

Using the two estimators $\hat{\alpha} = \sum_{t=1}^{T} \hat{u}_t \hat{u}_{t-1} \Big/ \sum_{t=1}^{T} \hat{u}_{t-1}^2$ and $\hat{\alpha}_{IV} = \sum_{t=1}^{T} \hat{u}_t^2 \Big/ \sum_{t=1}^{T} \hat{u}_t \hat{u}_{t-1}$, Choi (1994) proposed the Durbin-Hausman statistic (*DHS*) as

$$DHS = (\hat{\alpha}_{IV} - \hat{\alpha})^2 \div \left\{ \hat{s}^2 \hat{\delta} \left(\sum_{t=1}^{T} \hat{u}_{t-1}^2 \right)^{-1} \right\}, \tag{5}$$

where $\hat{s}^2 = T^{-1} \sum_{t=1}^{T} (\hat{u}_t - \hat{\alpha}\hat{u}_{t-1})^2$, $\hat{\delta} = \hat{s}^2 / \hat{\sigma}^2$, $\hat{\sigma}^2 = T^{-1} \sum_{t=1}^{T} (\hat{u}_t - \hat{\alpha}\hat{u}_{t-1})^2 + 2T^{-1} \sum_{s=1}^{l} d_{sl}$ $\sum_{t=s+1}^{T} (\hat{u}_t - \hat{\alpha}\hat{u}_{t-1})(\hat{u}_{t-s} - \hat{\alpha}\hat{u}_{t-s-1})$, and d_{sl} denotes the lag window.

We can use the *DHS* to test the null hypothesis in equation (4). If the *DHS* is found to be significant at conventional levels, then we can conclude that the $(m+1)$-vector time series z_t is cointegrated. The critical values of the *DHS* are tabulated in Choi (1994).

C. LA-VAR approach

In this subsection, we briefly explain the LA-VAR approach developed by Toda and Yamamoto (1995). Let us suppose that an n-vector time series y_t is generated by the following VAR model:

$$y_t = c + J_1 y_{t-1} + \cdots + J_k y_{t-k} + \varepsilon_t, \tag{6}$$

where k is the true lag length, ε_t is a vector of error terms with zero mean and a positive definite covariance matrix, c is a vector of constant terms, and $J_1,\ldots,J_k$ are parameter matrices of autoregressive terms.

We formulate the null hypothesis that the j-th variable does not Granger-cause the i-th variable as follows:

$$\mathrm{H}_0 : J_{ij}(1) = \cdots = J_{ij}(k) = 0, \tag{7}$$

where $J_{ij}(h)$ is the (i,j) element of the matrix $J_h (h = 1,2,\ldots,k)$. To test the restriction in equation (7), we estimate the following VAR model:

$$y_t = \hat{c} + \hat{J}_1 y_{t-1} + \cdots + \hat{J}_p y_{t-p} + \hat{\varepsilon}_t, \tag{8}$$

where p is equal to the true lag length (k) plus the maximum order of integration ($d_{\max}$), and $\hat{c}, \hat{J}_1,\ldots,\hat{J}_p, \hat{\varepsilon}_t$ denote the OLS estimates. Note that the maximum order of integration must not exceed the true lag length of the VAR model (i.e., $d_{\max} \leq k$). Furthermore, the restriction in equation (7) should not include $\hat{J}_{k+1},\ldots,\hat{J}_p$ because their true values are known to be zero.

Using the standard chi-square distribution, we can test any restrictions on the parameter matrices $\hat{J}_1,\ldots,\hat{J}_k$ in the VAR model. To be specific, we only need to determine the true lag length and estimate the (k + $d_{\max}$) th-order VAR model in equation (8). Ignoring the parameter matrices of the last $d_{\max}$ autoregressive terms in the model in equation (8), we can test the restriction in equation (7) by using the standard Wald statistic. Therefore, within the framework of the LA-VAR approach, we can test for Granger-causality among time series variables in levels, while paying little attention to their integration and cointegration properties.

IV. Data

We use annual Japanese data in our investigation. The sample period is set as 1951–2007 because of data availability issues.[7] The data consist of the overall suicide rate, the overall unemployment rate, and the Gini coefficient. Data sources are the Statistics Bureau website and the MHLW Statistical Database, which can be accessed through the website of the Ministry of Health, Labour and Welfare.

For Japan, the only data available for calculating the Gini coefficient over a long period are the annual averages of monthly income per household. Hence, in this study, the Gini coefficient is calculated on the basis of the annual averages of monthly income per workers' household categorized by annual income quintile group. Referring to Daly, Wilson, and Johnson (2007), we use the income data for workers' households since their preferences are likely to depend on both their own and others' incomes. To increase the sample size, we use data for two-or-more-person workers' households.

V. Results

A. Unit root tests

Before estimating equation (1), it is necessary to examine the stationarity of each of the variables included in the equation, since we use time series data. In this paper, we use the unit root tests developed by Ng and Perron (2001). MZ_α and MZ_t are modifications of the unit root test statistics developed by Phillips and Perron (1988).

Table 1. Unit root test results

	Level		First difference	
Variable	MZ_α	MZ_t	MZ_α	MZ_t
lnS_t	–5.9853	–1.5948	-26.2145^{***}	-3.6178^{***}
lnU_t	–1.3271	–0.5840	-22.2571^{***}	-3.2982^{***}
lnG_t	–0.6116	–0.4411	-26.2320^{***}	-3.6163^{***}

Note: Both tests include a constant term. The bandwidth parameter is selected through the procedure described in Andrews (1991), which uses a first-order autoregressive model. The spectral estimation method used is the quadratic spectral (QS) kernel. *** indicates significance at the 1% level.

[7] In the case of Japan, data on the annual income of the quintile group (workers' households) are available from 1951.

The unit root test results are reported in Table 1. The tests do not reject the null hypothesis of a unit root for the variables in levels. However, the null hypothesis of a unit root is rejected for the variables in first differences at the 1% level. Therefore, as expected, all the variables are found to be integrated of order one.

B. Cointegration tests

Since we are now certain that all the variables are integrated of order one, the next step is to test cointegration for equation (1). We use the Durbin-Hausman test explained in Section III.

Table 2. Durbin-Hausman test for equation (1)

		Critical values		
Test	Statistic	1%	5%	10%
DHS	69.7198**	71.41	53.35	45.64

Note: The bandwidth parameter, selected through the procedure described in Andrews (1991), is 1.1. The spectral estimation method used is the QS kernel. ** indicates significance at the 5% level.

The cointegration test results for equation (1) are reported in Table 2. The null hypothesis of no cointegration is rejected at the 5% level. Hence, there is evidence that in the case of Japan, the suicide rate is cointegrated with income inequality and the unemployment rate.

C. Estimation of the suicide model

We can now estimate equation (1) using the DOLS and FMOLS methods. As explained in Section I, these methods correct for endogeneity and serial correlation in cointegrating regressions. Hence, we can expect these methods to provide better estimation results for equation (1).

The estimation results are reported in Table 3. All the parameter estimates are significant at the 1% level, and similar estimation results are obtained from both estimation methods. Hence, our estimation results are robust.

The estimation results for equation (1) can be summarized as follows. First, we find that income inequality is positively and significantly related to the suicide rate. This result is consistent with the discussion in Section I. The inequality elasticity (β_2) is 0.69. This result suggests that a 1% increase in the Gini coefficient increases the suicide rate by 0.69%.

Table 3. Estimation results for equation (1)

	Parameter estimate	Standard error
DOLS		
Constant term	3.8242***	0.2785
Unemployment rate	0.2726***	0.0640
Gini coefficient	0.6893***	0.1744
FMOLS		
Constant term	3.8868***	0.2257
Unemployment rate	0.2617***	0.0484
Gini coefficient	0.7275***	0.1440

Note: For the FMOLS estimates, the long-run variance-covariance matrix is estimated using the pre-whitened QS kernel with a first-order vector autoregressive model. For the DOLS estimates, the long-run variance is estimated using the QS kernel. The bandwidth parameter is selected through the procedure described in Andrews (1991). The number of leads and lags in the DOLS regression is 1. *** indicates significance at the 1% level.

Second, we find that the unemployment rate is positively and significantly related to the suicide rate. This result suggests that in Japan, suicide is countercyclical. In this respect, the result is consistent with those of Brainerd (2001), Chuang and Huang (1997), and Ruhm (2000). The unemployment rate elasticity (β_1) is 0.27. This result suggests that a 1% increase in the unemployment rate increases the suicide rate by 0.27%.

Table 4. Tests for parameter stability of equation (1)

		Critical values		
Test	Statistic	1%	5%	10%
SupF	11.4487	21.40	17.30	15.30
MeanF	6.4000	10.30	7.69	6.58

Note: SupF and MeanF are the test statistics for the null hypothesis of parameter stability, and the trimming region is specified as [0.15, 0.85].

Finally, we find that these parameter estimates are stable over the sample period. Table 4 presents two stability test statistics developed by Hansen (1992). In brief, SupF and MeanF are the test statistics for the null hypothesis of parameter stability, and these tests are applicable to the FMOLS estimator. The null hypothesis of parameter stability is not rejected at conventional significance levels. Therefore, there is evidence supporting the parameter stability of equation (1). From this result, we can reasonably state that equation (1) is successfully estimated for the sample period 1951–2007.

D. LA-VAR approach

At this point, it is clear that the relationship between the suicide rate and income inequality in Japan is explained well by the basic model in equation (1). To investigate this relationship in further detail, we examine the Granger-causality between the suicide rate and income inequality. We use a Granger-causality test based on the LA-VAR approach.

As explained in Section III, the maximum order of integration ($d_{\max}$) must not exceed the true lag length of the VAR model (k) within the framework of the LA-VAR approach (i.e., $d_{\max} \leq k$). The unit root test results reported in Table 1 indicate that $d_{\max} = 1$. To determine the appropriate lag length for the VAR model, we use the Akaike information criterion (AIC), the Schwartz Bayesian information criterion (SBIC), and the modified likelihood ratio (LR) test. In all three cases, the selected lag length is 1 ($k = 1$). Therefore, the LA-VAR approach is applicable to the data, and we can perform the following analysis on the basis of the VAR model with $k = 1$ and $d_{\max} = 1$.

Table 5. Causality test statistics: LA-VAR

Null hypothesis	Wald statistic	p-value
$\ln S_t$ *does not Granger-cause* $\ln U_t$	1.3891	0.2386
$\ln S_t$ *does not Granger-cause* $\ln G_t$	1.7150	0.1903
$\ln U_t$ *does not Granger-cause* $\ln S_t$	4.6007**	0.0320
$\ln U_t$ *does not Granger-cause* $\ln G_t$	0.1161	0.7333
$\ln G_t$ *does not Granger-cause* $\ln S_t$	4.5991**	0.0320
$\ln G_t$ *does not Granger-cause* $\ln U_t$	2.3585	0.1246

Note: ** indicates that the null hypothesis of no Granger-causality is rejected at the 5% level.

The Granger-causality test results are reported in Table 5. The null hypothesis that $\ln G_t$ does not Granger-cause $\ln U_t$ is rejected at the 5% level, but the null hypothesis that $\ln U_t$ does not Granger-cause $\ln G_t$ is not rejected at conventional levels. Hence, there is evidence supporting unidirectional Granger-causality from income inequality to the suicide rate. Furthermore, the same observation also applies to the unemployment rate.

To obtain additional information on the timing of causation, it may be useful to reexamine the lag structure of the suicide equation in the VAR system in greater detail. Therefore, we reexamine the lag length of the suicide equation, and test the null hypothesis that the suicide rate is affected by the income inequality and/or the unemployment rate with (k – 1) lags against the alternative specification of k lags. Specifically, we estimate the following equation:

$$\ln S_t = \mu + \sum_{i=1}^{k} \phi_i \ln S_{t-k} + \sum_{i=1}^{k} \varphi_i \ln U_{t-k} + \sum_{i=1}^{k} \theta_i \ln G_{t-k} + e_t, \tag{9}$$

where e_t is an error term and μ, $\phi_1,\ldots,\phi_k$, $\varphi_1,\ldots,\varphi_k$, and $\theta_1,\ldots,\theta_k$ are the coefficients to be estimated.

We focus on the significance of $\ln U_{t-k}$ and $\ln G_{t-k}$. For example, let $k = 4$. Then, the significance of $\ln G_{t-4}$ implies that the suicide rate is affected by income inequality with 4 lags; in this case, a suicide equation with 4 lags seems preferable. However, if $\ln S_{t-4}$, $\ln U_{t-4}$, and $\ln G_{t-4}$ are found to be insignificant, then a suicide equation with 3 lags would be preferable.

Table 6. Detailed results for lagged impacts (dependent variable: $\ln S_t$)

Independent variable	k = 4	k = 3	k = 2	k = 1
$\ln U_{t-k}$	0.5418	0.2774	0.0313	4.6007**
	(0.4617)	(0.5984)	(0.8596)	(0.0320)
$\ln G_{t-k}$	0.4011	0.2141	0.9062	4.5991**
	(0.5265)	(0.6435)	(0.3411)	(0.0320)
$\ln S_{t-k}$	0.0626	0.0011	0.5906	32.4280***
	(0.8024)	(0.9740)	(0.4422)	(0.000)
Joint significance	0.8104	0.3983	1.4956	83.1210***
	(0.8470)	(0.9406)	(0.6833)	(0.000)

Note: The table reports the Wald statistics. The numbers in parentheses are p-values. Beginning with the fourth lag (k = 4), we decrease the lag one by one until we first observe the significance of the largest lag at the 5% level. The LA-VAR approach is used to test the significance. *** and ** indicate significance at the 1% and 5% levels, respectively.

The results are summarized in Table 6. Beginning with the fourth lag (k = 4), we decrease the lag length one by one until we first observe the significance of the largest lag at the 5% significance level. Note that the LA-VAR approach is used to test the significance. We find that the second, third, and fourth lags in the suicide equation are insignificant at conventional levels. However, the first lag is significant at the 5% level. Furthermore, the same results are obtained from the joint significance test. Therefore, our results suggest that both income inequality and the unemployment rate affect the suicide rate with a one-year lag, since we use annual data.

E. Robustness checks

In this subsection, we verify the robustness of the empirical results obtained with the basic model in equation (1). In particular, it is necessary to consider the possibility of omitted variable bias, since the basic model in equation (1) is very small as compared to the models used in previous studies (e.g., Andrés 2005; Chen, Choi, and Sawada 2009; Daly, Wilson, and Johnson 2007; Daly and Wilson 2009). In this light, we extend the basic model as follows:

$$\ln S_t = \beta_0 + \beta_1 \ln U_t + \beta_2 \ln G_t + \beta_3 \ln P_t + \beta_4 \ln D_t + \beta_5 \ln F_t + u_t, \tag{10}$$

where P_t denotes the proportion of the population over the age of 65; D_t, the divorce rate; and F_t, the female labor force participation rate.[8]

To obtain data for P_t, we calculate the ratio of the population over the age of 65 to the total population. Similarly, to obtain data for F_t, we calculate the ratio of the female labor force to the total labor force. The data sources are the same as those reported in Section IV; however, the sample period is chosen as 1953–2007 because data on the female labor force are available only from 1953.

Following Herwartz and Theilen (2003), we use P_t as a measure of population aging. Japan's Cabinet Office (2006) points out that the country's upward trend in income inequality can be attributed mainly to the rapidly aging population. Hence, it is possible that the inclusion of P_t in the model will affect the significance of G_t, which is our main focus.[9] In other words, this investigation can help us establish the robustness of our results showing the impact of income inequality. Moreover, we use D_t and F_t as measures of social factors (e.g., Chen, Choi, and Sawada 2009; Chuang and Huang 1997).

MZ_α and MZ_t indicate that $\ln(P_t)$, $\ln(D_t)$, and $\ln(F_t)$ are integrated of order one.[10] The Durbin-Hausman statistic for equation (10) is 178.84. This result is significant

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[8] Although it would be preferable to include a higher number of variables in the model to test the robustness of our results, it is difficult to do so because of the small sample size. As Ericsson (1998) points out, the omission of important variables is likely to induce parameter instability and a lack of cointegration. However, our basic model in equation (1) does not exhibit these problems. Moreover, while omissions could potentially cause endogeneity bias, we use the DOLS and FMOLS methods to correct for any endogeneity bias. For these reasons, small extensions such as that in equation (10) seem to be useful.

[9] It is possible that population aging affects suicide rates. For example, see Chuang and Huang (1997).

[10] The unit root test results are not reported in the paper but are available from the author upon request.

Table 7. Estimation results for equation (10)

	Parameter estimate	Standard error
DOLS		
Constant term	2.1557***	0.6711
Unemployment rate	0.3929**	0.1799
Gini coefficient	0.6914***	0.2268
Proportion of population over the age of 65	–0.0997	0.2094
Divorce rate	0.1837	0.3564
Female labor force participation rate	–1.6346**	0.6067
FMOLS		
Constant term	2.1614***	0.5070
Unemployment rate	0.2791***	0.1061
Gini coefficient	1.0009***	0.2282
Proportion of population over the age of 65	–0.1121	0.1408
Divorce rate	0.2909	0.2385
Female labor force participation rate	–1.9931**	0.8327

Note: See the notes to Table 3 for the estimation procedures. *** and ** indicate significance at the 1% and 5% levels, respectively.

at the 1% level. Therefore, there is evidence supporting the existence of cointegration for equation (10).

The estimation results for equation (10) are reported in Table 7. We find that income inequality and the unemployment rate are positively and significantly related to the suicide rate in Japan. These results are consistent with those obtained from the estimation of our basic model in equation (1). Hence, we can reasonably state that our main results are robust.

It is also found that the divorce rate and proportion of the population over the age of 65 are not significant factors. However, the female labor force participation rate is negatively and significantly related to the suicide rate. This result suggests that an increase in female labor participation leads to a decrease in the female suicide risk and, consequently, to a decrease in the overall suicide risk.[11] Increased female labor participation may result in stronger social integration. In addition, household incomes generally increase when females participate in labor markets, and this may also contribute to the overall decrease in the risk of suicides.

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[11] Using the DOLS and FMOLS methods, we find that the female labor force participation rate is negatively and significantly related to the female suicide rate.

We have also estimated separate regressions by gender. In the analysis, the male suicide rate (S_t^m), female suicide rate (S_t^f), male unemployment rate (U_t^m), and female unemployment rate (U_t^f) are used instead of the overall suicide and unemployment rates. However, the Gini coefficient is the same as that used above, since in the case of Japan, the Gini coefficient cannot be calculated separately by gender over the sample period.

MZ_α and MZ_t indicate that $\ln(S_t^m)$, $\ln(S_t^f)$, $\ln(U_t^m)$, and $\ln(U_t^f)$ are integrated of order one. The Durbin-Hausman test shows evidence supporting the existence of cointegration for males and females. Using the DOLS and FMOLS methods, we find that overall income inequality is positively and significantly related to the male and female suicide rates. Hence, the results for the impact of income inequality reported above are robust even if we examine the impact separately by gender.[12]

VI. Conclusions

In this paper, we examine the relationship between the suicide rate and income inequality in Japan. We distinguish our work from the existing literature by using time series techniques such as the Durbin-Hausman test for cointegration, the DOLS and FMOLS methods, and a Granger-causality test based on the LA-VAR approach. Since our focus is on Japan, an empirical analysis based on Japanese time series data serves our purpose.

Our main findings can be summarized as follows: (i) the suicide rate, income inequality (Gini coefficient), and the unemployment rate are integrated of order one; (ii) the suicide rate is cointegrated with income inequality and the unemployment rate, and the parameter stability of the basic suicide model is supported; (iii) income inequality and the unemployment rate are positively and significantly related to the suicide rate; (iv) income inequality and the unemployment rate Granger-cause the suicide rate, but not vice versa; (v) the results showing the impact of income inequality are robust when we test a broader model (there, female labor force participation is negatively related to suicide rate); and (vi) the positive impact of income inequality is robust when we examine that effect separately by gender.

As Förster and Mira d'Ercole (2005) indicate, income inequality in Japan has increased consistently since the 1980s. In 2007, the share of non-regular workers reached approximately a third of employees, and this labor market dualism has

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[12] Detailed results are not reported in the paper for space reasons, but are available from the author upon request.

created a large segment of workers with lower wages, short-term job experience, and limited opportunities to enhance their human capital. These facts have raised serious concerns about equity (e.g., OECD 2008). Hence, it is likely that Japanese people tend to make interpersonal income comparisons. At the same time, the suicide rate in Japan appears to exhibit an upward trend similar to that of the Gini coefficient. Indeed, there is substantial evidence to support the argument that a significant relationship exists between the suicide rate and income inequality in Japan. On these grounds, it seems reasonable to conclude that the time series fluctuations in the suicide rate in Japan over the past 50 years can be partially explained by changes in income inequality.

It is important to consider the reason why our results are different from those reported in several previous studies. For example, Andrés (2005), Leigh, and Jencks (2007), and Minoiu and Andrés (2008) report that income inequality does not affect suicide. A possible explanation for this inconsistency is that the determinants of suicide are different in Japan. Chen, Choi, and Sawada (2009) demonstrate this point by using a dummy variable technique. It is also important to note that the panel data analyses of Andrés (2005), Leigh and Jencks (2007), and Minoiu and Andrés (2008) do not include Japanese data, and therefore, the inconsistency is likely to occur. In other words, the suicide and income inequality data for Japan may be outliers compared to the data for the other countries. In this respect, our results are complementary to those reported in the previous studies.

Finally, as to the implications of the paper's results for Japanese mental health care policy, we can reasonably state that it is important to consider both income distribution and labor market conditions in order to reduce the overall suicide rate in Japan. For example, the mental health care policies for males and females in the lowest income group are likely to play an important role in the prevention of suicides in Japan. Likewise, careful attention should be paid to people who lose their jobs, particularly during periods of economic recession, since overall suicide in Japan is countercyclical.

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