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The effect of staying at home on suicide during the COVID-19 pandemic

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【要旨】

Studies have reported a strong association between policy stringency and mental health problems during the COVID-19 pandemic, primarily among females, but the causal effect of people's stay-at-home behavior on mental health is not yet known. This study evaluated how pandemic-related confinement at home affected the incidence of suicide among Japanese females. We employ a shift-share IV design, assessing whether differential exposure to the pandemic shock led to changes in the outcome variable. We found that suicide increased among females under 20 years old as more people stayed at home. The results are robust across different model specifications. Counterfactual analyses show that at least 37% of suicides in the demographic group can be attributed to home confinement. Our results suggest that a substantial part of the observed increase in suicide rates among female children and adolescents was driven by lifestyle changes during the pandemic.

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The effect of staying at home on suicide during the COVID-19 pandemic

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February 29, 2024

Abstract

Studies have reported a strong association between policy stringency and mental health problems during the COVID-19 pandemic, primarily among females, but the causal effect of people's stay-at-home behavior on mental health is not yet known. This study evaluated how pandemic-related confinement at home affected the incidence of suicide among Japanese females. We employ a shift-share IV design, assessing whether differential exposure to the pandemic shock led to changes in the outcome variable. We found that suicide increased among females under 20 years old as more people stayed at home. The results are robust across different model specifications. Counterfactual analyses show that at least 37% of suicides in the demographic group can be attributed to home confinement. Our results suggest that a substantial part of the observed increase in suicide rates among female children and adolescents was driven by lifestyle changes during the pandemic.

Keywords: Mental health; Lockdown; Shift-share IV; Specification curve analysis

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1 Introduction

Suicide is a serious public health problem with detrimental effects on individuals and society. More than 700,000 people die by suicide every year (WHO, 2021), and suicide is the tenth and second leading cause of death among the population at large and young adults specifically in the United States (CDC, 2022). In some countries, the problem has become more serious in recent years. In the United States, for example, the suicide rate increased by 30% between 2000 and 2018. Suicide and suicide attempts in the United States are estimated to cost approximately 60 billion US dollars in medical and labor loss costs alone (Shepard et al., 2016). In Japan, the country under scrutiny in this study, the female suicide rate in 2019 was the second highest among OECD member countries (OECD, 2022). Suicide prevention is, therefore, one of the most important public health concerns worldwide.

The global COVID-19 pandemic that started in 2020 further increased the risk of mental health problems and suicidal behavior. To date, a number of economic and public health studies have shown an elevated risk of the symptoms of depression, an increase in calls to mental health helplines, suicide attempts, and self-harm (Brodeur et al., 2021; Brülhart et al., 2021; Dubé et al., 2021; Vahratian et al., 2021; John et al., 2020a). A slight decrease in the incidence of suicide was reported in the early stage of the pandemic, followed by a gradual increase in suicides and suicidal behavior (John et al., 2020b). Understanding the cause of this increase during the pandemic is an important scientific and policy concern. Specifically, this study sheds light on lifestyle changes caused by countermeasures to the pandemic and examines the impact of staying at home on suicide during the first year of the pandemic.

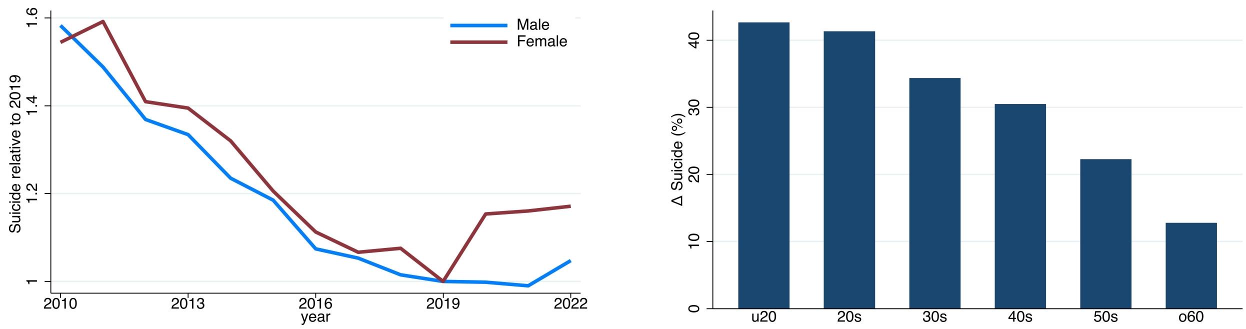
Suicide is rarely driven by a single cause, and suicide risk is associated with a combination of personal, relational, community, and social factors. Nonetheless, some evident risk factors could be considered related to suicide during the COVID-19 pandemic. One such factor is economic problems, together with financial instability. Previous studies indicate that working-age males are most vulnerable to macroeconomic shocks such as financial crises (Chen et al., 2009, 2015). Consistent with this finding, economic disturbances induced by the COVID-19 pandemic and social distancing policies were hazardous for individuals (Ando and Furuichi, 2022; Matsubayashi et al., 2022; Elbogen et al., 2020).

What is puzzling, however, is that existing studies show a clear and consistent pattern in which increases in suicide under the pandemic are more pronounced among young people and females

Figure 1: Suicide Trends in Japan: Impact of COVID-19

(a) Yearly Trends in Suicide Incidents by Gender

(b) Age-specific Percentage Changes in Female Suicide Incidents



Notes: Panel (a) displays the long-term yearly trend in the number of suicide incidents among men and women in Japan from 2010 to 2022, with 2019 as the base year. Panel (b) shows the percentage change in the number of suicide incidents among women after COVID-19, compared with the incidence before COVID-19, broken down by age group. The sample period spans from April 2019 to March 2021. The term "before COVID-19" refers to the period between April 2019 and March 2020, while "after COVID-19" pertains to the period from April 2020 onwards.

in Japan (Tanaka and Okamoto, 2021; Sakamoto et al., 2021; Ueda et al., 2021). Tanaka and Okamoto (2021) argues that the increase in suicides in the summer of 2020 was primarily driven by females and young people, with increases in fatality of 37% and 49% for females and for children and adolescents, respectively. This trend are confirmed by the data shown in Figure 1, where the increase in suicide is greater among females and, in particular, among those under age 30. These segments of the population have been thought to be less susceptible to economic problems. The difference between the affected population in the pandemic condition and the population affected in past macroeconomic shocks is likely to suggest the involvement of another factor distinct from traditional economic problems.

One major risk factor in relation to the pandemic is disconnection from society. Early public health responses against the COVID-19 pandemic included strong social distancing measures such as lockdowns and stay-at-home orders. Although the intensity of such policies varied from country to country, most developed countries, including Japan, kept large segments of society at home in the early stages of the pandemic[1]. The WHO warned that social disconnection during the pandemic could increase the risk of mental illness. One study validated this finding by showing a positive association between the stringency of social distancing policies and the prevalence of mental health problems (Aknin et al., 2022).

[1]The COVID-19 policy details are found in the Appendix A.1.

In this paper, we examine the causal impact and the degree of influence of staying at home on female suicide using Japanese data to understand the mechanism underlying the increase in suicide among young females. Previous studies have examined the impact of social distancing on various outcomes, including mental health, leveraging regional differences in the degree and/or timing of stay-at-home policies (Baek et al., 2021; Altindag et al., 2022; Serrano-Alarcón et al., 2022). In this paper, we assess the impact using a direct measure of staying at home to capture the actual behavior of individuals. This is important because voluntary social distancing, as opposed to policy-induced social distancing, has been shown to represent a substantial part of observed behavioral responses (Yan et al., 2021). This matters even more in the context of Japan, where curfews imposed under the state of emergency had no legal binding force through fines or arrests, and as a result, the declaration of the state of emergency did not necessarily serve as a good proxy of the degree to which people stayed at home.

An empirical challenge in testing the effect of stay-at-home behavior on suicide is that home confinement is potentially endogenous. For example, mental health status could be an unobserved confounding factor that could affect home confinement as well as suicide. To address this issue, we employ a shift-share instrumental variable (IV) design. Specifically, our analysis exploits geographical variation in exposure to the pandemic and tests whether *differential* exposure to the shock led to *differential* changes in suicide incidence. We employ an IV strategy where a change in individuals' stay-at-home behavior is predicted by prepandemic commuting behavior. In this study, we focused on females because the increase during the pandemic was more pronounced for females, as shown in Figure 1a.

This study contributes to the literature in three ways. First, we add to the economics literature on mental health by examining physical disconnection from society as a risk factor for suicide. To date, the economic literature on psychological well-being and suicide has focused primarily on economic factors (Hamermesh and Soss, 1974; Darity and Goldsmith, 1996; Ruhm, 2000). Second, we shed light on individual patterns of home confinement as the mechanism underlying the increase in suicide rates during the COVID-19 pandemic. Understanding the pathway through which suicide rates increase has important implications for public policies regarding both infectious disease control and suicide prevention. Additionally, it is essential to quantify the social costs of public health responses during the pandemic in terms of human lives. Third, we employ the shift-share IV design to obtain a causal impact. Mobility tends to be endogenous in terms of outcome variables related to individual decisions, and addressing it is an important empirical consideration.

2 Empirical model

2.1 Setup

To estimate the effect of staying at home on the incidence of suicide, we consider the following structural equation:

$$\ln(1 + Suicide_{mt}) = \alpha_m + \delta \times t + \beta StayHome_{mt} + \varepsilon_{mt}, \tag{1}$$

where m indexes the municipalities and t indexes the time period. The outcome variable of interest is the natural logarithm of one plus the number of *female* suicide cases, $Suicide_{mt}$, in municipality m in period t [2]. We consider two time periods, that is, a pre-COVID-19 period for $t = 0$ (from April 2019 to March 2020) and a post-COVID-19 period for $t = 1$ (from April 2020 to March 2021) [3].

The explanatory variable of our focus is the degree of staying at home, $StayHome_{mt}$, of residents of municipality m in period t. It is potentially endogenous and influenced by unobserved confounding factors such as area-specific psychological traits and environmental conditions. These factors may simultaneously affect both suicidal and stay-at-home behaviors. The OLS estimates of β could be biased due to these confounding factors. We control for municipality-specific fixed effects α_m and common time trends $\delta \times t$.

In practical applications, when addressing municipality-specific fixed effects within the panel data structure, one common approach to employ is a first-difference specification designed to eliminate the influence of the municipality fixed effect, denoted as α_m. This approach can be expressed as follows:

$$\Delta \ln(1 + Suicide_m) = \delta + \beta \Delta StayHome_m + \Delta\varepsilon_m, \tag{2}$$

[2] In the following tables and figures, we report the semielasticity of suicide with respect to mobility, calculated from the estimated coefficient $\hat{\beta}$ based on the following equation: $\hat{\beta} \cdot (1 + Suicide)/Suicide$. Thus, we could multiple the numbers in the tables by 100 to obtain a percentage change in suicide.

[3] We adopt this time frame because the number of COVID-19 cases increased rapidly at the end of March, and the government declared the first state of emergency on April 7th, as discussed in Section A.1. We do not consider the period after April 2021, when vaccines became available, and people subsequently started returning to normal life. The sensitivity of our estimation results to the choice of periods is examined through a specification curve analysis conducted in Section 4.3

where Δ represents the first-differencing operator.

To mitigate endogeneity concerns regarding the variable $StayHome_{mt}$ in Equation (1) or $\Delta StayHome_m$ in Equation (2), we employ a shift-share instrument. This method introduces an additional dimension, distinct from both the cross-sectional dimension and the time dimension, aimed at reducing the influence of potential confounders on our causal estimates. To achieve this, we express the variable $StayHome_{mt}$ as the average residents' proportion of time spent at home in municipality m during period t as:

$$StayHome_{mt} = \sum_{i \in N_m} \left(\frac{1}{n_m} \right) s_{it}.$$

In the equation, i represents residents, N_m denotes the set of municipality m residents, n_m indicates the total resident count, and s_{it} signifies the proportion of time resident i spends at home during period t. Importantly, s_{it} is influenced by municipality-specific psychological and environmental factors, making $StayHome_{mt}$ an endogenous variable within the structural equation. In the context of the shift-share instrumental variable approach, $1/n_m$ embodies the share-related factor, whereas s_{it} corresponds to the shift-related element. Consequently, the endogenous variable is articulated as the inner product of these share and shift components.

Utilizing the inner-product structure of the endogenous variable, we construct a shift-share instrument, categorizing residents into K types based on stay-at-home behavior. Assuming similar stay-at-home propensities among residents of each type k, we define s_{ikt} as $s_{ikt} = g_{kt} + \xi_{ikt}$. Here, g_{kt} indicates the average proportion of time that type k residents spend at home in period t, while ξ_{ikt} captures the idiosyncratic deviation from a typical stay-at-home propensity for each resident i of type k in period t. It is important to note that the individual-specific term ξ_{ikt} might be correlated with various confounding factors in municipality m.

Accordingly, we reformulate the stay-at-home variable specific to each municipality as follows:

$$StayHome_{mt} = \sum_{k \in K} \left(\frac{n_{mk}}{n_m} \right) g_{kt} + \sum_{k \in K} \sum_{i \in N_{mk}} \left(\frac{1}{n_m} \right) \xi_{ikt}, \tag{3}$$

where N_{mk} is the cohort of type-k residents in municipality m, and n_{mk} is their number. The first term, representing the shift-share instrument $ShiftShare_{mt}$, isolates the exogenous variation in $StayHome_{mt}$ from the endogenous individual component related to ξ_{ikt}. With $z_{mk} = n_{mk}/n_m$ denoting the proportion of type-k residents in m, the shift-share instrument, $ShiftShare_{mt} =$

$\sum_k z_{mk} g_{kt}$, is composed of two elements: the share component (z_{mk}), which is predetermined and governing exposure to shocks, and the shift component (g_{kt}), which is a common trend among type-k residents across municipalities.

2.2 Canonical Case: Two Types

To illustrate the shift-share instrumental variable estimation, let us use a simplified scenario to focus on the differential impact of COVID-19 on two types of residents: *commuters* and *noncommuters*. Suppose that noncommuters (represented as $k = 0$) predominantly stayed home, while commuters (represented as $k = 1$) were mostly away before the pandemic started. Emergency declarations in the post-COVID-19 period led both groups to largely remain at home. This change is captured by setting the following average stay-at-home time proportions: $g_{10} = 0$ and $g_{00} = g_{01} = g_{11} = 1$. Thus, for any resident i of type k in municipality m, $ShiftShare_{mt} = \sum_k z_{mk} g_{kt} = (t-1) z_{m1} + 1$, where z_{m1} is the proportion of commuters in municipality m in the pre-COVID-19 period. In a time-difference form, given that $\Delta g_1 = 1$ and $\Delta g_0 = 0$, we have a simple expression as $\Delta ShiftShare_m = z_{m1}$.

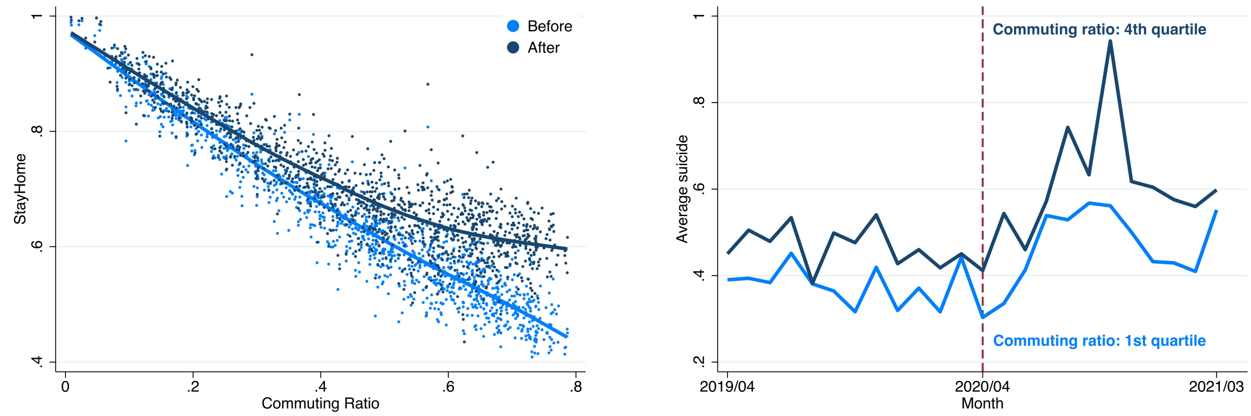
This approach, often referred to as a *differential exposure design*, exploits the stark contrast in stay-at-home duration triggered by COVID-19[4]. Noncommuters maintain their longer stay-at-home tendency, whereas commuters newly experience working from home under the new state of emergency order. Therefore, "treatment" municipalities with more commuters thus experience greater COVID-19 exposure than "control" municipalities with fewer commuters. The effect is gauged by the commuter population's relative change, aligning with the difference-in-differences (DiD) methodology in a regression framework, albeit with a continuous treatment variable.

Two key assumptions must be satisfied to estimate an unbiased treatment effect. First, the shift-share instrumental variable must accurately represent the stay-at-home variable, a necessity known as the *relevance* condition, to prevent bias due to weak instrumental variables. This entails a significant correlation between $\Delta StayHome_m$ and $\Delta ShiftShare_m$, or equivalently, between $\Delta StayHome_m$ and the commuting ratio z_{1m}. Figure 2a displays scatter plots that link stay-at-home rates to commuting ratios, illustrating that municipalities with higher commuting ratios typically have lower stay-at-home rates both before and after the outbreak of COVID-19. Notably,

[4]See Nunn and Qian (2014) and Kearney and Levine (2015) for similar identification strategies under differential exposure design.

Figure 2: Relevance and Pre-trend: Two-Type Case

(a) Relevance: Commuting Ratio vs. Stay-at-Home (b) Pre-trend: Suicide Trends by Commuting Patterns



Notes: Panel (a) depicts the relationship between the commuting ratio z_{m1} and the stay-at-home variable $StayHome_{mt}$ at two distinct time points, $t = 0$ and $t = 1$. Panel (b) compares the average number of suicide incidents between the first and fourth quartiles of the commuting ratio z_{m1}, covering the sample period from April 2019 to March 2021. A vertical dotted line marks April 2020, dividing the analysis into two periods: Pre-COVID-19 (prior to April 2020) and Post-COVID-19 (from April 2020 onwards). The commuting ratio's definition can be found in Appendix C.

the variation in stay-at-home rates across the periods (depicted by the vertical distance between the dark and light blue dots in the figure) is more pronounced in municipalities with higher commuting ratios. This pattern suggests a positive correlation between the change in stay-at-home rates over the two periods and the commuting ratio, reinforcing the validity of the relevance assumption with empirical evidence, despite the graphical nature of the depiction.

Second, consistent with the DiD methodology, the treatment and control groups must exhibit *parallel trends* under a counterfactual scenario. This parallel trend assumption, vital for validating the instrumental variable in a differential exposure design, is challenged if regions with varied commuting habits display different suicide trends in the pre-COVID-19 period. However, Figure 2b, which compares the average number of female suicide incidents across municipalities with different commuting ratios, shows nearly parallel prepandemic trends but a noticeable increase in suicides in areas with higher commuting ratios in the postpandemic period, resulting in a trend divergence. While the initial parallel trends are highlighted, careful interpretation is necessary, as differentiating true deviations from noise can be challenging. Further analysis of the parallel pre-trends is detailed in Section 4.2.

2.3 Shift-Share IV: Multiple Types

In the canonical case, a single municipal characteristic, the commuting ratio, defines the shift-share instrument. The two-type example provides a useful, intuitive illustration of the exposure design. However, as highlighted in the studies by Christian (2017) and Jaeger (2020), relying exclusively on variation among a limited number of types may undermine the assumption of parallel trends between the treatment and control groups in a differential exposure design. To mitigate these issues, our analysis employs an expanded-type shift-share instrument that exploits the variation in a municipal attribute across different types. This enhancement allows for a more robust identification of variations. Furthermore, the introduction of this instrument facilitates the utilization of the diagnostic tools proposed by Goldsmith-Pinkham et al. (2020).

In our expanded analysis, we categorize residents by their commuting times, assigning a commuting time of zero to those who do not commute, referred to as noncommuters. As detailed in Section 3, our empirical analysis identifies six specific commuting time brackets. Each bracket, denoted as k, is assumed to exhibit a uniform propensity for staying at home. It is expected that noncommuters with zero commuting time are more likely to stay at home in the prepandemic period. In contrast, individuals with longer commute times are likely to spend more time away due to the distance of their workplaces; thus, they are presumed to have a lower propensity to stay at home. This analytical approach enables us to discern variations in stay-at-home behavior across different commuter groups, moving beyond the binary distinction between commuters and noncommuters. Specifically, for noncommuters ($k = 0$), we set $g_{0t} = 1$ for both pre- and post-COVID-19 ($t = 0$ and $t = 1$, respectively) in the same way as in the two-type case. Conversely, for commuters ($k = 1..., 5$), the pre-COVID-19 stay-at-home rates differ across commuting categories. In the post-COVID-19 period, influenced by the state of emergency orders, there was an increase in the average work-from-home duration. This results in $g_{k0} \leq g_{k1}$ across all commuting types k.

The impact of emergency declarations and restrictions on commuting affected commuter types to varying degrees. For instance, medium- and long-distance commuters were likely to experience a more significant shift toward staying at home than noncommuters and those with shorter commutes. Consequently, the time change in stay-at-home propensity, represented by $\Delta g_{kt} = g_{k1} - g_{k0}$, shows distinct patterns across different commuter types k. This variation underscores the diverse effects of COVID-19-related measures on individuals' commuting habits and work-from-home dynamics.

Expanding on the analysis that includes multiple commuter types, our empirical model consists of the following equations. The structural equation is given by:

$$\Delta \ln(1 + Suicide_m) = \delta + \beta \Delta \widehat{StayHome}_m + \Delta\varepsilon_m. \tag{4}$$

The estimated variable, $\Delta \widehat{StayHome}_m$, is derived from the following first-stage regression:

$$\Delta StayHome_m = \delta^f + \pi \Delta ShiftShare_m + \Delta\varepsilon^f_m. \tag{5}$$

Here, the first-time differenced shift-share instrument is defined as

$$\Delta ShiftShare_m = \sum_{k=1}^{K} z_{mk} \times \Delta g_k, \tag{6}$$

where z_{mk} represents the proportion of commuters of type k in municipality m before COVID-19, and Δg_k indicates the first time-difference stay-at-home propensity for type k commuters, a type-specific common trend applicable to all municipalities. Finally, the reduced-form regression is presented as follows:

$$\Delta \ln(1 + Suicide_m) = \delta^r + \sum_{k=1}^{K} \gamma(z_{mk} \times \Delta g_k) + \Delta\varepsilon^r_m. \tag{7}$$

In this case, $\gamma = \beta \times \pi$.

Our identification strategy relies on the assumption of share exogeneity, leading to the following exclusion restriction:

$$\mathrm{E}\left(z_{mk}\Delta\varepsilon_m\right) = 0 \text{ for } k = 1, \cdots, K. \tag{8}$$

This condition implies that z_{mk}, as a share, serves as a single instrument. The shift-share instrumental variable can be seen as a linear combination of shares, each weighted by a shift. The shift-share estimator $\hat{\beta}$ obtained in this system is a weighted sum of just-identified instrumental variable estimators $\hat{\beta}_k$, each using a separate share as an instrument (Goldsmith-Pinkham et al., 2020). These weights, known as *Rotemberg weights*, are particularly useful when multiple instruments are employed. The key idea is that Rotemberg weights quantify how much the misspecification of a particular instrument contributes to the overall bias of the estimator. A high Rotemberg weight of a specific instrument implies that any bias in this instrument has a larger impact on the overall bias in the shift-share estimator. Therefore, the Rotemberg weights enable researchers to refine their instrument selection, potentially improving estimate credibility.

3 Data

Suicide: The monthly suicide statistics, sourced from the National Police Agency (NPA) and provided by the Ministry of Health, Labour and Welfare (MHLW) (MHLW, 2021), are a product of collaborative efforts between these two organizations. The NPA is responsible for gathering data, which the MHLW then publishes[5]. The data collected incidents at the municipal level based on the location of residence and were aggregated every month. As mentioned above, we categorized the monthly data into two periods: pre- and post-COVID-19. The data include detailed information on biological sex and age groups, in ten-year age increments up to 79 and aggregated data for those 80 years or older[6].

Our analysis focuses specifically on female suicides. As illustrated in Figure 1a, the suicide rate among women post-COVID-19 notably increased by more than 15% between 2019 and 2020. However, this trend was not uniform across all age groups. Figure 1b shows the percentage change in national suicide incidents by age group, with a more pronounced increase particularly observed among young women. The data indicate an approximate 42.7% increase in this demographic after the outbreak of COVID-19.

Stay-at-Home variable: We measure the extent of stay-at-home behavior in each municipality during the pre-COVID-19 and post-COVID-19 periods using mobile phone location data. The data, provided by Agoop, a subsidiary of one of Japan's major mobile phone companies, offers hourly population counts in each municipality. These counts are derived from users' time spent in each municipality and are adjusted for demographic characteristics[7]. It should be noted that

[5]In Japan, only doctors can issue death certificates. The Medical Practitioners Law requires them to report unusual deaths to the NPA within 24 hours. The NPA then conducts comprehensive investigations, including physiological tests, reviews of suicide notes and emails, family interviews, and document assessments to determine the cause of death.

[6]For other demographic characteristics, if there are two or fewer suicides in a municipality, the number is masked for confidentiality reasons, and we are not able to use the data for the analysis.

[7]Agoop is funded by SoftBank, one of Japan's largest cell phone companies, and possesses the GPS information of SoftBank cell phone users.

Agoop's data are available for the period from January 2019 onward and cover individuals aged 15 and above.

The stay-at-home variable for a municipality m in period t is defined as the ratio of the municipality's *daytime population* to its *nighttime population* during that period. For this calculation, the daytime population is averaged using data from 11 am to 2 pm, and the nighttime population is calculated based on data from 1 am to 4 am. This variable measures daily shifts in the resident population, highlighting the contrast between daytime and nighttime numbers. As residents typically stay at home at night, the nighttime population tends to be smaller than its daytime counterpart. Consequently, the values of the stay-at-home variable range from 0 to 1, where a higher value indicates less outflow from the municipality and a greater inclination toward staying at home.

The Agoop data provide valuable insights into residents' movements between municipalities[8]. Although these data are aggregated at the municipal level and the analysis does not include the detailed time spent at home found in studies based on SafeGraph data, the data still serve as a reliable indicator of stay-at-home behavior[9]. In Appendix Section A.2, we establish the reliability of our stay-at-home variable, computed from the Agoop data, by demonstrating its correlation with the Google mobility index, which is designed to measure time spent at home[10]. This correlation reinforces the effectiveness of our stay-at-home measure as a valuable proxy for assessing stay-at-home behaviors.

The stay-at-home variable varies significantly across different types of municipalities, reflecting distinct patterns of resident mobility. For instance, business districts experience a large influx of nonresidents and some resident outflow during the day, resulting in lower values, while suburban

[8]Population count data provided by Agoop's Papilio service are structured to provide data by prefecture, by municipality, and at specific locations. At the prefecture level, the data enable the identification of the prefectural origin of individuals. For municipalities and specific locations, the data can distinguish whether individuals live in the same municipality or come from different municipalities. To define our municipality-specific stay-at-home measure, we use nighttime and daytime population counts of those who live in the same municipality, excluding individuals coming from other municipalities.

[9]SafeGraph is a major source of foot traffic data for US studies to quantify the mobility of individuals. The data are often used to measure the degree to which people stay at home in a certain geographical area. The data provide information on *time spent at home* in each area. For example, Yan et al. (2021) used information on the median time spent at home to measure the degree to which people stayed at home at the county level. Hsu and Henke (2021) measure the degree to which people stayed at home by dividing the number of individuals (with mobile devices) who stayed home all day by the total number of individuals at the county level. Unfortunately, information on time spent at home is not available in the Agoop data.

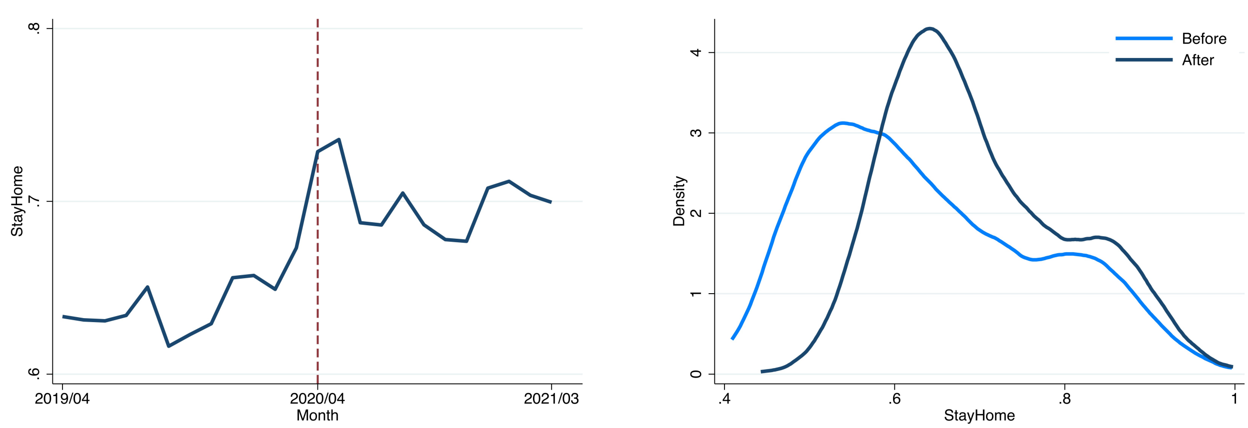
[10]Google's Mobility Index provides information on how the time people spend at home has changed since the start of the pandemic compared to prepandemic levels. While the Google mobility index captures changes in time spent at home, it is available only at the prefecture level, with only 47 variations.

areas show a significant daytime reduction in the resident population due to commuting, leading to higher values. Detailed explanations and observable fluctuations in the stay-at-home variable can be found in Appendix Figure B1, where the distinctions between a business district and a suburban residential area are depicted.

The outbreak of COVID-19 and the subsequent declaration of a state of emergency significantly impacted the stay-at-home behavior of people across Japan. Figure 3a illustrates the national average change in the stay-at-home variable over time. There was a notable increase in the index in April 2020, immediately following the outbreak of the pandemic. The index remained above prepandemic levels throughout 2020 and 2021, with some observable seasonal variations. Furthermore, the extent of the shift to stay-at-home behavior varied across regions after the COVID-19 outbreak. Figure 3b shows the distribution of the stay-at-home variable before and during the pandemic. After the outbreak of the pandemic, the distribution underwent two significant changes: a shift to the right, indicating an increase in stay-at-home behavior nationwide, and a narrowing of the distribution, which points to less variability among municipalities. Although stay-at-home behavior generally increased after the outbreak of the pandemic, the degree of this increase was not uniformly distributed across municipalities.

Figure 3: Stay-at-Home Trends and Distribution Before and After COVID-19

(a) Trend (b) Distribution



Notes: Panel (a) shows the trend of the stay-at-home variable between April 2019 and March 2021. The lines indicate the average for the stay-at-home variable in Japan. Panel (b) shows the distribution of the stay-at-home variable. Before COVID-19 refers to the period between April 2019 and March 2020, and after COVID-19 refers to the period between April 2020 and March 2021. The stay-at-home variable is defined by Equation 3.

Commuting time and work from home: Our shift-share instrumental variable comprises two components. First, individuals are classified into K categories based on commuting time.

The proportion of residents in different commuting time brackets within a municipality during the pre-COVID-19 period forms the share (z_{mk}) of the IV. Second, the nationwide average tendency of individuals who worked from home in each commuting time bracket, both before and after COVID-19, indicates the shift (g_{kt}).

To determine the share component, we divide residents into six categories based on commuting duration. Specifically, $k = 0$ corresponds to noncommuters with zero-minute commuting time; $k = 1$ represents commuters traveling up to only 30 minutes; $k = 2$, $k = 3$, and $k = 4$ represent mid-distance commuters with commute times of more than 30 and equal to or less than 60 minutes (30-60 minutes), more than 60 and equal to or less than 90 minutes (60-90 minutes), and more than 90 and equal to or less than 120 minutes (60-120 minutes), respectively; and $k = 5$ represents long-distance commuters who travel more than 120 minutes.

We base this classification on data from the 2018 Housing and Land Survey of Japan conducted by the Statistics Bureau. The survey collected information on the commuting habits of household heads. The survey sample comprises individuals who live in cities and wards and in counties with populations of 15,000 or more[11]. Our analysis incorporates 1,241 out of 1,891 municipalities for which commuting time data are available. In the first column of the Appendix, Table B2 provides the average share of commuters in each category.

Regarding the shift components g_{kt} for each k commuter type, we use the propensity to *work from home* as a proxy for the inclination to stay at home, reflecting the significant adoption of work-from-home practices during the COVID-19 pandemic, as documented by Okubo (2021, 2022). In Japan, the state of emergency issued in response to COVID-19 did not enforce compliance with staying at home through legal penalties. Instead, companies made voluntary requests of their workers to work from home. Consequently, some workers were allowed to continue commuting to their workplace during the pandemic, indicating that not everyone shifted uniformly to work from home even amidst an increase in COVID-19 infections in late 2020. We can, therefore, infer that the changes in stay-at-home tendencies largely paralleled the adoption of work-from-home practices. Importantly, the adoption rate of work-from-home practices varied across industries, occupations, regions and commuting times. Our paper's identification strategy leverages these variations, specifically analyzing differences in work-from-home practices based on commuting times across municipalities.

[11]The dataset made available to the public aggregates statistics at the municipality level.

The work-from-home data are derived from a survey conducted by Okubo (2021)[12][13]. The prepandemic data represent the work-from-home proportion in January 2020, and the postpandemic data reflect the proportion in April or May 2020. These values are presented in the second and third columns of Appendix Table B2. In the pre- and post-COVID-19 periods, the proportion of individuals working from home varied substantially across commuting time categories. Generally, the longer the commuting time is, the greater the tendency to work from home. Moreover, the outbreak of COVID-19 led to an increase in the proportion of people working from home across all commuting time categories. The category with the most significant increase in work-from-home rates is those with 90-120 minutes of commuting time, with a 21 percentage point increase in individuals opting to work from home. This trend reflects the substantial impact of the pandemic on work and commuting behaviors.

4 Results

4.1 Main results

The baseline results for females are shown in Table 1. The first column presents the OLS estimates, indicating that a 1% point increase in the stay-at-home variable is associated with a 1.11% reduction in suicide. However, the OLS estimate is likely to be overestimated because of possible confounding factors such as psychological and environmental traits. To address this issue, we employ the shift-share IV. The first stage by Equation (5) and the IV results by Equation (4) are presented in Columns (2) and (3), respectively. The first-stage result shows a clear and strong association between the difference in the stay-at-home variable and the difference in the shift-share IV. In addition, the effective F statistic exceeds the threshold value at the conventional level, rejecting the null hypothesis of the weak IV. The IV estimate again shows a positive sign. However, the effect size decreases with increasing standard error, and thus, the estimates are no longer statistically significant. Column (4) shows the reduced-form results indicated by Equation (7). The estimate of the shift-share IV is positive but small in magnitude, indicating that municipalities that were more exposed to the COVID-19 shock tended to have a greater increase in

[12] Okubo (2021) surveyed nationwide workers in December 2020 to understand changes in work style, lifestyle, and attitudes caused by the COVID-19 pandemic. The total number of responses was 10,523. The work-from-home data for each commuting time used in our analysis are based on Table 1-17-1 of Okubo (2021), aggregated from more detailed time brackets.

[13] As illustrated in Section 2.2, noncommuting residents are assumed to always work from home ($g_{00} = g_{01} = 1$).

Table 1: Effect of Staying at Home on Suicide: Females

	OLS	1st Stage	IV	Reduced form
	(1)	(2)	(3)	(4)
$\Delta StayHome$	1.109		0.827	
	(0.432)		(0.554)	
	[0.010]		[0.136]	
$\Delta ShiftShare$		1.620		1.339
		(0.037)		(0.901)
		[0.000]		[0.137]
Effective F statistic		1964.183		
τ=10%		23.109		
Observation	1241	1241	1241	1241

Notes: We estimate the first-order time difference as in Equation (4). In the regression for Columns (1), (3), and (4), the outcome variable is defined as the logarithm of one plus the number of female suicide cases and we convert the coefficient to the semi-elasticity of suicide by using the equation specified in footnote 2. In the regression for Column (2), the outcome variable is the stay-at-home variable. Cluster-robust standard errors are in parentheses. P values are in brackets. The effective F statistics are those developed by Montiel Olea and Pflueger (2013).

suicide rates, although the estimate is not statistically significant.

Importantly, the data during the pandemic have heterogeneity in the incidence of suicide. As discussed in Section 1, an increase in suicide during COVID-19 was not uniform but was more pronounced in some demographic groups, especially young people. This suggests that the detrimental effect of a change in stay-at-home behavior may also occur within a certain demographic group. To examine the heterogeneity in the effect, we conduct a subsample analysis by age group. We consider the following age groups: those under 20; those in their 20s; those in their 30s;those in their 40s, those in their 50s, and those aged 60 years or older.

The results are shown in Table 2. Panel A shows the IV results, and Panel B shows the reduced-form results. In all age groups, the sign of the coefficient is positive, indicating that staying at home tended to increase the likelihood of suicide. Furthermore, the effect of staying at home is far greater for females under 20 years old than for other age groups, and it is statistically significant at the conventional level. The magnitude of the increase is approximately 5%, associated with a 1 percentage point increase in the staying-at-home variable for females under 20, whereas the corresponding value is 1 to 2% for all the other age groups, with the oldest group showing the least pronounced increase. The prepandemic average number of suicide cases for females under 20 years of age is 0.176 per municipality, as shown in Appendix Table B1, and the increase before and after the pandemic in $StayHome$ is 6.1%, resulting in an increase in suicide due to staying at home that corresponds to an increase of 0.228 per municipality. We will more rigorously analyze

Table 2: IV Estimates by Age Group

	(1) Under 20	(2) 20-29	(3) 30-39	(4) 40-49	(5) 50-59	(6) Over 60
Panel A: IV						
Δ*StayHome*	4.823	1.492	1.760	1.338	1.743	1.213
	(2.026)	(1.189)	(1.291)	(0.989)	(1.048)	(0.772)
	[0.017]	[0.210]	[0.173]	[0.176]	[0.096]	[0.116]
Panel B: Reduced form						
Δ*ShiftShare*	7.811	2.416	2.851	2.167	2.822	1.965
	(3.288)	(1.930)	(2.096)	(1.603)	(1.701)	(1.253)
	[0.018]	[0.211]	[0.174]	[0.176]	[0.097]	[0.117]
Observation	1241	1241	1241	1241	1241	1241

Notes: Cluster-robust standard errors are in parentheses. P values are in brackets. The outcome variable is defined as the logarithm of one plus the number of female suicide cases. We convert the coefficient to the semielasticity of suicide by using the equation specified in footnote 2. In panel A, we estimate the first-order time difference as in Equation (4) in different age female groups. In panel B, we report the estimation result in Equation (7).

the magnitude of this effect to discuss the degree of attribution of staying at home to the increase in suicide incidence by conducting a counterfactual analysis in Section 4.4. The results from the reduced-form analysis are qualitatively consistent with the IV results.

4.2 Estimation Validity

Our analysis revealed empirical evidence indicating a causal link between the stay-at-home variable and a significant increase in suicide rates among young women, particularly those under the age of 20, during the COVID-19 period in Japan. To confirm the validity of these findings, we conduct robustness checks in this section. By following the framework set forth by Goldsmith-Pinkham et al. (2020), we scrutinize the necessary conditions required for the shift-share instrumental variable estimator to be unbiased.

Rotemberg Decomposition: We utilize *Rotemberg decomposition*, as introduced in Section 2.3, to evaluate the robustness of our estimated outcomes. This technique breaks down the estimated value of the structural equation, $\hat{\beta}$, which relies on the shift-share instrument $ShiftShare_{mt}$, into a weighted sum. In particular, $\hat{\beta}$ consolidates individual estimates $\hat{\beta}_k$, each originating from a distinct instrumental variable z_{mk} for $k = 0, \cdots, 5$, resulting in $\hat{\beta} = \sum_k \hat{\alpha}_k \hat{\beta}_k$. The Rotemberg weights $\hat{\alpha}_k$ play a pivotal role in pinpointing which instruments might be prone to misspecification. In the case of shift-share instruments, these weights identify which shares potentially introduce

Table 3: Rotemberg Diagnosis

	$\hat{\alpha}_k$	$\hat{\beta}_k$	$\hat{F}_k$	95 perc. C.I.
Panel A: Shares				
Commuting time (60,90] mins	0.659	0.188	1681.095	[2.448, 11.213]
Commuting time (30,60] mins	0.551	2.414	722.220	[-2.618, 7.456]
Commuting time (90,120] mins	0.185	4.451	439.269	[-1.651, 10.416]
Commuting time > 120 mins	0.003	4.013	26.636	[-12.010, 20.775]
Commuting time (0,30] mins	-0.397	4.619	1807.293	[0.626, 8.595]
	60-90 min	30-60 min	60-90 min 30-60 min	All
Panel B: IV estimates				
$\Delta StayHome$	6.820	2.415	5.173	4.505
	(2.246)	(2.570)	(2.040)	(2.002)
	[0.002]	[0.347]	[0.011]	[0.024]
Effective F statistics	1964.183	722.220	881.521	11.026
τ=10%	23.109	23.109	11.618	22.854
Over ID test			2.964	7.131
			[0.085]	[0.129]
Observations	1241	1241	1241	1241

Notes: Cluster-robust standard errors are in parentheses. P values are in brackets. Panel A presents the shift-share diagnostics as recommended by Goldsmith-Pinkham et al. (2020). The computation is based on a Stata package developed by the authors. Panel A reports four key metrics for Rotemberg decomposition − Rotemberg weights $\hat{\alpha}_k$, the just-identified coefficients $\hat{\beta}_k$, and the first-stage F-statistics for the just-identified instruments $\hat{F}_k$ for each commuter type k. The 95% confidence intervals are robust to weak instruments, as calculated using the method proposed by Chernozhukov and Hansen (2008), spanning from -10.00 to 5.00 in increments of 0.01. Panel B presents the estimated coefficients for the impact of stay-at-home on suicide among females under 20 years old, associated with the highest and second-highest Rotemberg weight shares (60-90 minutes and 30-60 minutes), employing a single instrument approach (as depicted in the first and second columns). It further presents the coefficients estimated using these two shares as instruments (in the third column) and the coefficients obtained by employing all commuter shares as multiple instruments (in the fourth column). Additionally, we include the first-stage F statistic and, where applicable, the p value for the Sargan overidentification test to assess the validity of the instrumental variables used.

bias, particularly when the exclusion restriction, as detailed in Equation (8), might be invalid.

The results of the Rotemberg decomposition are presented in Table 3 Panel A. A full range of diagnostic statistics are reported in Table B4 in Appendix B. Using the shares of individuals with varying commuting times in municipalities during the pre-COVID-19 period as instrumental variables, we find that the instrument with the highest Rotemberg weight is associated with the share of individuals with 60-90 minutes of commuting time. This is followed by the share of individuals commuting for 30-60 minutes[14].

We employ the shares with the highest and second-highest Rotemberg weights as individual

[14] According to the shares perspective by Goldsmith-Pinkham et al. (2020), our shift-share instrument is equivalent to using shares of individuals with varying commuting times as instruments. This implies that the exogeneity assumption should be interpreted within the context of these shares.

and combined instruments to investigate the impact of a stay-at-home variable on suicide among females under 20 years of age. The findings, as outlined in Table 3 Panel B, demonstrate that the estimated effects are in line with the findings obtained from the shift-share instrument. The results of the Montiel Olea and Pflueger tests (Montiel Olea and Pflueger, 2013) show that the hypothesis of weak instrumental variables is rejected when we use the shares of individuals with 60-90-minute and 30-60-minute commutes, both as a single instrument and in combination. Conversely, when all commuting time brackets are employed separately as multiple instruments, they are found to be weak. Additionally, to address potential misspecifications when multiple instrumental variables are used, we conduct Hansen's J-test for overidentification. According to the F statistic and p value provided in Table 3, the exogeneity of the share instrument z_{mk} is not rejected at the 5 percent significance level.

Parallel Pre-trend: A potential threat to our identification strategy is the presence of pre-trends. Although we have demonstrated visual evidence of parallel pre-trends in Section 2.2, relying solely on this evidence is inadequate for rigorous analysis. Therefore, we implemented additional checks for parallel pre-trends, as suggested by Goldsmith-Pinkham et al. (2020).

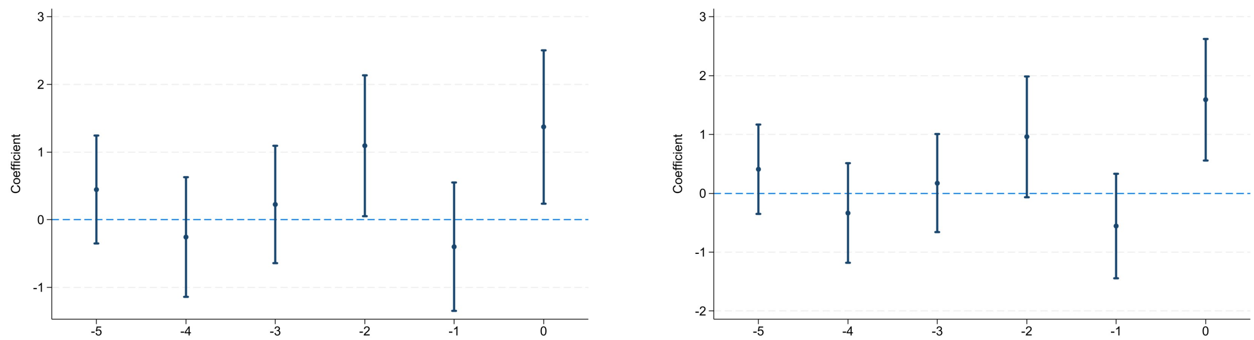
To assess the assumption of parallel pre-trends, we performed a regression analysis in which our primary focus was on examining the predictive power of these instruments for changes in suicidal behavior among young females in the *pre-COVID-19 period*. Figure 4 plots the coefficient of the instrumental variable for the following reduced-form regression:

$$\Delta \ln(1 + Suicide_{m\ell}) = \delta^r + \gamma_\ell Z_m + \Delta\varepsilon^r_m, \tag{9}$$

where $\Delta \ln(1 + Suicide_{m\ell}) \equiv \ln(1 + Suicide_{m\ell+1}) - \ln(1 + Suicide_{m\ell})$ represents the l-th order difference in the logarithm of the number of suicides of females under 20 in the *lead direction*, and the instrumental variable Z_m can take one of two forms, $\Delta ShiftShare_m$ or the highest Rotemberg weight share z_{m2}, which is the share of commuters with a 60-90-minute commute. To facilitate comparison, we plotted baseline estimates at $\ell = 0$, representing the coefficients from the baseline reduced-form regression as outlined in Equation (7). Here, $\ell = 0$ denotes the year 2020 as the reference point, and we extend our analysis back to $\ell = -5$, which corresponds to 2015. The findings consistently indicate no systematic positive impact of commute time on pre-COVID-19 suicide rates among females under 20. This lack of a significant trend in the pre-COVID-19 period supports our presumption that the share-based instrumental variables are uncorrelated with pre-COVID-19 trends in the suicidal behavior of females under 20.

Figure 4: Pre-trend Test

(a) Shift-Share IV (b) Single IV with Commute Time of 60-90 Minutes



Notes: The dot shows the estimated semielasticities of suicide with respect to the exposure variable (a) commute time IV and (b) commute time 60-90 minutes IV for females under 20 years of age with their 95% confidence intervals for the post-COVID-19 period ($t = 0$) and pre-COVID-19 period ($t < 0$). The semielasticity is calculated based on the estimated coefficient γ_ℓ of Equation (9). We use the stay-at-home variable and the baseline specification, where we do not include time-varying control variables.

Group-specific Time Trend: Our approach to identifying changes in suicide rates hinges on a comparative analysis among municipalities before and after the COVID-19 pandemic. Given the perspective of the share proposed by Goldsmith-Pinkham et al. (2020), our analysis uses commuter share variation as the instrumental variable. Specifically, commuters traveling 60-90 minutes, distinguished by the most-significant Rotemberg weight, are essential for elucidating causal relationships. Therefore, our analysis contrasts municipalities with a significant proportion of 60-90-minute commuters against those with a smaller proportion.

In the differential exposure design, a principal concern is the presence of unobserved variations in characteristics among municipalities that were classified into the treatment and control categories. The observed changes in suicide rates among young females may not exclusively stem from differences in commuting time distributions. Other factors, such as the degree of urbanization and the nature of local industries, might also play a significant role. If these elements drive the suicide trend after the pandemic started, the observed correlation between post-COVID-19 stay-at-home increases and suicide rates, as indicated by regression analyses, may not necessarily reflect a causal relationship. The observed effects might stem from distinct municipal attribute trends over time rather than exclusively from changes in stay-at-home behaviors.

To establish a causal relationship, controlling for time trends specific to municipal attributes,

Table 4: The Effect of Stay-at-Home on Suicides of Females Under 20: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta StayHome$	4.823	4.532	4.192	6.333	4.760	5.163	5.029	5.319
	(2.026)	(2.012)	(2.750)	(3.189)	(2.126)	(2.224)	(2.302)	(2.206)
	[0.017]	[0.024]	[0.127]	[0.047]	[0.025]	[0.020]	[0.029]	[0.016]
Group specific trends								
City		x		x				
Industry			x	x				
Others				x				
Local labor market								
Unemployment rate					x		x	
Active job opening ratio						x	x	
Functional form	log-linear	log-linear	log-linear	log-linear	log-linear	log-linear	log-linear	ihs-linear
Effective F statistics	1964.183	1990.049	1164.216	836.720	1677.856	1654.951	1654.951	1964.183
$\tau = 10\%$	23.109	23.109	23.109	23.109	23.109	23.109	23.109	23.109
Observations	1241	1241	1241	1241	1241	1241	1241	1241

Notes: Cluster-robust standard errors are in parentheses. P values are in brackets. In Columns (1)-(7), the outcome variable is defined as the logarithm of one plus the number of female suicide cases. The outcome variable is transformed in Column (8) with the inverse hyperbolic sine function. In group-specific trends, City is a dummy variable indicating municipal classification as a city; Industry represents the shares of the primary, secondary, and tertiary sectors; and Others encompass variables such as the youth rate, self-employment rate, labor force participation rate, and single-person household rate, all as outlined in Table B3.

termed group-specific trends, is essential. The structural models incorporating these differential trends can be formulated as follows:

$$\Delta \log(1 + Suicide_m) = \delta + \beta \Delta StayHome_m + \sum_{s=1}^{S} \phi_s W_{sm} + \Delta \nu_m \tag{10}$$

In this model, $W_m = (W_{1m}, \cdots, W_{Sm})$ is a set of municipal characteristics, and ϕ_s represents a common time trend for groups sharing the characteristic s, which serves as factor loading in a linear factor model for time series analysis. The baseline Equation (4) incorporates an unobserved error component, expressed as $\Delta\varepsilon_m = \sum_{s=1}^{S} \phi_s W_{sm} + \Delta\nu_m$. If specific time trends tied to each group influence suicide incidence within municipalities, this could compromise the exclusion restriction given by Equation (8), as Z_{km} and W_{sm} might be correlated for some k and s. Such a scenario would result in omitted variable bias when estimating the causal effects of home confinement on suicide using the baseline model.

Acknowledging the potential influence of group-specific time trends, Table 4 presents additional regression analyses incorporating urban-specific and industry-specific trends as factor loadings in estimating Equation (10). The results in Column (1) serve as a baseline in Table 2, showing estimates without considering group-specific time trends for reference. The findings in Columns (2) and (3) indicate that including these trends does not significantly alter the estimated impact of stay-at-home orders on suicide among young women. Specifically, when controlling for urbanization with a dummy variable denoting whether a municipality is a city or not, the effect of home confinement on young women's suicide incidence remained statistically significant at the 5% level. Conversely, when categorizing industries into primary, secondary, and tertiary sectors and accounting for the varying ratios of industrial composition within municipalities, the estimate of the impact of home confinement on young women's suicide is positive but not statistically significant. Nonetheless, a small change in these estimates from the baseline, when incorporating a range of controls, indicates that group-specific trends do not drive our previous findings.

In addition to differences in urbanization and industry type, variations in other municipality attributes may also affect the prevalence of suicide among young women, influenced by group-specific commuting patterns. However, accounting for factor loadings across all municipality attributes and controlling for them in regression analyses is a daunting task because numerous potential attributes could be driving these group-specific trends. Instead, we could focus on the factors that strongly correlate with the share type with the highest Rotemberg weight, the segment of 60-90-minute commuters. Table B3 details the regression analysis of the share of 60-90-minute commuters against community characteristics in the pre-COVID-19 era. It reveals significant correlations between this commuter share and key municipality attributes such as age composition, employment patterns, and the prevalence of single-person households[15]. Given that Rotemberg weights emphasize the instruments most susceptible to endogeneity in the estimated parameters, as explored in Goldsmith-Pinkham et al. (2020), these attributes could introduce notable estimation bias via group-specific trends, which requires thorough investigation.

A factor-loading model, represented by Equation (10), was estimated to control for time trends in the municipality characteristics highly correlated with the share of 60-90-minute commuters and city and industry dummies. The results, displayed in Column (4) of Table 4, reveal that the estimates remain positive and statistically distinct from zero. Therefore, even with adjustments for group-specific trends, there is a positive causal effect of home confinement on the suicide of young women.

Time-Varying Labor Market Conditions and Other Functional Forms: A remaining concern is the unobservable changes in labor-market conditions related to the pandemic. In Japan,

[15]Employment patterns include overall employment rates and distinctions between employees and the self-employed.

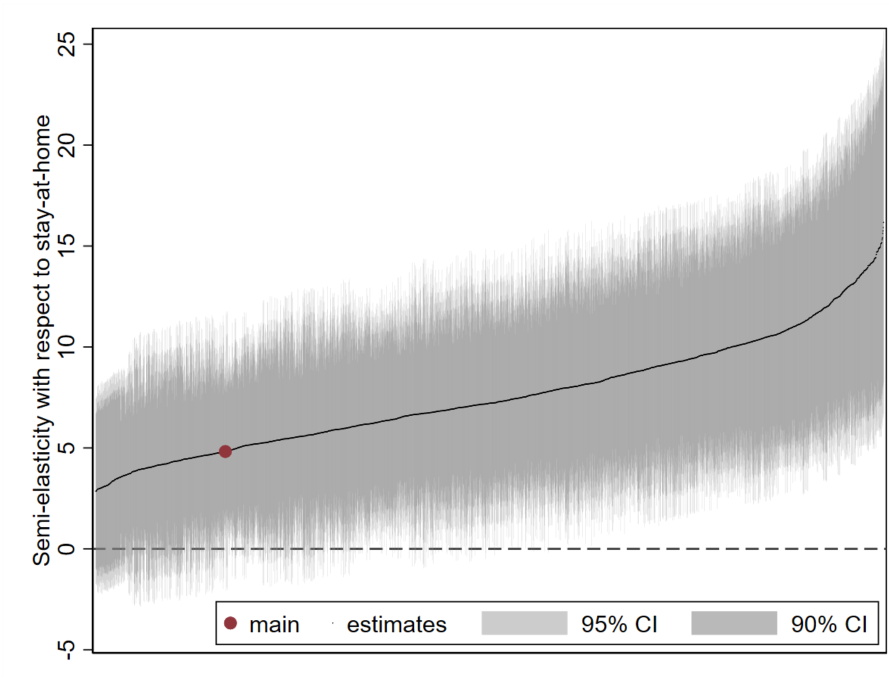
previous research indicates a correlation between worsening labor-market conditions, particularly unemployment, and an increase in suicide rates (Chen et al., 2009, 2015). There may be a causal relationship linking stay-at-home behaviors, which could exacerbate downturns in the regional economy, to worsened local labor-demand conditions and, consequently, an increase in suicide among young women. To check whether this path exists, we include the unemployment rate and the job opening-to-applicant ratio for each municipality in our analysis. The results displayed in Columns (6)-(7) of Table 4 indicate that the estimated parameter of the stay-at-home variable remains positive and statistically significant even after controlling for those labor-market conditions. Notably, when compared to baseline estimates without controls for labor-market conditions, the magnitude of this effect diminishes slightly. This suggests, prima facie, that the impact of home confinement on the suicide of women under 20 is a direct effect rather than one mediated through declining labor-market conditions. However, interpreting these regression results notably requires caution. The local job opening-to-applicant ratio, potentially influenced by our treatment variable, staying at home, presents a "bad control" problem, as described by Angrist and Pischke (2008). This issue could introduce bias into our estimates. Appendix D contains a detailed discussion on potential bias, explained using a *Directed Acyclic Graph (DAG)*.

Finally, to enhance the robustness of our results, we conducted further analysis on the functional form of our model. Initially, we replaced the $\log(1 + Suicide_{mt})$ transformation with an inverse hyperbolic sine transformation for the dependent variable, defined as $\text{arcsin}(Suicide_{mt}) = log(Suicide_{mt} + \sqrt{1 + Suicide_{mt}^2})$. The outcomes, presented in Column (8) of Table 4, continue to demonstrate a statistically significant effect of the stay-at-home variable on suicide among young women.

4.3 Specification Curve Analysis

A growing body of literature discusses the credibility and reproducibility of research in economics and other fields (Christensen and Miguel, 2018). One of the issues is specification searching, where model specifications are determined based on results. To demonstrate how sensitive the results are to model specifications and other decisions about the research design, we conduct a specification curve analysis (Simonsohn et al., 2020). This approach visualizes the magnitude of the estimated effect across a range of specifications, presenting the effects sorted by their magnitude. Specification curve analysis thus acts as both an extension and a formalization of traditional robustness checks.

Figure 5: Specification Curve Analysis



Notes: The figure shows the specification curve analysis for females under age 20 using the stay-at-home variable. Each dot shows the semielasticity of suicide with respect to the stay-at-home variable, with different sets of covariates, IVs, and sample periods. The total number of specifications is 3,072, and the first-stage F value exceeds 100 in all specifications. Specifically, 3,072 is the product of 2 specifications of the outcome variable $\times$ 2 IV choices $\times$ 2^6 (with and without 6 factors for time trend) $\times$ 2^2 (with and without 2 control variables for economic conditions) $\times$ 3 period choices (including March 2020 and 2021; including March 2021 but not March 2020; excluding March 2020 and 2021). The red dot is the estimate in our baseline specification.

In our study, we explored different model specifications considering various factors. These factors include the presence or absence of group-specific trends and local labor-market conditions that might correlate with commuter share, as shown in Table B3. In addition, we considered the choice of instrumental variables (utilizing a shift-share variable as one IV or the segment with the highest Rotemberg weight as a single IV), functional form (log-linear or inverse hyperbolic sine transformations), time periods (adjusting the boundary between the pre-COVID-19 and post-COVID-19 periods by approximately one month), and the treatment of ambiguous months (whether to include or exclude March 2020). The total number of specifications amounts to 3,072, and the first-stage regression's F value exceeds 100 in all formulations.

Figure 5 displays the estimated parameters $\hat{\beta}$ pertinent to these models, arranged in order of magnitude. The red dot corresponds to our baseline estimate in Table 2; the smallest estimate is 2.857 (at the left end of the graph), and the largest is 16.170 (at the right end). This indicates that in approximately 77.6% of specifications, the coefficient is significantly different from zero at the 5% level, which reinforces the robust causal relationship between stay-at-home behavior and suicide rates in females under 20.

4.4 Counterfactual Analysis

Given these results, we conduct a counterfactual analysis to quantify how much of the increase in suicide in females under 20 years of age can be attributed to stay-at-home behavior. Following the estimated empirical model, we calculate a counterfactual number of suicide cases at the pre-COVID-19 stay-at-home level and compare it with a simulated number of suicides with the actual post-COVID-19 stay-at-home level. To be precise, we estimate our model in Equation (1) and predict the counterfactual/actual suicide incidence using the stay-at-home variable in the pre- and post-COVID-19 periods as follows:

$$\ln(1+\widehat{Suicide}_{m,counterfactual}) = \widehat{\alpha_m} + \widehat{\delta}\times 1 + \widehat{\beta} StayHome_{m,0} + \varepsilon_{m,1}, \tag{Counterfactual}$$

$$\ln(1+\widehat{Suicide}_{m,actual}) = \widehat{\alpha_m} + \widehat{\delta}\times 1 + \widehat{\beta} StayHome_{m,1} + \varepsilon_{m,1}. \tag{Actual}$$

Then, we reported the aggregated change in suicide incidence based on the pre-COVID-19 period.

$$\Delta\widehat{Suicide} = \frac{\sum_{m=1}^{M}\widehat{Suicide}_{m,counterfactual} - \widehat{Suicide}_{m,actual}}{\sum_{m=1}^{M}\widehat{Suicide}_{m,actual}}. \tag{11}$$

where M is the number of municipalities.

In this simulation, we select two model specifications that correspond to the smallest and largest point estimates $\hat{\beta}$ in the specification curve analysis 4.3. Therefore, we can consider the calculated numbers as lower and upper bounds of the contribution of stay-at-home behavior. Our simulation revealed that approximately 37.4-42.2% of national suicides were caused by home confinement, and these estimates suggest that the effect of stay-at-home behavior was substantial[16].

[16] According to our data, the actual number of suicides among females under 20 years of age during the pre-COVID-19 period was 218. The smallest estimated model specification showed that the simulated number of suicides was 171.929, and the counterfactual number of suicides was 236.252. According to the largest estimated model specification, the simulated number of suicides was 192.084, whereas the counterfactual number of suicides was 273.100.

5 Discussion

One of the greatest social problems that occurred during the pandemic was the deterioration in mental health. The most serious consequences were increased suicides. Our IV estimates indicated that the increase was attributable to home confinement. The effect was heterogeneous by age group, and the most affected population was females under 20 years of age. The result was robust across different model specifications, with choices of the IVs, as well as with alternative model types.

Studies on the negative effects of COVID-19 show that the pandemic has had a heavy burden on young females, and our results align with these studies. Review papers on the effect of the pandemic on mental health have identified risk factors for distress as including female gender identity, adolescent age, young adult age, and student status (Xiong et al., 2020; Penninx et al., 2022). Furthermore, using a large-scale, nationally representative survey in the UK, a study reported that the prevalence of psychiatric disorders and loneliness is greater among females and young people than among the rest of the population, suggesting that young females are more vulnerable to the pandemic than others are (Li and Wang, 2020). Moreover, studies from Norway, the United States, and Canada reported an increase in cases of eating disorders, which are highly related to mental health disorders, in children and adolescents compared with incidence rates during the prepandemic period (Otto et al., 2021; Toulany et al., 2022; Surén et al., 2022). Although which aspect of the pandemic affects the mental health of females and young people has not been examined, these studies argue that heightened trends of mental disorders are associated with social changes induced by restrictions placed on this population's lives and activities and that the disruption of social lives during the pandemic is likely to be greater among young people (Li and Wang, 2020). The COVID-19 pandemic affected almost all the population, but these studies suggest that the mental effects of lifestyle changes induced by the pandemic were especially detrimental to that particular population. Our results are in line with these findings, indicating that physical disconnection from society was one of the key pathways for such adverse effects on mental health among young females.

Our results are not necessarily inconsistent with U.S. research showing that increased suicide is associated with a return to in-class schooling (as opposed to school closure) for the following two reasons (Hansen et al., 2022). First, the backgrounds of Japan and the USA during the pandemic differed. Japan showed a consistently high rate of female suicides during the COVID-19 pandemic, which was not observed in other countries, including the US (Pirkis et al., 2022). Second, our study does not aim to examine the effect of schooling mode on mental health. Rather, we focus on the effect of home confinement, which includes a wider aspect of lifestyle changes, including relationships with family members and the opportunity to meet friends outside of school. To this end, the variation we exploit to identify the impact of home confinement differs from the variation used to identify the impact of a change in the school mode. Specifically, since we aim to examine the effects of home confinement during the pandemic compared with patterns in the prepandemic period, the time-series variations we use are those before and after the pandemic started, where the postpandemic period is aggregated as a single period. The postpandemic periods include not only the initiation but also the termination of school closures. This means that the period of the analysis that we focused on is not aligned with the study that aimed to identify the effect of school openings.

Using a regression discontinuity design based on an age cutoff, a previous study demonstrated that lockdown deteriorated the mental health of elderly people (Altindag et al., 2022). Although the RD design sharply identifies the effect of lockdown policies, the nature of the design does not permit analysis of how the effect differs by age. Our shift-share IV estimate indicates that, in the context of Japan, heterogeneity is important, and the effect on disconnection from society is more serious among young people in terms of suicide, the worst consequence of mental disorders.

There are several possible mechanisms through which home confinement affects mental health. Social disconnection through home confinement itself elevates the risk of mental illness morbidity through the feelings of isolation and loneliness (Loades et al., 2020). In addition, in the context of COVID-19, people tended to stay at home across the population, including adults, and therefore, some of the observed effects among young people could be related to family-related issues such as domestic violence or abuse, as reported in other countries (Leslie and Wilson, 2020; Arenas-Arroyo et al., 2021; Berniell and Facchini, 2021; Hsu and Henke, 2021). Furthermore, staying at home may hinder access to treatment and care in mental health services. All of these factors could be related to the increased risk of suicide that we observed. Indeed, an analysis of the cause of Japanese youth suicides during the pandemic using time-series data revealed periodic increases attributed to family-related and social concerns, whereas there was a notable increase in suicides linked to mental illness as the pandemic progressed into the later months of 2020 (Goto et al., 2022).

Early public health responses against the COVID-19 pandemic include social distancing measures such as lockdowns and stay-at-home orders, and these measures could be policy options for future infectious-disease pandemics, especially before pharmaceutical interventions become available. The adverse effects of these pandemic responses on the mental health of children and adolescents were reported from the experiences of H1N1 influenza and SARS (Sprang and Silman, 2013). Our results show that the effect was devastating in the case of the COVID-19 pandemic, demonstrating that collective social distancing policies impose high social costs on both individuals and society in the worst form as lives are lost. Public policy-making should be built upon the awareness of such risks and implement countermeasures for high-risk populations as a part of an effort to enhance pandemic preparedness.

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Appendix

A Additional information

A.1 Background

Policies on COVID-19: The first COVID-19 cases in Japan were reported on January 16, 2020, with little increase in the number of cases until the end of March. The earliest measure taken was to order the closure of schools at the end of February, and in response, most schools decided to close until the semester was over at the end of March.

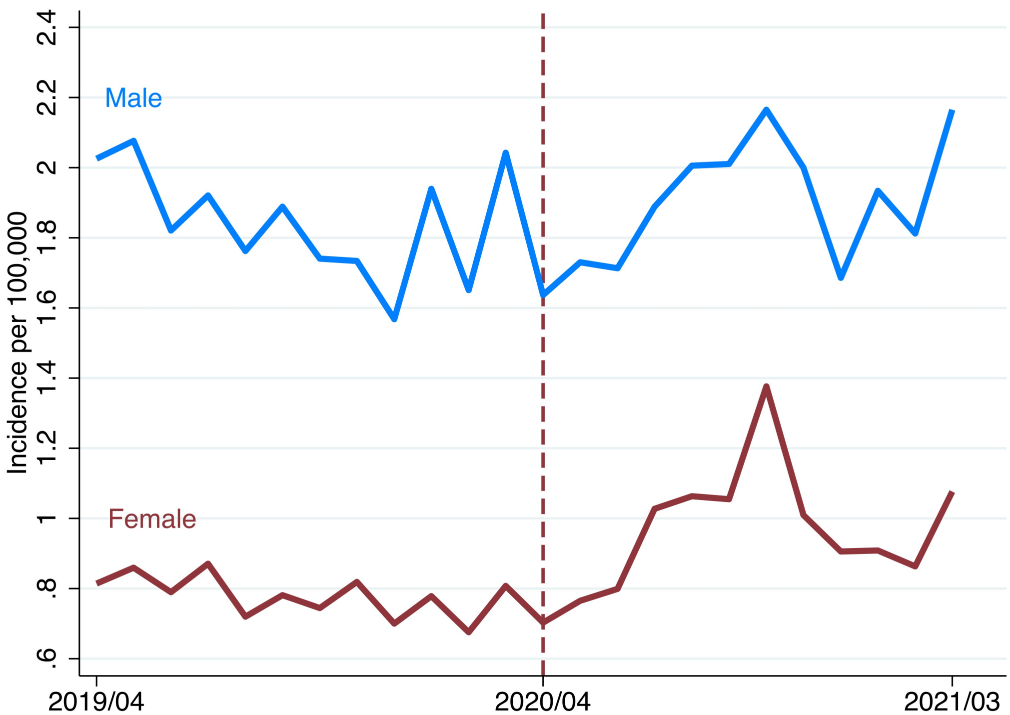
The first action taken by the government and affecting all of society was the declaration of the state of emergency. On April 7, 2020, the first state of emergency was declared in seven prefectures, including Tokyo[17]. Nine days later, the state of emergency was extended to all prefectures in Japan. The first declaration of the state of emergency decreased the number of people leaving their homes by 8.5% (Watanabe and Yabu, 2021). The state of emergency was gradually lifted depending on the pandemic situation[18]. Even after the state of emergency was lifted, mobility did not substantially recover because of various government interventions for social distancing. These interventions included encouraging working or studying from home and the early closure of restaurants and bars. In addition to the effect of government interventions, people's behavior was affected by new social norms (Takahashi and Tanaka, 2021). Consequently, staying at home continued until March 2021, as shown in Section 3.

Trend in suicide: In Japan, suicide cases reached their highest record in 1998 after the economic crisis and remained high until 2009. However, because of the government's effort to prevent suicide, the number of cases decreased until the pandemic started. In 2020, the suicide rate increased for the first time since 2010. Figure A1 shows the suicide rate between April 2019 and March 2021. For females, the suicide rate was approximately 8 per 10,000 people as of June 2020; however, the trend then began to increase, reaching the highest level of more than 13 per 10,000 people, and remained at a higher level in the first half of 2021. For males, the relationship with COVID-19 is less clear than it is for females.

[17] These prefectures include Tokyo, Kanagawa, Chiba, and Saitama, as well as Osaka, Hyogo, and Fukuoka.

[18] Decisions on declaring and terminating the state of emergency were made mainly with the following three factors: the number of cases per population, medical surges, and PCR testing volume for COVID-19.

Figure A1: Suicide incidence per 100,000 population, April 2019 - March 2021



Notes: Data shows suicide incidence per 100,000 people in Japan between April 2019 and March 2021. A vertical dotted line marks April 2020, dividing the analysis into two periods: Pre-COVID-19 (prior to April 2020) and Post-COVID-19 (from April 2020 onwards).

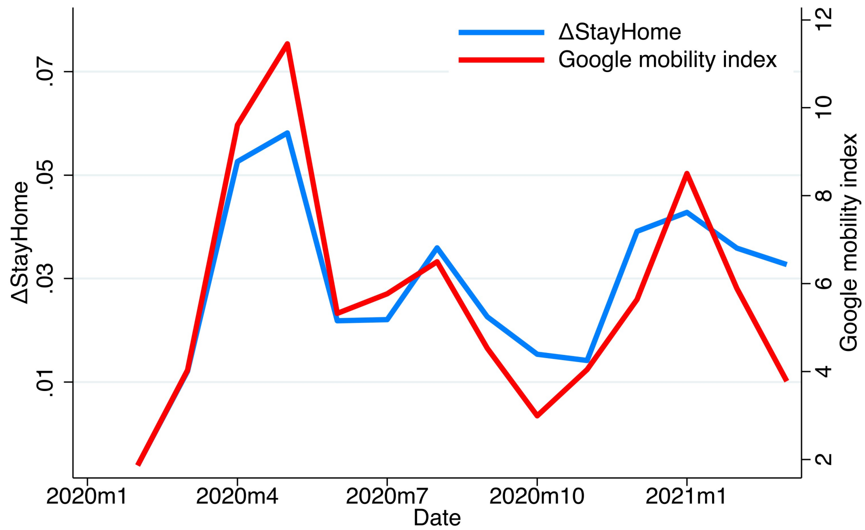
A.2 Correlation with the Google mobility index

To confirm the reliability of our stay-at-home variable, we obtained a correlation with the Google mobility index. Google provided the mobility index to offer timely information on individual travel during the COVID-19 pandemic. The daily mobility data are publicly available as "COVID-19: Community Mobility Report." The Japanese data are available at the prefecture level starting in February 2020. The data are available as a change compared to the median value of a reference day that is the same day of a week during the prepandemic period, where the prepandemic period is designated from January 3rd to February 6th. Among the six location categories, we focus on residence as our measure of stay-at-home behavior. The Google mobility index shows the percentage change in time spent in the residential area from the prepandemic period. We take the monthly average of the daily data of the prefecture-level Google mobility index between February 2020 and December 2021 and obtain the correlation coefficient with the difference in the monthly stay-at-home variable between January 2020 and each month at the prefecture level using a total of 1081 (=23 months47 prefectures) data points. The correlation between our stay-at-home variable and the Google mobility index is 0.74.

Next, we closely examine the correlation in the time series direction. Figure A2 in the Appendix shows the time series plot of the stay-at-home variable and the Google mobility index for residences between February 2020 and December 2021. Our stay-at-home variable closely follows the Google mobility index of residence throughout the period of our analysis.

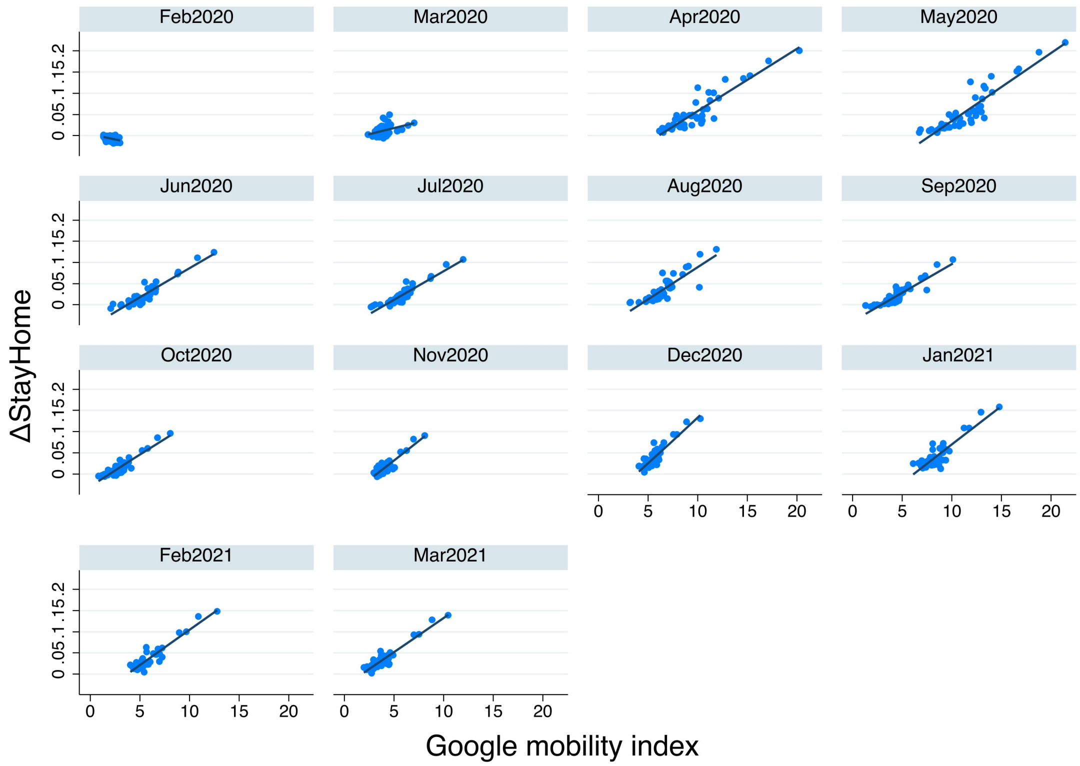
Furthermore, we explored the association in the regional direction. Figure A3 in the Appendix shows the association between the stay-at-home variable and the Google mobility index of residence in each month from February 2020 to March 2021. In the first two panels that show the association in the prepandemic period, there was almost no regional variation in either of the variables. However, starting in April 2020, diversity emerged. In all the sample periods, we see a clear positive correlation, confirming that our measure shows stay-at-home behavior at the individual level.

Figure A2: Time Series Association between the Stay-at-Home Variable and the Google Mobility Index



Notes: The figure shows the plot of the national average of $\Delta StayHome$ (blue) and the Google mobility index (red). $\Delta StayHome$ shows the change from January 2020 to be consistent with the definition of the Google mobility index.

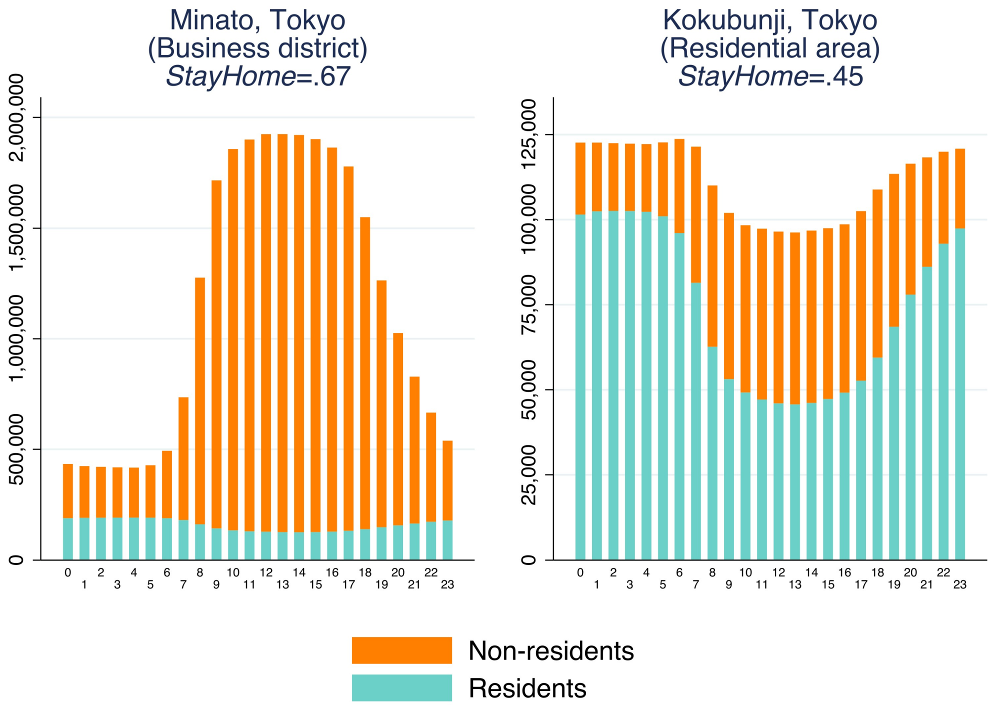
Figure A3: Regional Association between the Stay-at-Home Variable and the Google Mobility Index



Notes: Each panel shows the scatterplot of the prefecture average of $\Delta StayHome$ and its linear fit. $StayHome$ shows the weighted average of the municipality-level data to obtain the prefecture average, and $\Delta StayHome$ shows the change from January 2020 to be consistent with the definition of the Google mobility index.

B Additional figures and tables

Figure B1: Foot Traffic Data: Examples



Notes: Light green shows resident population counts, and orange shows nonresident population counts for each hour. The data shows the average population in each hour in April 2019. Minato Ward, Tokyo, is an example of a business district, and Kokubunji City, Tokyo, is an example of a residential district. The stay-at-home rate is 0.67 for Minato Ward and 0.45 for Kokubunji City. A greater stay-at-home value indicates a higher tendency to stay in the municipality.

Table B1: Descriptive Statistics

	Total				Before		After	
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: Suicide and stay-at-home index								
Female suicide (cases)	5.175	6.266	0	48	4.633	5.534	5.717	6.880
Female suicide under 20	0.213	0.532	0	5	0.176	0.475	0.251	0.581
Female suicide 20-29	0.612	1.245	0	17	0.507	1.041	0.716	1.412
Female suicide 30-39	0.550	1.037	0	10	0.469	0.941	0.630	1.119
Female suicide 40-49	0.828	1.325	0	11	0.719	1.171	0.938	1.455
Female suicide 50-59	0.796	1.314	0	10	0.716	1.204	0.876	1.413
Female suicide 60s or over	2.175	2.575	0	20	2.044	2.416	2.305	2.719
StayHome	0.670	0.123	0.409	0.998	0.640	0.132	0.701	0.106
Panel B: Shares, shifts, and IV								
Commuting ratio	0.464	0.194	0.009	0.787	0.464	0.195	0.464	0.195
Commuting time 0 mins	0.017	0.009	0.000	0.114	0.017	0.009	0.017	0.009
Commuting time (0,30] mins	0.589	0.175	0.142	0.929	0.589	0.175	0.589	0.175
Commuting time (30,60] mins	0.270	0.100	0.033	0.610	0.270	0.100	0.270	0.100
Commuting time (60,90] mins	0.090	0.084	0.000	0.431	0.090	0.084	0.090	0.084
Commuting time (90,120] mins	0.025	0.029	0.000	0.213	0.025	0.029	0.025	0.029
Commuting time > 120 mins	0.009	0.008	0.000	0.086	0.009	0.008	0.009	0.008
Work from work ratio (commuting time 0 mis)	1.000	0.000	1.000	1.000	1.000	0.000	1.000	0.000
Work from work ratio (commuting time (0,30] mins)	0.055	0.025	0.030	0.080	0.030	0.000	0.080	0.000
Work from work ratio (commuting time (30,60] mins)	0.153	0.078	0.075	0.230	0.075	0.000	0.230	0.000
Work from work ratio (commuting time (60,90] mins)	0.200	0.094	0.106	0.294	0.106	0.000	0.294	0.000
Work from work ratio (commuting time (90,120] mins)	0.214	0.106	0.108	0.320	0.108	0.000	0.320	0.000
Work from work ratio (commuting time > 120 mins)	0.223	0.021	0.202	0.244	0.202	0.000	0.244	0.000
Shift-Share IV	0.116	0.053	0.040	0.261	0.069	0.013	0.163	0.032
Panel C: Time-invariant covariates								
Primary industry ratio	0.060	0.063	0.000	0.395				
Secondary industry ratio	0.259	0.075	0.081	0.512				
Tertiary industry ratio	0.681	0.096	0.430	0.919				
City dummy	0.782	0.413	0.000	1.000				
Young rate	0.124	0.019	0.057	0.207				
Middle rate	0.583	0.043	0.413	0.748				
Elderly rate	0.285	0.057	0.149	0.518				
Labor force rate	0.569	0.039	0.387	0.699				
Self-employment rate	0.100	0.032	0.042	0.246				
Single person household rate	0.139	0.028	0.032	0.231				
Panel D: Time-varying covariates								
Active opening ratio	1.361	0.644	0.000	8.935	1.586	0.723	1.136	0.453
Unemployment rate	2.436	0.493	1.250	3.600	2.195	0.386	2.677	0.471
Observations	2482				1241		1241	

Notes: The sample period is between April 2019 and March 2021. Before COVID-19 indicates the period between April 2019 and March 2020, and after COVID-19 indicates the period between April 2020 and March 2021. The definitions of the variables are provided in the main text or in Appendix C.

Table B2: Descriptive Statistics for Commuter Type

Commuting time	k	$\bar{z}_k$	g_{k0}	g_{k1}
0 mins	0	0.017	1.000	1.000
(0, 30] mins	1	0.589	0.030	0.080
(30, 60] mins	2	0.270	0.075	0.230
(60, 90] mins	3	0.090	0.106	0.294
(90, 120] mins	4	0.025	0.108	0.320
$>$ 120 mins	5	0.009	0.202	0.244

Notes: Commuter type is represented by $k = 0, 1, 2, 3, 4, 5$. $\bar{z}_k$ represents the average share of each commuter type k across municipalities. In each municipality m, the share of each commuter type is calculated based on the 2018 Housing and Land Survey of Japan. g_{k0} and g_{k1} represent the proportion of those who worked from home before and after the pandemic, respectively. The data are obtained from Table 1-17-1 of Okubo (2021)

Table B3: Correlation between the Share of 60-90-Minute Commuters and Municipality Characteristics

	(1)	(2)	(3)	(4)	(5)
City	0.096		0.000	0.016	0.016
	(0.003)		(0.005)	(0.004)	(0.004)
	[0.000]		[0.938]	[0.000]	[0.000]
Primary industry share		-0.398	-0.398	0.293	0.357
		(0.031)	(0.031)	(0.241)	(0.206)
		[0.000]	[0.000]	[0.225]	[0.083]
Secondary industry share		-0.114	-0.114	-0.037	0.024
		(0.020)	(0.020)	(0.236)	(0.189)
		[0.000]	[0.000]	[0.875]	[0.900]
Tertiary industry share		0.211	0.211	0.434	0.490
		(0.008)	(0.009)	(0.226)	(0.180)
		[0.000]	[0.000]	[0.055]	[0.007]
Young rate (under 15)				-1.786	-1.774
				(0.211)	(0.203)
				[0.000]	[0.000]
Middle rate (between 15-64)				0.125	0.144
				(0.187)	(0.185)
				[0.503]	[0.435]
Elderly rate (above 64)				-0.267	-0.243
				(0.181)	(0.173)
				[0.139]	[0.160]
Employment rate				0.103	
				(0.127)	
				[0.418]	
Employee rate				-0.010	
				(0.098)	
				[0.919]	
Self-employment rate				-0.388	-0.380
				(0.197)	(0.115)
				[0.049]	[0.001]
Labor force rate				-0.618	-0.598
				(0.077)	(0.068)
				[0.000]	[0.000]
Single person household rate				2.190	2.154
				(0.099)	(0.091)
				[0.000]	[0.000]
Adj. R-Square	0.470	0.666	0.666	0.784	0.784
Observations	1241	1241	1241	1241	1241

Notes: Cluster-robust standard errors are in parentheses. P values are in brackets. The dependent variable is the share of commuters whose commuting time ranges from 60 to 90 minutes (the highest Rotemberg weight share). All variables are derived from data in the census in 2015. The definitions of the variables are provided in the main text or in Appendix C.

Table B4: Rotemberg Decomposition Diagnostics

	Sum	Mean	Share		
Panel A. Negative and positive weights					
$\hat{\alpha}_k \leq 0$	-0.397	-0.397	0.221		
$\hat{\alpha}_k > 0$	1.397	0.349	0.779		
	$\hat{\alpha}_k$	Δg_k	$\hat{\beta}_k$	$\hat{F}_k$	Var(z_k)
Panel B. Correlations					
$\hat{\alpha}_k$	1.000				
Δg_k	0.702	1.000			
$\hat{\beta}_k$	0.230	0.509	1.000		
$\hat{F}_k$	0.057	0.311	0.680	1.000	
Var(z_k)	0.765	0.608	0.370	0.609	1.000
	$\hat{\alpha}_k$	Δg_k	$\hat{\beta}_k$	$\hat{F}_k$	95 % C.I.
Panel C. Share Statistics					
Commuting time (0,30] mins	-0.397	0.050	4.050	1807.293	[0.549, 7.535]
Commuting time (30,60] mins	0.551	0.155	2.117	722.220	[-2.296, 6.537]
Commuting time (60,90] mins	0.659	0.188	5.980	1681.096	[2.146, 9.831]
Commuting time (90,120] mins	0.185	0.212	3.902	439.269	[-1.447, 9.132]
Commuting time > 120 mins	0.003	0.042	3.519	26.637	[-10.530, 18.215]
	α weighted sum	share of overall β	Mean		
Panel D: $\hat{\beta}_k$ for positive and negative weights					
Negative	-1.609	-0.381	4.050		
Positve	5.838	1.381	3.880		

Notes: The table presents the shift-share diagnostics as recommended by Goldsmith-Pinkham, Sorkin, and Swift (2020). The statistics are computed using a Stata package developed by the authors. Panel A delineates the aggregate, average, and distribution of negative and positive Rotemberg weights, $\hat{\alpha}_k$, across different commuter types k. Panel B elucidates the pairwise correlations among four key metrics for Rotemberg decomposition – Rotemberg weights $\hat{\alpha}_k$, the first difference in telework ratio Δg_k, the just-identified coefficients $\hat{\beta}_k$, and the first-stage F statistics for the just-identified instruments $\hat{F}_k$ – and the variance across municipalities for each commuter type k, denoted as $Var(z_k)$. Panel C shows the key statistics for each commuting time ratio, including the 95% confidence intervals that are robust to weak instruments, as calculated using the method proposed by Chernozhukov and Hansen (2008), spanning from -10 to 5 in increments of 0.01. Lastly, Panel D provides insights into the variability of the just identified coefficients $\hat{\beta}_k$ in relation to the positive and negative Rotemberg weights for each commuter type k.

C Control Variables

The data sources for the control variables used in the robustness check are explained below.

Local labor market: We used two variables, the active job-opening ratio at the municipality level and the prefecture-level unemployment rate, to control for local labor-market conditions. The active job-opening ratio is frequently used to measure macroeconomic conditions at the local level, and it is defined as the ratio of active job openings to the number of active applicants. The Ministry of Health, Labour, and Welfare provides monthly data specific to the level of the public employment security office on request. On average, one public employment security office covers a few municipalities. We used the same number of active job-opening ratios for municipalities covered by the same public employment security office. Some municipalities are divided into several districts, which are covered by different public employment security offices. In that case, we used the municipality's average active job-opening ratio of the public employment security offices. The active job-opening ratio was calculated by dividing the number of openings by the number of job seekers in each public employment security office. We used the average active job-opening ratio for the before- and during-COVID-19 periods.

We also included unemployment rates on a prefecture basis. Based on the *Labor Force Survey* conducted and reported quarterly by the Ministry of Internal Affairs and Communications at the national level in Japan, estimates of the prefecture–quarterly unemployment rate can be obtained using a time-series model. Since only quarterly–prefecture data were available, the same numbers were used for the same quarter for all the municipalities in the same prefecture. We included the average unemployment rate in the quarterly data before and during the COVID-19 pandemic.

Industry composition and city dummies: To control for time trends, we included a set of variables to indicate the industry composition of the municipality and a city dummy.

The variables to indicate the industry composition show the share of workers in the 20 industries based on the Japan Standard Industry Classification (https://www.soumu.go.jp/english/dgpp_ss/seido/sangyo/san13-3.htm), which includes the following industry categories: agriculture and forestry; fisheries; mining and quarrying of stone and gravel; construction; manufacturing; electricity, gas, heat, and water; information and communications; transport and postal activities; wholesale and retail trade; finance and insurance; real estate and goods rental and leasing; scientific research, professional and technical services; accommodations, eating and drinking services; living-related and personal services and amusement services; education, learning support; medical, health care and welfare; compound services; services, N.E.C.; government, except elsewhere classified; industries unable to classify. We used the 2015 census data for the prepandemic period and the 2020 data for the pandemic period, as the census survey was conducted in October of that year.

For a city dummy to control for urban areas, we create binary variables to take unity if a municipality is a city and zero otherwise.

Other variables: Some of the specifications included socioeconomic and demographic information at the municipality level. The demographic information included the age composition of three age groups: under 15, 15-64, and 65 years or older. We also include the labor force participation rate, self-employment rate, and single-person household rate. The labor force participation rate is defined as the sum of the number of people who are working and who are unemployed but seeking jobs divided by the total population aged 15 years or older. The self-employment rate is defined as follows: The numerator is the sum of those who own their business, including homeworkers and those with and without employees, and the denominator is the number of workers. The single-person household rate is the share of the households that consist of a single person to the total number of households. These variables are taken from the 2015 Census Survey by the Statistical Bureau.

Commuting ratio: In the empirical model section, we established a canonical model with two types as an illustration. The commuting ratio for each municipality is obtained by the 2015 Census Survey by the Statistics Bureau and defined as the sum of the number of residents working at home and the number of residents working or studying within their own municipality divided by the total number of students and workers aged 15 years or older.

D DAG: Bad Control

Angrist and Pischke (2008) describe variables that could be impacted (postdetermined) by the treatment as "bad controls," advising against their inclusion in a regression model, even if their inclusion might alter the regression coefficients. Conversely, they define "good controls" as variables thought to have been established at the point when the regressor of interest was determined (predetermined).

In the context of this paper, the treatment variable, stay-at-home behavior, is likely to affect local labor-market dynamics, including unemployment rates. This aspect classifies the local labor-market condition as a postdetermined variable. This characteristic suggests that it might serve as a "bad control" in the regression analysis estimating the causal effect of stay-at-home behavior on suicide rates among young women.

We employ causal diagrams to distinguish when postdetermined variables affected by the treatment can be considered "good" or "bad." Using directed acyclic graphs (DAGs), we provide visual summaries of causal relations in various typical scenarios. When including labor market–related variables in the regression, these summaries could provide a biased estimate of the causal effect of staying at home on young women's suicidal behaviors.

Graphically, the potential causal paths under various assumptions are illustrated through diagrams. We represent the outcome of interest, the number of female suicides, by Y. The endogenous stay-at-home variable is denoted by S, and the shift-share instrumental variable is denoted by Z. If we represent labor-market conditions by M, it is influenced by stay-at-home S and, in turn, affects the outcome Y. This influence is depicted through the path $S \to M \to Y$ so that M serves as a mediator. In Figure D1a, a confounder U is assumed to affect both the outcome Y and the endogenous variable S. The instrumental variable Z is assumed to only affect S (i.e., exclusion restriction), and S influences Y through M. The direct effect of S on Y, when M is controlled, is the average change in Y when S is altered exogenously by one unit, known as the controlled direct effect as per Pearl (2009). To estimate the controlled direct effect using the instrumental variable S, it is necessary to control M to close the backdoor path $Z \to S \to M \to Y$. Hence, in this scenario, M is a "good control" and should be included in the regression analysis to estimate the direct effect of S on Y.

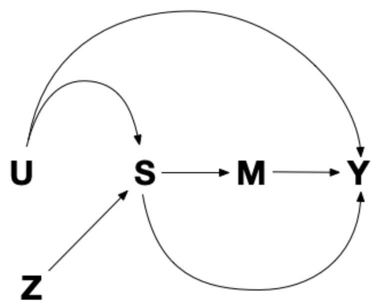
Conversely, Figure D1b shows a situation where the confounder U affects not only Y and S but also M. In this case, controlling M would open a colliding path $Z \to S \to M \leftarrow U \to Y$, making it impossible to identify the direct effect of S on Y using Z as an instrumental variable. Therefore, M is a "bad control". Additionally, Figures D1c and D1d illustrate cases where another confounder V affects both the mediator M and the outcome Y. In Figure D1c, even though the confounder U does not affect the mediator M, controlling M opens the colliding path $Z \to S \to M \leftarrow V \to Y$, making M a "bad control". Similarly, in Figure D1d, where the confounder U affects the mediator

M, controlling M opens both paths $Z \rightarrow S \rightarrow M \leftarrow U \rightarrow Y$ and $Z \rightarrow S \rightarrow M \leftarrow V \rightarrow Y$, reinforcing M as a "bad control." Therefore, in these scenarios, M should not be included in the regression analysis using Z as an instrumental variable.

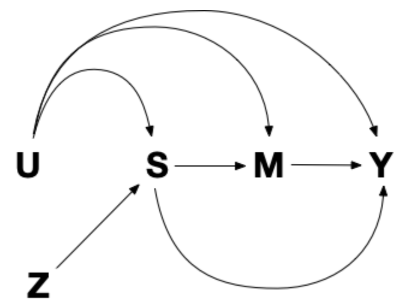
In summary, in the situation depicted in Figure D1a, the local labor-market condition M is a "good control" and helps unbiasedly estimate the direct effect in the regression analysis. However, in the other scenarios shown from Figure D1b to Figure D1d, M becomes a "bad control" and should not be included in the regression analysis.

Figure D1: DAG: Good or Bad Controls

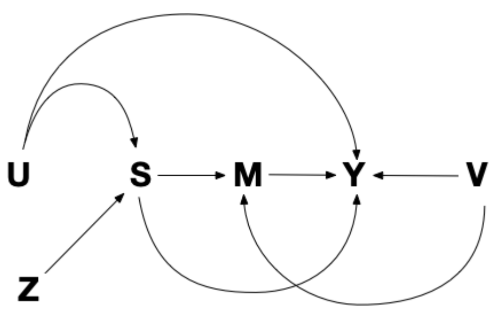
(a) One confounder with M unconfounded by U



(b) One confounder with M confounded by U



(c) Two confounders with M unconfounded by U



(d) Two confounders with M confounded by U