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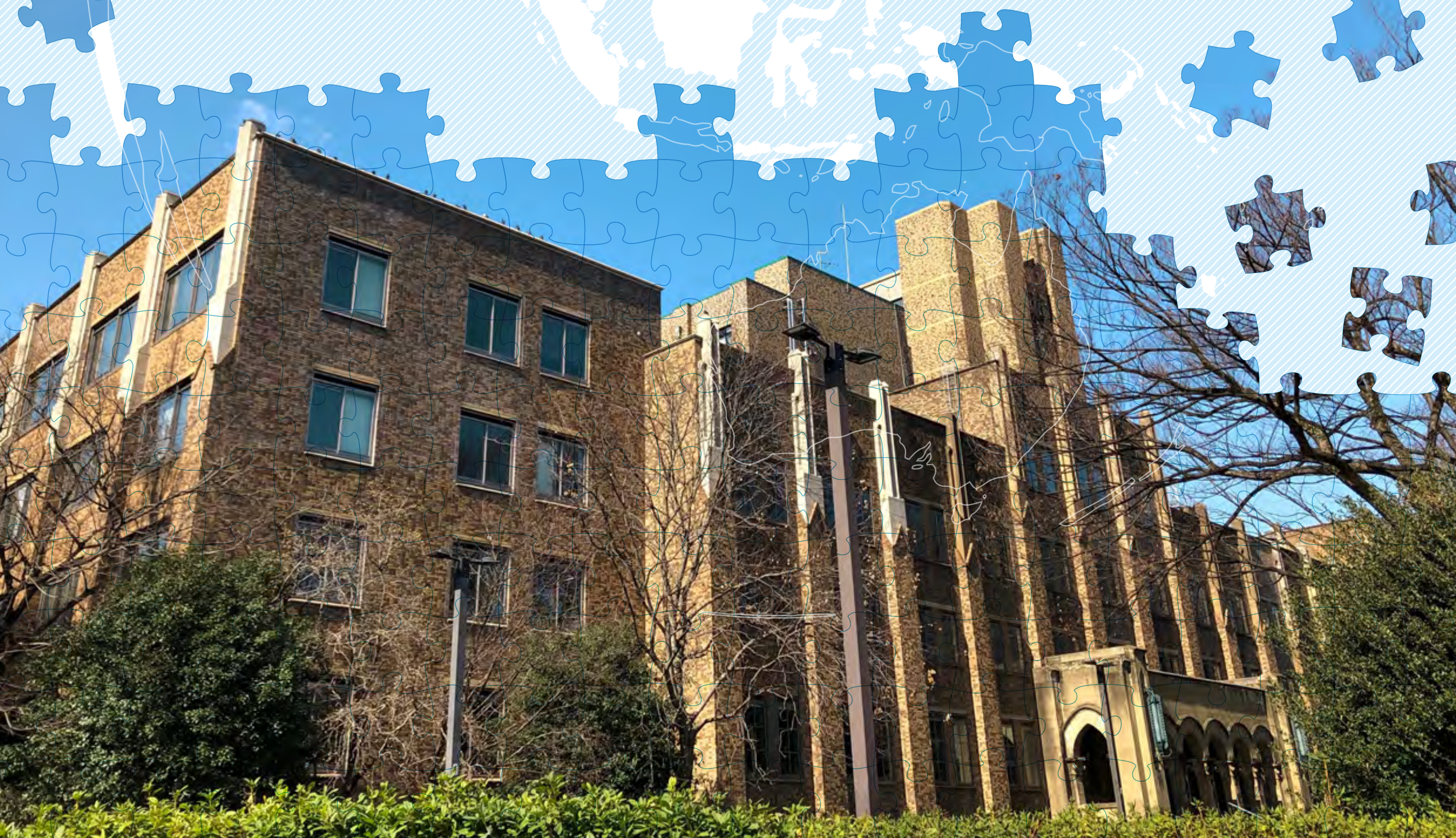
In-home death: Impact on housing prices and rents in Tokyo Metropolitan Area



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SDGs
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
16 PEACE, JUSTICE AND STRONG INSTITUTIONS

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In-home death: Impact on housing prices and rents in Tokyo Metropolitan Area

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Abstract

This study utilizes unique information about death incidents in residential buildings to examine their effects on property prices and rents within the building. Analyzing data on death incidents and property transactions in the Tokyo Metropolitan Area through the staggered difference-in-differences approach, the study finds that a death incident results in approximately a 5% reduction in sale prices of nearby properties in the same residential building, while the negative spillover effect on rents is minimal. Further investigations attribute these divergent outcomes to the likelihood that buyers are better informed than renters about incidents in the neighborhood they move into before signing contracts. Despite a death incident being notified to prospective buyers and renters only if it occurred on the property to be transacted, our finding of the negative spillover effect suggests that, in accordance with current Japanese law, the notice obligation should be extended to transactions involving other properties in the same residential building. Additional analyses on heterogeneous impacts show that the negative effect on prices intensifies in housing markets characterized by lower demand and specific adverse conditions.

1. Introduction

Some cultures conceive of death as sinister and ominous, a conception more dominant in Asian than in Western cultures. According to the Asian Pacific Values Survey (ISM, 2015), for instance, 17.4% of respondents in Japan responded that they were "afraid or scared" of "ghosts, hauntings, and possessions by evil spirits," compared to 6.8% in the US. This psychological tendency of the Japanese respondents may partly and implicitly originate in their belief in Mahayana, one of the three major schools of Buddhism.

In Japanese cultural and religious belief, the soul of a dead person who experienced an unexpected and unfortunate death cannot enter Nirvana, unable to become a Buddha without leaving any regrets in the current world. When people are unable to ascend to Nirvana, they are said to fail to "*jobutsu*" in Japanese traditional terminology. The soul of a person who was unable to *jobutsu* is believed to stay and wander around the current world with grudge, resentment, and sadness. The invisible soul of a dead person with a deep-seated grudge is perceived as sinister, which may create a fear of being haunted or possessed by ghosts.

In the same survey (ISM, 2015), 19.3% of respondents in India gave the same response, the highest among all countries in this survey. In India, the majority (80% as of 2010) adheres to Hinduism (Hakkett et al., 2012), a belief system centered around reincarnation, the process of a person's spirit returning to life in another physical form until achieving perfection. Hindu teachings suggest that reincarnation can take the form of a human (*manusya*) or an animal (*tiryak*), while in the case of traumatic death, the person becomes a ghost (*Preta*), roams around the previous house, and causes unfortunates to people dwelling in the house.[1] The survey indicates that people living in such religious cultures as Mahayana and Hindu tend to hold a belief in the presence of earthbound spirits, harboring a stronger sense of defilement toward human death than their non-believing counterparts.

People who have negative perceptions of the death of others may dislike situations likely to remind them of death. Since housing is an essential element in daily life, they may hesitate to live in residences connected to other people's deaths, seeing such places as negative and ominous atmospheres. Residential properties where an in-home death has occurred, meaning that the past residents have died inside the house, may induce psychological discomfort, which could have implications for the potential buyers' or renters' willingness to pay for such properties.

In-home death encompasses various fatal incidents occurring within residential properties, including deaths due to disease, accidents, suicides, and murders. Properties where such incidents occur are sometimes considered psychologically flawed or stigmatized due to perceived lingering negative effects, influencing potential buyers and renters in the neighborhood. Perceptions of human deaths vary across areas based on cultural backgrounds and religious beliefs, but some research shows that the occurrence of death incidents in houses is adversely evaluated in housing markets in some Asian countries. In Hong Kong, where beliefs in Feng Shui, which originated in Confucianism,

[1] Chap. 20, vv. 8-12, 45 and Chap. 22, vv. 8-13, Garuda Purana.

strongly influence housing decisions, in-home deaths are considered to generate excess negative energy, rendering the properties unsuitable for habitation based on Feng Shui (Chang and Li, 2018; Battacharaya, 2021). Alias et al. (2014) found that in-home deaths adversely affected the Malaysian housing market in their questionnaire-based survey.

The negative association between the occurrence of in-home death incidents and housing prices indicates the unfavorable impression of death in cultures that perceive it as a sinister phenomenon. As already mentioned, religious teachings that view death as ominous were historically prevalent in Japan. This study investigates whether in-home deaths are associated with reduced housing prices among properties in Japan, especially in the Tokyo Metropolitan Area. This study leveraged a unique dataset of locational information on properties where in-house deaths occurred, in combination with detailed housing transaction data. A decline in property prices or rents after the occurrence of in-home deaths would suggest that the other persons' deaths are thought to be sinister in Japanese culture.

Based on the empirical results of the study, we further discuss how deficient the current Japanese disclosure rules are to potential buyers and renters regarding the occurrence of in-home deaths. From the consumer side, being sufficiently informed of the psychologically adverse features of the properties is important. If evidence suggests that in-home death induces disutility among residents, it should be carefully taken into account according to appropriate guidelines to give prospective buyers sufficient information about the properties.

Specifically, we examined the presence of stigma inherent in in-home death by estimating its impact on housing values in properties near where the death occurred. We took this approach under the assumption that housing price reflects people's perceptions of dwelling attributes. Considering that not everyone becomes aware of in-home deaths in the neighborhood where they live or move into, the impact of in-home death on housing values depends not only on perceptions of human death but also on rules governing the disclosure of in-home death in real estate transactions. Disclosure rules vary across countries. In most US states and provinces in Canada, the general rule is caveat emptor, meaning that property dealers are not required to disclose unless explicitly asked by their transaction partners (Edminston, 2010; Spaulding Decon, 2023). Conversely, Hong Kong and Japan, along with some US states, including Alaska and California, require dealers to inform their counterparts about in-home death incidents.[2] However, some of the disclosure rules can be ambiguous, leading to complications, as seen in the case of Japan.

Japan's property transaction law prohibits dealers from "misrepresenting or intentionally failing to disclose a fact when soliciting for the conclusion of a contract if the fact has a critical influence on decisions by counter partners."[3] However, the extent to which an in-home death influences counterparties' decisions can depend on various factors, such as when, where, and how the incident occurred, while the law lacks clarity on when disclosure is required. In response, dealers have established best practices.[4] These ambiguities led to numerous court cases where buyers and renters took legal action against dealers for failing to disclose, resulting in significant social costs. Moreover, this ambiguity could potentially encourage discriminatory practices by landlords against elderly tenants, as landlords seek to mitigate the risk of death due to disease or solitary death, which has been increasing and will continue to increase due to population aging.[5]

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[2] The existence of such regulations implies that in-home deaths considerably impact people's anxiety and property transactions in the region. For instance, the reason why California mandates dealers to disclose such incidents to their counter partners may be partly due to the large proportion of Asian people residing in the state.

[3] Article 47 item 1 of the Building Lots and Buildings Transaction Business Act.

[4] Generally, dealers would notify their counterparties only if a death incident occurred within the property being transacted, but not if it took place in a different property even within the same apartment building. Additionally, if someone previously lived in the property where the incident occurred, subsequent occupants would not be informed.

[5] According to Vital Statistics published by the Ministry of Health, Labour, and Welfare, approximately 90% of accidental in-home deaths occur in elderly households (MHLW, 2021).

In response to this situation, the Japanese government established a committee in 2019, which subsequently issued "the guidelines for in-home death disclosure" in 2021, specifying more detailed disclosure requirements (MLIT, 2021). These guidelines stipulate that dealers must inform counterparts about a death incident if it occurred on the property being transacted.[6] Importantly, a death that occurred in another property does not require disclosure. Given that the property transaction law mandates disclosure of any information influencing people's decisions, the government alleges that people do not view a death incident in a different property as a significant factor when making a housing selection, even if it occurred in the same residential building. According to the committee meeting minutes, the guidelines were formulated based on past practices and legal precedents rather than being grounded in evidence-based research.

One motivation of this study is to provide empirical evidence regarding the government's claim that in-home death causes psychological stigma exclusively within the property itself, not in another property in the same building. To pursue this purpose, we conduct a hedonic analysis using data on in-home deaths and housing transactions. The database on in-home deaths was accessed from *Oshimaland.com*, an online platform that compiles death information from user postings. As mentioned earlier, one distinct feature of this research, compared to other studies in the literature, is that not all buyers and renters are aware of death incidents analyzed in this study.[7] The estimated impact of incidents on housing values is a combination of the psychological impact and awareness level of buyers and renters concerning the incident. In extreme cases where in-home deaths in a particular area are entirely unknown, housing values in the area remain unaffected by the incidents. Thus, the effect on housing values can be interpreted as the lower bound of the psychological impact, and any price change detected due to in-home death ensures the presence of stigma associated with the incident.

Another distinct feature is that the impact of in-home death reveals the presence of stigma stemming from the past incident independent of material defects and expectations toward future events. Generally, residents may feel uneasy about their residence for a variety of reasons, including poor neighborhoods, environmental issues, and crime and disaster risks. The negative impacts of such misfortunes can be ascribed to at least one of three types of anxieties, which pertain to anticipated future events, present events, and past events. The example of the first type includes the perceived risk of a future natural disaster.[8] The second type of anxiety arises from the disutility that residents are experiencing in the present, such as environmental contamination.[9] The third type is attributed to the stigma from a past event, such as a suicide in a property. The last type does not involve any physical or material impact in the present unlike the second type and is not associated with the likelihood of another in-home death in the future in the property, unlike the first type. Although the former two types have predominantly been explored in the previous hedonic literature, research focusing on the

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Nakagawa (2004) and Suzuki et al. (2022) provide evidence of discrimination by landlords against single elderly applicants seeking to move into their apartments.

[6] There is no obligation to disclose in cases of death due to disease or solitary death without the need for special cleaning, which is conducted when a corpse has been left unattended for a long time without being noticed by anyone. The special cleaning is more likely to be required during the summer season when high temperatures accelerate decomposition. The notice obligation extends for three years from the incident for lease contracts, while there is no time limit for sale contracts.

[7] The website's access is increasing over time according to the Google search trends on the website, "*Oshima-teru,*" the Japanese translation of *Oshimaland* (Yajima and Sadayuki, 2023). This increasing trend simultaneously suggests that the website is still accessed by just a portion of individuals searching for housing.

[8] People adjust their perceived risk of living in a particular area by reviewing published hazard maps, sex offender registries, and crime rates (Pope, 2008; Linden & Rockoff, 2008; Tang and Lee, 2023). Calamities such as earthquakes, typhoons, and epidemics can also elevate subjective perceived risk and consequently influence housing prices (Zhu et al., 2016; Gibson & Mullins, 2020; Wolf & Takeuchi, 2022; Liu and Tang, 2021).

[9] The example includes instances of environmental contamination, pollution, and noise (Boyle & Kiel, 2001; Congdon-Hohman, 2013; Dealy et al., 2017; Jensen et al., 2014; Walsh & Mui, 2017).

third type is scarce.[10] When analyzing the cases of in-home deaths, it is academically interesting to note that the impact is primarily attributed to the third type, rather than the former two types of anxieties.

Despite numerous news articles and reports across countries highlighting the significant impact of in-home death on the property itself (Vasel, 2016; Goh, 2022; Cahill, 2022), empirical assessments based on sophisticated econometric methods are scarce. Among the limited studies, Chang and Li (2018) and Bhattacharya et al. (2021) analyze sales data in Hong Kong and discover a significant decline in property prices following the occurrence of a death incident within the condominium building.[11] Sadayuki (2020) analyzes cross-sectional rent data in Tokyo in 2011 and shows that the rent is lower in an apartment building with an in-home death incident compared to a building without such an incident. In his study, however, there remains a possibility of endogeneity, where a death incident might be more likely to occur in less expensive buildings.

Our study makes four contributions to the existing literature. First, we incorporate building-level fixed effects in the regression to fully account for the locational endogeneity and the unobservable effect of building-specific attributes. In addition, we employ the staggered difference-in-difference (SDiD) approach proposed by Sun and Abraham (2021) to address the potential estimation biases related to treatment effects that stem from the differential treatment timings (in our case, the timing of death) and heterogeneous impact across treatment units. While Chang and Li (2018) and Bhattacharya et al. (2021) employed the conventional two-way fixed effects DiD method and event study design, such approaches are unsuitable for situations involving staggered treatment timings or cases where treatment effects differ according to the characteristics of the property. The approach of Sun and Abraham (2021) provides robust estimates under such a situation.

Second, our results reveal that in-home death induces price reduction not only in the property that experienced a death incident but also in other properties in the same building. This finding suggests that the stigma around death incidents extends beyond the in-home death property itself, which contrasts with the assertion in the government's guidelines. This result implies that complying with the current law requires dealers to disclose not only death incidents that occurred in the transaction property but also those that occurred in other properties in the same building.

Third, our transaction data enables us to examine impacts on sales and rents rather than focusing on one or the other, as in previous studies. Recent discussions in the field of regional science highlight the heterogeneity between rental housing and sales housing markets, especially concerning the impacts of dwelling amenities (e.g., Caplan et al., 2021; Kuroda and Sugasawa, 2023). Our analysis shows that the in-home death induces a reduction in prices but not in the rents of neighboring properties within the building. These results on price and rent remain robust across various estimations employing different samplings and model specifications. We then delve into potential mechanisms for the differential outcomes between sales and rents. After examining several mechanisms with available data, the most plausible explanation for the differential outcomes appears to be the difference in awareness levels between prospective buyers and renters regarding in-home deaths in the building they move into: Compared to renters, buyers invest more time and effort searching housing and, thus, are more likely to be aware of incidents in the building before signing contracts. One notable observation is a sharp rise in lease transactions following an incident, suggesting that properties from

[10] In many studies, the estimated impact can result from a combination of stigma and other types of anxiety. For instance, Zhu et al. (2016) found a negative impact of the Fukushima Daiichi nuclear disaster in 2011 on land prices near nuclear power plants in China, arising from stigma and changes in perceived risk associated with nuclear power plants. In such cases, distinguishing between these effects can be challenging. A study by Dealy et al. (2017) on methamphetamine labs estimates the decline in housing prices upon the discovery of labs, attributed to stigma and material defects. They also assessed the price recovery after the removal of labs and contaminations, noting that the price did not fully recover to its initial level, where they interpret the gap as stigma stemming from the post-existence of methamphetamine labs.

[11] The local government of Hong Kong maintains information about in-home deaths within its jurisdiction, making it relatively accessible for researchers.

which incumbent renters move out after the incident are immediately replaced by new renters who are not aware of the death incident in the building.

Lastly, our study encompasses a broad geographic scope, including four prefectures—Tokyo, Saitama, Kanagawa, and Chiba, which together constitute the Tokyo Metropolitan Area, the world's largest city. This approach contrasts with that of previous studies, which focus on a limited geographic area, such as Hong Kong and Tokyo prefecture, where housing markets exhibit a high degree of homogeneity in terms of regional and socioeconomic characteristics. The significance of regional heterogeneities in influencing residents' behavior has been emphasized in previous research on various disamenities, including disasters (Bakkensen and Barrage, 2017), epidemics (Liu and Tang, 2021), and crime (Kim and Lee, 2018). Our study area showcases a remarkable diversity, spanning from urban areas characterized by the 9th highest cost of living globally (Mercer, 2022) to rural areas featuring the highest vacancy and elderly rates worldwide (OECD, 2020; World Bank, 2021). This variation in regional characteristics allows us to investigate heterogeneous impacts of in-home death. The data show that the negative impact on in-home deaths is more pronounced in areas with high vacancy rates and murder rates, suggesting that the impact is more severe in a housing market with low demand and specific adverse conditions. This insight is corroborated by additional analyses, which reveal larger negative impacts on transactions during the off-season in the real estate market, as well as in older buildings.

The rest of the paper is structured as follows. Section 2 outlines this study's empirical design, data sources, and variables. Section 3 demonstrates the main results and robustness checks. Then, Section 4 discusses potential mechanisms contributing to the differential impacts on prices and rents. Section 5 provides heterogeneity analyses. Finally, Section 6 concludes the paper.

2. Empirical strategy and data

In this section, we present our empirical strategy and data used to ascertain the impact of in-home deaths on property sale prices and rents within buildings. We apply a staggered difference-in-difference (SDiD) method as death incidents occur at different timings across buildings (i.e., treatment timings are staggered across buildings). To estimate an average treatment effect on the treated (ATT) of such impact with staggered treatment timings, the conventional SDiD analysis has employed an indicator variable, which equals one for treated individuals after its treatment period, along with individual and time fixed effects and time-varying covariates. However, recent studies have highlighted that the conventional SDiD approach may not give a valid estimate of the ATT (Athey and Imbens, 2022; Baker et al., 2022; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). They show that the estimated ATT under the conventional SDiD method is biased unless the treatment effect is homogeneous across treated individuals and across the relative treated period (i.e., the time elapsed since the initial treatment), even when the treatment timings are random. Although in-home deaths seem to occur randomly in terms of timing, the homogeneity of treatment effect across individuals and time is not likely to hold because the impact of in-home death may vary by the socioeconomic characteristics of people living in the neighborhood and also because it can increase or decrease over time. This study adopts the SDiD estimation proposed by Sun and Abraham (2021) to address the potential estimation bias inherent in the conventional SDiD approach.

To estimate the impact of in-home deaths on prices and rents within buildings, the SDiD requires information on transactions before and after the occurrence of death incidents in buildings where an incident occurred. For this purpose, our analysis draws on two extensive datasets. The first dataset comprises information on in-home deaths recorded in *Oshimaland.com*, an online platform that compiles death-related information from user-contributed posts. The second dataset contains property transactions sourced from the Real Estate Information Network System (REINS), furnished by the Real Estate Transaction Promotion Center (RETPC).

The following two subsections detail the estimation strategy and data manipulation to clarify our estimation strategy.

2.1. *Empirical model*

Our baseline SDiD model, constructed based on the hedonic price model (Rosen, 1974) with Sun and Abraham's (2021) procedure, is as follows:

$$ln(price_{ijt}) = \boldsymbol{\beta X_{ijt}} + \sum_{e}\sum_{l\neq-1} \gamma_{e,l}\ \mathbb{I}\{f(t-E_j) = l\} * \mathbb{I}\{g(E_j) = e\} + \mu_j + \boldsymbol{\tau}(t) + \epsilon_{ijt}$$

where the dependent variable, $ln\ (price_{ijt})$, is the natural logarithm of the nominal price or rent of property i in building j, transacted in year-month *t*. On the right side of the equation, we control for the building-level fixed effect, μ_j, and time fixed effects, $\boldsymbol{\tau}(t)$. The building fixed effects address the endogeneity attributable to locational and building-specific characteristics, allowing us to focus on the price variation within the building.[12] The time fixed effects consist of year fixed effects and month fixed effects, which capture the unobservable housing price dynamics over the years and the seasonal price fluctuations.[13] To account for the within-building price variation across properties, we include a vector of property-level attributes, $\boldsymbol{X_{ijt}}$, such as the floor area, floor level, and the age of the building at the time of the transaction. $\boldsymbol{\beta}$ is a vector of parameters associated with the property-level attributes. Note that building-specific attributes commonly used in hedonic analysis, such as the distance to CBD and building structure, are omitted from the model as their effects are encapsulated within the building-level fixed effect. ϵ_{ijt} is an error term.

Our variables of interest are interactions of two indicators, $\mathbb{I}\{f(t-E_j) = l\} * \mathbb{I}\{g(E_j) = e\}$, where $\mathbb{I}\{x\} = 1$ if x is true, and $\mathbb{I}\{x\} = 0$ otherwise. Here, E_j represents the Gregorian calendar year-month of death incident occurrence in building *j*, *l* denotes the number of years, and *e* denotes a Gregorian calendar year. In the first indicator, the function $f(.)$ converts the number of months into the integer number of years. For instance, $f(11) = 0$, $f(12) = 1$, and $f(100) = 8$. Therefore, the first indicator is regarding the relative treated years, which equals 1 if the property *i* is transacted *l* years after the incident occurred in building *j*. In the second indicator, the function $g(.)$ converts a Gregorian calendar year-month to a simple Gregorian year. For instance, $g(\text{January 2020}) = 2020$. Therefore, the second indicator is regarding a treatment cohort, which equals one if the incident in the building occurred in year *e*. A set of properties for which the second indicator equals one is referred to as the *e*-year-death-building cohort. For instance, if the death incident in building *j* occurred in year 2020, then all transaction properties in the building belong to the 2020-death-building cohort. Finally, given the interaction of these two indicators, the parameter $\gamma_{e,l}$ reflects the impact, *l* years after the incident occurred in year *e*, on the price or rent within the building. Here, one year before the incident, $l = -1$, serves as the reference period. For $l \leq -2$, the parameter is expected to serve as a placebo coefficient, allowing us to test the assumption of parallel trends.

To obtain the ATT (or the placebo effect) at relative treated period *l*, we take the weighted average of treatment effects $\widehat{\gamma_{e,l}}$ over the cohorts;

$$\widehat{\nu_l} = \sum_{e} w_e * \widehat{\gamma_{e,l}}$$

where w_e is the estimated share of the *e*-year-death-building cohort.

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[12] As explained in subsection 2.3, not all death incidents are detectable at the property level, but only at the floor or building level. In addition, the sample size becomes substantially small when the sample is restricted to repeat sales where multiple transactions in the same property take place. Therefore, we control for building-fixed effects instead of property-fixed effects in our specification.

[13] We employ a robustness check in subsection 3.2, controlling for municipality-by-year fixed effects, and show that the main result is not influenced by the potential area-specific time trends.

The conventional SDiD approach discards the second indicator of the treatment cohort, $\mathbb{I}\{g(E_j) = e\}$, and use only the first indicator of relative treated time to directly estimate the impact l years after the incident, as in the previous studies on in-home deaths (Chang and Li, 2018; Bhattacharya et al., 2018). However, under such a conventional SDiD approach, the estimate on ATT does not only reflect the pure comparison between treatment and control groups but is also influenced by comparisons of price evolution among the treatment group. As proposed by Sun and Abraham (2021), the introduction of the second indicator regarding the treatment cohort in the equation allows us to extract the results only from comparisons between treatment and control groups. In our case, the sample size is insufficient to construct treatment cohorts at every monthly level, while we employ treatment cohorts at the yearly level to mitigate the potential influence of intra-treatment group comparisons on the estimation result.

Besides the issue of staggered treatment timings, another challenge of applying the DiD method to in-home death studies, including ours and previous studies (Chang and Li, 2018; Bhattacharya et al., 2018; Sadayuki, 2020), is the lack of comprehensive official data on in-home death. The difference-in-differences method requires a sample of treatment and control groups. In this study, as we are interested in estimating the effect of in-home death within the building, the sample for the treatment group is property transactions in buildings that experienced an in-home death incident during the study period, and the sample for the control group is those in buildings that have no in-home death incident that occurred during the study period. However, the construction of a control group in our study setting is challenging because, as will be discussed later in more detail, the in-home death data in our study and previous studies is based mostly on public postings and does not cover all incidents; therefore, the absence of posting for a specific building does not necessarily mean that no death incident occurred in the building.

To deal with the issue of potential incompleteness of the data to the extent possible, we take advantage of the estimation procedure proposed by Sun and Abraham (2021). In particular, we restrict our sample to property transactions in buildings in which a death incident occurred during the study period and use the last-year-death-building cohort (i.e., property transactions in buildings in which a death incident occurred during the final year of our study period) as a control group. In other words, we use property transactions that occurred before incidents in the last-year-death-building cohort as the (not-yet treated) control group. While it remains possible that some buildings with recorded incidents may have unrecorded ones, we adopt this approach based on the assumption that buildings with a recorded incident are less likely to have unrecorded incidents than buildings with no record. Another advantage of this sample selection process is that excluding buildings with no incident record allows us to construct treatment and control groups that have similar characteristics in a way that both groups have experienced death incidents at some point in time.

2.2. *Study area*

This study centers on the Tokyo Metropolitan Area, an expansive region comprising Tokyo, Saitama, Chiba, and Kanagawa prefectures. The area boasts a population of around 35.6 million people as of 2020, accounting for more than a quarter of the population in Japan and covers 13,600 km^2 across 212 municipalities. A notable distinction from previous study areas such as Hong Kong (7.3 million people in 1,100 km^2) and Tokyo prefecture (13.2 million people in 2,100 km^2) lies in the sheer scale and diversity of the study area of this research.

The Tokyo Metropolitan Area contains the central business district (CBD) of Tokyo, characterized by its highly expensive housing market akin to that of Hong Kong. This study area also encompasses suburban and rural areas encircling the Tokyo CBD. Some of these rural areas exhibit a decline in real estate markets, often marked by dwindling housing demand and elevated vacancy rates. We leverage this substantial regional heterogeneity within our study area to unravel underlying mechanisms of the impact of in-home death incidents on property transactions.

2.3. In-home death data

The in-home death data originates from *Oshimaland.com*, a privately operated online platform that aggregates information regarding deaths that occurred in residential properties. Public users contribute to this database by posting details about death incidents that they find, such as the date of occurrence, address, and description of the incident, rendering it the most comprehensive source of in-home death information accessible in Japan. As of November 2020, the dataset encompasses approximately 61,000 records of in-home death incidents across Japan, with a subset of approximately 23,000 incidents recorded in the Tokyo Metropolitan Area.[14]

Figure 2.1 illustrates an example of a snapshot from *Oshimaland.com*. Locations of in-home deaths posted on the website are represented by flame symbols on the map. By clicking one of the symbols, a window describing the selected incident pops out (the left panel in Figure 2.1), which provides the information on its occurrence date, street address (masked by authors), and description of the incident. For example, the snapshot in Figure 2.1 shows a case of a suicide that occurred in November 2015 in a certain residential building, along with information on a detailed room number. Not all postings provide the address of the incident on the property or floor level. The location of the incident is identified, at least at the building level, by the street address or the name of the building on the map, where the flame symbol is pinned down. The format in which the flame symbols are displayed may influence a prospective buyer or renter's decision as to which buildings to avoid, rather than how far away from the in-home death property they should live because it is perceived as if the entire building is the source of the death incident.

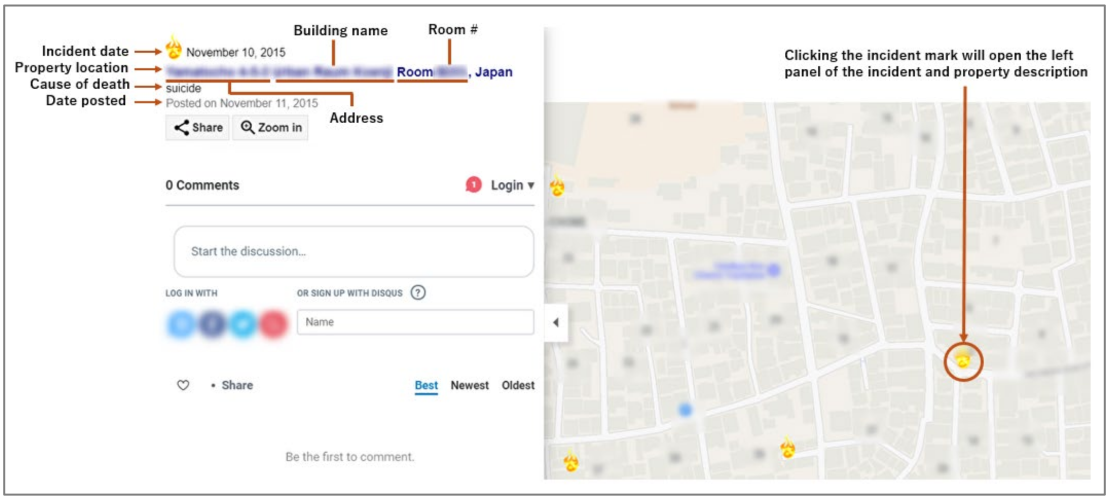

Figure 2.1: A snapshot from *Oshimaland.com*

As this data is based on anonymous postings, some may have concerns about its reliability. For instance, some landowners and real estate agents may intentionally post incorrect information on their competitor's properties. To address such potential false postings, the website implements a comment field (Figure 2.1) where public users can report any misinformation regarding the incident. Once comments are posted, the website administrator investigates and removes any postings deemed to be misinformation. In addition, we exclude false postings while constructing the dataset for analysis, containing the date of occurrence, address, and description of incidents by cleansing registered information on each incident along with the associated comments.[15]

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[14] On November 19, 2020, the administrator of *Oshimaland.com* kindly provided us with the raw data of public postings registered on the website. The volume of postings has consistently risen since that date. As of January, 2024, the number of postings stands at approximately 82,000.

[15] Appendix A describes the data cleansing process in detail. In Appendix C, scatter plots between the number of records and the number of households across municipalities are illustrated to provide the evidence that the distribution of the sample used in the estimations is unlikely to be spatially biased to high-population municipalities.

2.4. Property transaction data

The property transaction data is sourced from the REINS, which serves as Japan's most comprehensive Multiple Listing Service (MLS). Spanning from 2012 to 2020, the dataset encompasses approximately 740,000 sales and 1,690,000 leases in our study area. Each entry in the dataset contains information about the contracted price or rent, contract date, address, and a range of attributes about both the contracted property and its building, such as room count, floor area, floor level, building age, and proximity to the nearest station.

The property transaction data is matched to the in-home death data at the building level using the street address and building name to extract samples in buildings in which death incidents occurred. To simplify the analysis, we retain buildings in which a death incident occurred only once. As mentioned earlier, property transactions between 2012 and 2019 from the 2020-death-building cohort (i.e., property transactions in buildings in which death incidents occurred in 2020, the last year of the study period) serve as the control group, and transactions between 2012 and 2019 from other cohorts are used as the treatment group.[16] To facilitate the DiD estimation, the sample of the treatment group is restricted to those in buildings in which at least one transaction took place both before and after the occurrence of an in-home death incident in the building. These selections narrow the sample to 3,681 sales across 315 buildings and 6,183 leases across 572 buildings. Figure 2.1 shows the geographic distribution of our estimation sample, with red circles and blue x-marks representing locations of sale and rent samples, respectively.[17]

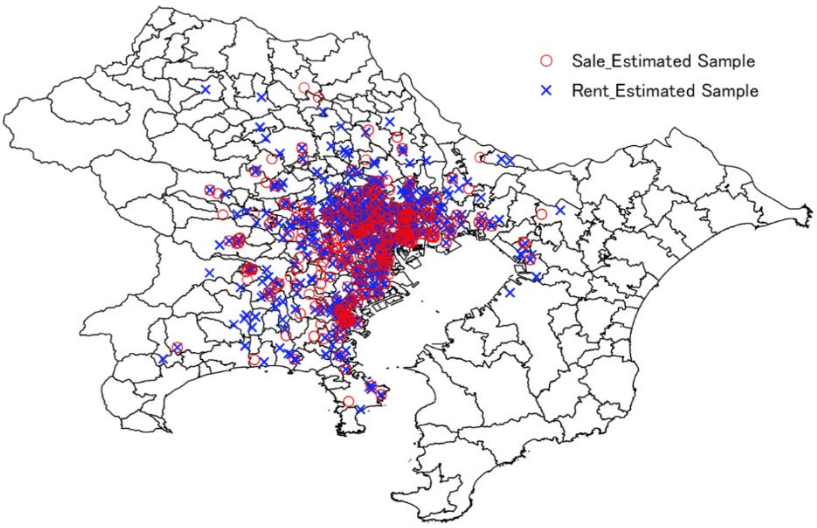

Figure 2.1: Distribution of properties to be examined

Notes: The lines represent the borders of 212 municipalities in the Tokyo Metropolitan Area. Red-colored circles show the locations of sales properties matched with death incidents recorded in *Oshimaland.com* that are displayed in Figure 2.1. Blue-colored crosses show those of the rental units.

Table 2.1 displays the numbers of property transactions, buildings with at least one transaction, and death incidents across cohorts.[18] The annual sample size of property transactions ranges approximately from 250 to 500 for sales and from 600 to 800 for leases.

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[16] An alternative estimation is conducted by adding 2019-death-building cohort to the control group to provide the robustness of the main result in Section 3.2 and Appendix E.

[17] In Appendix C, we present the distribution of overall in-home deaths recorded on *Oshimaland.com*.

[18] The number of death incidents equals the number of buildings in which a death incident occurred in the specific year because the study sample of buildings is restricted to those with a single incident. Appendix C provides the numbers of property transactions and buildings with any transaction by years of time lag since the incident.

	Property for Sale			Property for Rent		
	# of transactions	# of buildings with transaction(s)	# of death incidents	# of transactions	# of buildings with transaction(s)	# of death incidents
2012	216	93	6	672	252	14
2013	366	152	16	619	265	29
2014	384	173	34	601	244	39
2015	335	149	23	654	240	45
2016	441	177	35	783	280	56
2017	526	182	28	748	270	38
2018	503	183	44	772	283	77
2019	495	190	25	711	269	35
2020	415	179	104	623	260	239
Total	3,681		315	6,183		572

Table 2.1: The number of transactions and buildings by year
Notes: The table shows the numbers of property transactions, buildings with transaction(s), and death incidents for each year between 2012 and 2020.

Summary statistics of variables used in the estimation are described in the top panel in Table 2.2, along with statistics for the overall sample before selection in the bottom panel. In the estimation sample, the average housing price is JPY 41.4 million (approximately USD 296 thousand, based on an exchange rate of JPY 140/USD 1), and the average monthly housing rent is JPY 95.9 thousand (USD 685). Properties for sale tend to be superior to properties for lease in terms of housing attributes, reflecting the general socioeconomic difference between buyers and renters; housing owners generally have higher incomes than renters (MIC, 2018).

Compared to the overall sample, our estimation sample properties tend to be in tall (21.84 vs. 9.39 floors on average) and old (19.06 vs. 17.88 years on average) buildings. These differences are due to the nature of sample construction for the SDiD analysis. Since the SDiD regression using the building fixed effects requires that the treatment group has at least one transaction for both before and after the in-home death incident in each building, a building with a larger number of properties has a higher probability of being a part of the estimation sample. In addition, a larger and older building is more likely to experience an in-home death and transaction within the study period.

	Property for Sale				Property for Rent			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Sample Used in Estimation								
Property Characteristics								
Property price/rent (1,000 JPY)	41,400	29,200	1,400	270,000	95.93	73.26	20	1,180
# of rooms	2.20	0.89	1	5	1.41	0.67	1	5
Floor area (m2)	62.52	22.49	12.59	188.16	34.04	28.55	7.38	1714.31
# of floors in the building	21.84	16.27	1	55	9.73	10.07	2	55
Floor level	11.71	11.30	1	55	5.32	6.11	1	55
Age of building (year)	19.06	13.63	0	52	24.23	13.36	0	77
Period Information								
Period since death (month)	-5.35	40.7	-103	97	-16.86	38.68	-104	101
# of buildings	315				572			
# of properties	3,681				6,183			
Total REINS Data								
Property price/rent (1,000 JPY)	26,100	18,900	1,000	850,000	82.93	136.59	21	3,050
# of rooms	2.54	0.84	1	9	1.39	0.64	1	7
Floor area (m2)	64.41	20.42	5.16	820.9	33.50	16.36	5	710.13
# of floors in the building	9.39	6.63	1	96	4.59	4.16	1	98
Floor level	5.21	4.59	1	98	2.84	2.60	1	60
Age of building (year)	17.88	11.10	0	92	19.64	12.29	0	93
# of properties	754,792				1,698,390			

Table 2.2: Summary statistics

As mentioned earlier, not all locations of in-home deaths are identified at the property level. Of the 3,681 observations for sale (6,183 observations for rent), 2,560 (4,326) are confirmed not to be properties where an in-home death occurred, while 26 (126) were identified as in-home death properties. The remaining 1,105 for sale (1,731 for lease) are ambiguous as to the location of the in-home death property. Throughout the analyses in this paper, except in subsection 3.3, we employ all the available samples regardless of whether or not a death incident occurred on the property to retain a sufficient sample size. Therefore, the estimated impacts of in-home death demonstrate the mixture of two effects: the direct effect on the in-home death property itself and the spillover effect on other properties in the same buildings. Because the weight of the direct effect is expected to be substantially small, the estimate mostly represents the spillover effect within the building. In subsection 3.3, we attempt to disentangle these two effects by employing two sets of subsamples. As will be demonstrated, the magnitude of point estimates is much greater for the direct effect compared to the spillover effect, while confidence intervals of direct effect tend to be large due to the small sample size.

3. Estimation results

This section presents the primary results on the impact of in-home death on property price and rent within a building. We begin by presenting the estimation and the interpretation of the baseline model's results, followed by introducing alternative estimations that use different samples and model specifications to ensure the robustness of the findings.

3.1. Main results

Figure 3.1 displays the evolution of SDiD estimates for sales (left panel) and rents (right panel) across time elapsed from an in-home death. The 95% confidence intervals are represented by the light blue shadow with clustered standard errors at the building level.[19] Before the occurrence of an in-home death incident, there were no statistically significant differences between treatment and control groups in both sale prices and rents, supporting the validity of the parallel trend assumption. Post-trendlines, however, show distinct patterns for the two panels.

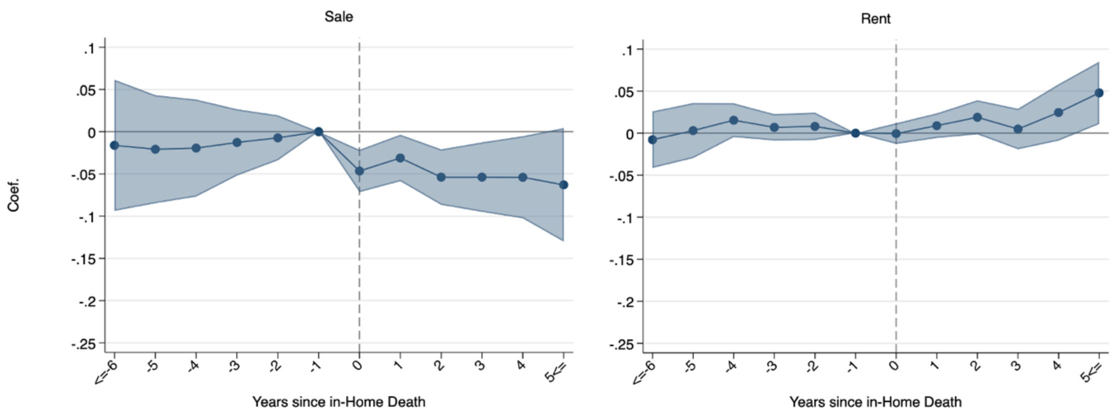

Figure 3.1: Main results
Notes: The left panel shows the result for sales prices, and the right panel shows the result for rents. Blue plots are point estimates of treatment effects, with the horizontal axis representing the years from in-home death incidents to property transactions. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

In the left panel, we observe a significant price decline immediately following an in-home death, with the negative effect persisting for more than five years. The estimated coefficients indicate that an in-home death leads to a reduction of 3.1-5.4% in the prices of other properties within the same building. This reduction is equivalent to JPY 1.28-2.22 million or USD 9,100-15,900 (assuming an exchange rate of JPY 140/USD 1) for a property with the sample average price. While results are not directly comparable across studies due to methodological differences,[20] our estimates closely align with or are slightly lower than, estimates concerning the negative effect of an incident on other property prices within the same building in Hong Kong; 4.2-5.9% in Chang and Li (2018) and 7.1-9.7% in Bhattacharya et al. (2021).

The right panel reveals no discernible effect on rents after an in-home death, followed by a modest upward trend. The result fails to indicate any evidence of a negative spillover effect on rents within the building. A possible explanation for the observed rent increase is that landlords subscribed to a security service or enhanced security systems in their rental apartment buildings after the incident. Landlords may find it difficult to increase rents immediately after the installation of new security systems due to some effects of a death incident. After several years after the incident, when the negative effects fade, landlords can gradually raise rents to reflect the improved facilities in the building.

3.2. Robustness checks

To ensure the robustness of our main results, we perform five additional estimations: (1) using a sample without the top 5% and bottom 5% of prices or rents instead of excluding the top 1% and bottom 1%; (2) using the natural logarithm of per-floor-area price or rent as the dependent variable

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[19] The sample with prices or rents above and below 1% are excluded from the estimation. All the estimated coefficients and standard errors including those of control variables are demonstrated in Appendix D.

[20] Previous studies conduct the difference-in-differences approach and compare properties with a death incident to those in other buildings in the same estate (Chang and Li, 2018) or to those in other estates where no death incident is recorded (Bhattacharya et al., 2021).

instead of the natural logarithm of price or rent; (3) using clustered standard errors at district (*"cho-cho"*)[21] level instead of at building level; (4) controlling for predicted year-by-municipality fixed effects instead of considering year fixed effect alone; and (5) using 2014-2018 death-building cohort as the treatment group and 2019-2020 death-building cohort as the control group, instead of 2013-2019 death building cohort as the treatment group and 2020 death-building cohort as the control group. Regarding (4), the predicted year-by-municipality fixed effects are estimated by employing hedonic regression using all REINS samples, which are then used as an explanatory variable in SDiD estimations. This approach allows us to address multicollinearity while controlling for regional-specific time trends at a finer level.

The outcomes of the SDiD estimates for these alternative scenarios are presented in Appendix E. These results collectively demonstrate that our main findings remain robust and are unaffected by (1) varying levels of sample trimming, (2) changes in the functional form of the dependent variable, (3) the choice of standard errors assumption, (4) the incorporation of municipality-specific time trends, and (5) the adjustment of treatment and control group cohorts, concerning the presence of major external events such as the Great East Japan Earthquake in 2011 and the subsequent COVID-19 epidemic.

3.3. Spillover effects and direct effects

As mentioned earlier, not all locations of in-home deaths are identified at the property level. Approximately 30% of sale properties and 27% of lease properties are ambiguous as to the location of the in-home death property. In this subsection, we employ subsamples to disentangle the spillover effect (the impact of an incident on another property) and the direct effect (the impact on the in-home death property itself). We construct subsamples as follows. For property transactions that took place after the incident in the building, the subsample is limited to properties on different floors than the floor on which the incident occurred for the spillover-effect examination, while the other subsample is limited to properties identified as in-home death properties for the direct-effect examination. For transactions that took place before the incident, because none of them is influenced by the incident that follows, the entire sample of buildings in which transactions of in-home death properties after the incident are observed is used to retain a sufficient sample size.

Figure 3.2 demonstrates the estimation results on the spillover effect for sales (left panel) and for rents (right panel). The results are almost identical to the main results in Figure 3.1. Importantly, the results suggest that the negative impact of a death incident on the price extends beyond floors, exhibiting a significant negative spillover effect.

[21] *Cho-cho* is a unit of administrative division in Japan, used for population statistics such as the national census. Each municipality is composed of 50~100 *cho-cho* districts. The estimation sample encompasses 83 municipalities for sale analysis and 110 municipalities for rent analysis.

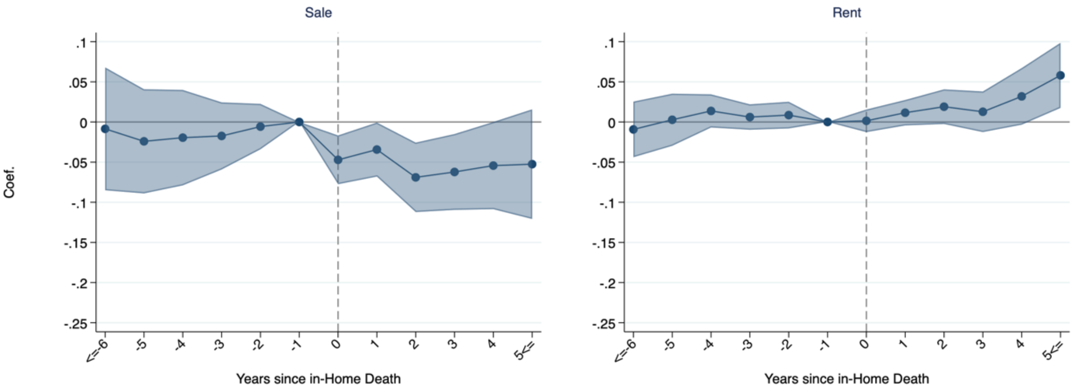

Figure 3.2: Spillover effect beyond floors
Notes: The left panel shows the result for sales prices, and the right panel shows the result for rents. Blue plots are point estimates of treatment effects, with the horizontal axis representing the years from in-home death incidents to property transactions. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level. The post-incident sample is restricted to properties on a different floor than the floor on which an in-home death incident occurred, while the pre-incident sample includes entire properties in buildings where the post-incident sample exists.

Figure 3.3 shows the results of the direct effect. Because of the small number of individuals in the transactions for in-home death properties, we estimate an average treatment effect over post-treatment years. The magnitude of the negative impact on the in-home death property itself is approximately 10%, which is twice the impact on another property in the same building. However, the estimate is not statistically significant at the 10% level due to the small sample size. Interestingly, the negative impact on rents turns out to be statistically significant at approximately 7% in magnitude. The presence of the negative direct impact, despite the absence of the negative spillover effect, on rents may be attributable to the difference in the magnitude of stigma and obligation of disclosure between in-home death properties and others.

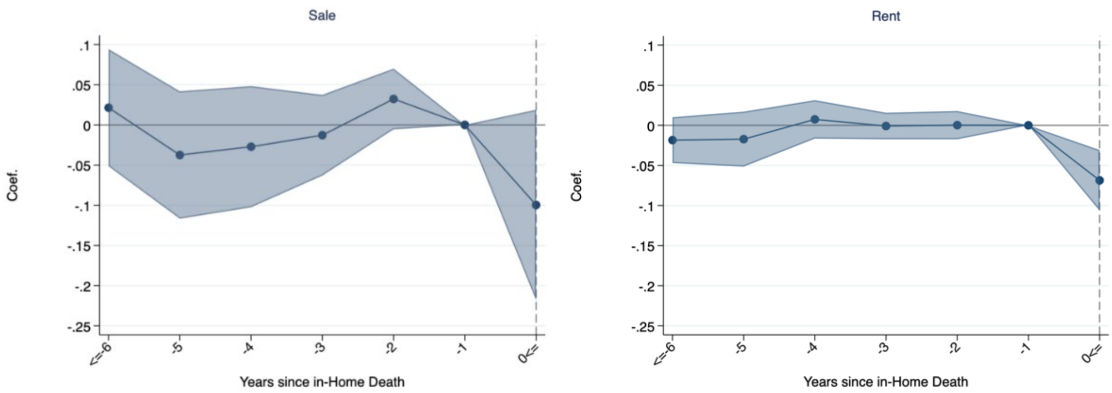

Figure 3.3: Direct effect on in-home death property
Figure Notes: The left panel shows the result for sales prices, and the right panel shows the result for rents. Blue plots are point estimates of treatment effects, with the horizontal axis representing the years from in-home death incidents to property transactions. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level. The post-incident sample is restricted to properties in which an in-home death incident occurred, while the pre-incident sample includes entire properties in buildings where the post-incident sample exists.

3.4. *Policy implication on disclosure rules*

Now we briefly relate what we found so far in the baseline analysis with a policy implication. Japan's property transaction law requires property dealers to inform potential buyers/renters of any matter that could influence their decisions. However, the law does not specify particular situations where dealers must disclose in-home deaths. Given the ambiguity of the law, dealers would notify their counterparties only if a death incident occurred on the property being transacted, but not if it took place on a different property. The recently published guidelines for in-home death disclosure (MLIT, 2021) also suggest that dealers should follow this practice. Our results show that the stigma around death incidents extends not only within the properties where death incidents occurred but also to other properties in the same building, suggesting that complying with the current law requires disclosing death incidents in the same building regardless of where in the building they occurred.

4. Mechanisms of differential spillover effects on price and rent

The analysis in the preceding section confirmed that in-home deaths negatively impact property prices but not nearby rents. In this section, we explore three potential channels that could explain these different results: (1) the difference in awareness of incidents between buyers and renters, (2) the difference in preferences between buyers and renters, and (3) the rigidity of rents.

4.1. *Difference in awareness*

The first potential explanation is that buyers are more aware of in-home deaths in the building they move into compared to renters. According to the disclosure guidelines issued by the government, dealers must notify counter-partners about past death incidents only if they occurred in the transactional property, with no obligation to disclose if an incident occurred in different properties. Therefore, buyers and renters could only know about an incident that occurred on a different property within the same building through self-initiated exploration, such as searching the *Oshimaland* website or inquiring with dealers.

The empirical finding reported in the previous section reveals that an in-home death incident results in a price reduction for the in-home death property and other properties within the same building. This finding indicates that potential buyers are aware of past death incidents in the building they are moving into, regardless of the disclosure rule. In contrast, the rent is negatively associated with a death incident only for the in-home death property, not for other properties in the building. These results strongly suggest that renters move in without being aware of the death incidents in the building unless they are informed about the incident by dealers under legal obligation. Buyers, who typically dedicate more time to their housing search compared to renters (AlbaLink, 2016b; Suumo, 2016; NAHB, 2023), are more likely to have explored the *Oshimaland* website, resulting in more buyers being aware of the incidents than renters. This information disparity could partly account for the more pronounced negative impact on price compared to the impact on rent.

4.2. *Difference in preference*

The second possibility is that the psychological impact, or the degree of stigma, of in-home death is more substantial for buyers than renters. The magnitude of the point estimate regarding the direct negative impact of in-home death on the price of the property itself is slightly larger than that on the price of rent (Figure 3.3). However, two issues arise before concluding that the degree of stigma is greater for buyers than renters. First, the confidence intervals for the results in Figure 3.3 are too large to confirm the difference. Second, the estimates are regarding a small group of buyers and renters who purchased and rented in-home death properties, which does not necessarily indicate the psychological impacts of representative buyers and renters.

Given these concerns, we employ a subsample analysis to explore the potential difference in psychological impacts between buyers and renters. We hypothesized that higher-income households, prevalent among buyers, have a higher willingness to pay to avoid living near properties with death incidents due to their lower tolerance for such events. If this is true, we anticipate that a more substantial impact on prices would be observed for properties purchased by higher-income households.[22] Unfortunately, we cannot directly test this hypothesis because information on individual income is not available in our data. Instead, we divide samples by median price (or rent) and compare SDiD estimates between higher-priced and lower-priced properties, assuming that households' income and housing values are positively correlated. Contrary to our expectation, the result in the left panel of Figure 4.1 indicates that the impact on price is more pronounced for low-priced properties.[23] Based on these results, in-home death is less likely to have a greater psychological impact on buyers than on renters.

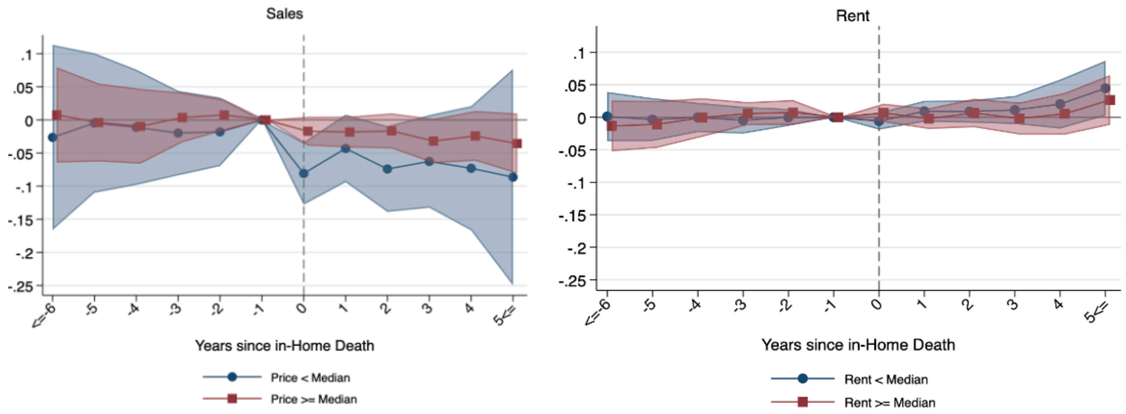

Figure 4.1: High-priced and low-priced properties
Notes: Blue plots are point estimates of treatment effects for the low-priced subsample (lower than the median), and red plots are those for the high-priced subsample (higher than the median), with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level. The left panel shows the result for sales prices, and the right panel shows the result for rents.

4.3. Rent rigidity

The third possibility is that landlords are resistant to reducing rents. This hypothesis is rooted in two underlying factors. First, Japan's property transaction law stipulates that existing tenants can request rent reductions if their rents are higher than the rents of comparable properties in the neighboring.[24] Consequently, landlords of rental apartment buildings may be reluctant to lease vacant units at a lower rate because existing renters could request a reduction in their rents. However, this does not apply to individual condominium owners who own a single property and do not care about what other renters request from the property owners. Therefore, condominium rents can be more susceptible to the impact of death incidents compared to rents in rental apartment buildings. To examine this possibility, we narrow the sample to transactions in buildings where both rent and sale transactions are observed, ensuring that the selected buildings are indeed condominiums. Then, we use this sample to estimate the impact on condominium rents. The results in Figure 4.2 show a negligible impact on condominium rents, implying that the rent rigidity is not due to landlords being apprehensive about existing renters requesting rent reductions.

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[22] Another possible reason that higher-income households can be more sensitive to a death incident in their housing decisions is that they have more flexibility in housing choices compared to lower-income households, who are more likely to face financial constraints.
[23] An online survey conducted by AlbaLink (2021a) in Japan reports that higher-income respondents demonstrate a higher willingness to move to a property where a death incident occurred, which aligns with our findings. AlbaLink (2021a) points out a possibility that their questionnaire result may be because richer people tend to be more realistic and rational.
[24] Article 32 of the Building Lots and Buildings Transaction Business Act.

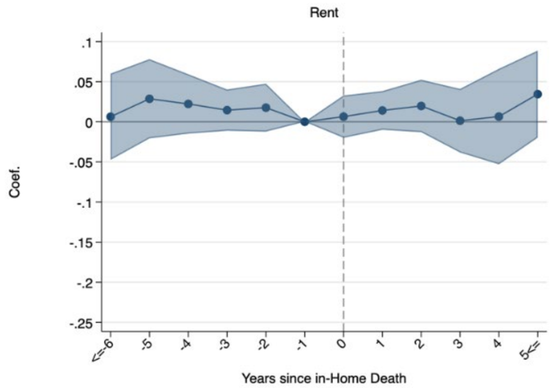

Figure 4.2: Condominium rents
Notes: Blue plots are point estimates of treatment effects for rents. Samples are limited to transactions in condominium buildings. The light-colored area is the corresponding 95% confidence interval based on clustered standard errors at the building level.

The second factor relates to landlords facing difficulties in raising rents for their rental properties due to the standard lease contract prevalent in Japan, which offers tenants substantial protection.[25] In contrast to the fixed-term lease contract more common in Western countries, the standard lease contract allows renters to remain in the apartment as long as they abide by the law. Landlords feel reluctant to reduce rents for vacant properties following an incident because this could lead to missing out on an opportunity to raise rents when the stigma fades. To address this situation, landlords might consider reducing move-in fees for new renters, thereby making the prospect of renting more attractive. This approach could involve lowering the deposit, brokerage fee, "reikin" (non-refundable payment or "key money"), or even offering a short-term period of free rent.

To examine the effect of in-home death on move-in fees, we regress the number of months of rent equivalent to move-in fees (i.e., the sum of the deposit, brokerage fee, and "reikin" divided by the monthly rent) on indicators regarding the relative treated years (i.e., the number of years between the incident and the transaction). Building fixed effects are also included to control for building-specific factors. The outcome depicted in Figure 4.3 shows a decreasing trend of move-in fees within the building over time, while this trend is not attributed to the occurrence of in-home deaths. Therefore, landlords are unlikely to reduce move-in fees in response to such incidents as a means to attract new renters.

[25] Article 28, Act on Land and Building Leases.

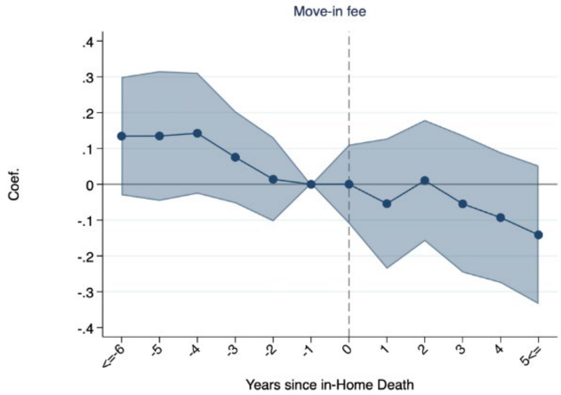

Figure 4.3: Move-in fees
Notes: Blue plots are point estimates of treatment effects, with the horizontal axis representing the years from in-home death incidents to property transactions. The light-colored area is the 95% confidence interval based on clustered standard errors at the building level.

4.4. Discussion

In the previous subsections, we explored potential mechanisms contributing to the different results on price and rent. In subsection 4.1, we postulated that buyers are more likely to be aware of incidents in the building they move into compared to renters when signing their contracts. The minimal impact on the rent can be partly (or fully) explained by the possibility that renters who are not aware of in-home death in the building move into the building. Rent is only negatively impacted by an in-home death that occurred on the property because the renter is informed about the incident by the dealer before finalizing their rental agreement. In subsection 4.2, we attempted to discern differences in psychological impacts between buyers and renters by segmenting properties for sale based on typical demographic differences between buyers and renters and observing whether distinct effects on price exist. However, our data did not provide evidence to support the hypothesis that different outcomes were driven by varying preferences between buyers and renters. In subsection 4.3, we assessed whether landlords avoid reducing rents due to the potential risk of existing tenants requesting rent reductions. This assumption was refuted by examining condominium rents. In addition, we explored whether landlords opt to reduce move-in fees to attract new tenants without lowering rents. However, our findings did not substantiate this possibility. In sum, the most likely channel that led to the differential results on prices and rents is the difference in awareness level between buyers and renters.

To offer further insights, Figure 4.4 demonstrates SDiD estimates concerning transaction frequencies for sales and rentals within buildings. The building is the unit of observation for this analysis. To avoid the influence of a high frequency of transactions in newly built apartments, samples are limited to buildings with ages over 10 years. The dependent variable is the number of transactions normalized by the average annual transaction count before the incident occurred. The estimation employs building and time-fixed effects, along with indicators regarding the relative treated years. The result depicted on the right panel displays an immediate surge in rental transactions within the building following a death incident. In contrast, the increase in transactions for sales following an incident is less pronounced, as shown in the left panel. While a comprehensive understanding of the effect of in-home deaths on residents' movements requires additional information, such as vacancy and listing data, this finding suggests a significant possibility that the surge in rental apartment vacancies stems from existing renters moving out due to the incident, with these vacancies being swiftly replaced by new renters. Given the absence of a negative spillover effect on rents, the sudden increase in transaction frequency following a death incident within the building implies that new renters likely moved in without being aware of the incident that occurred in the building.

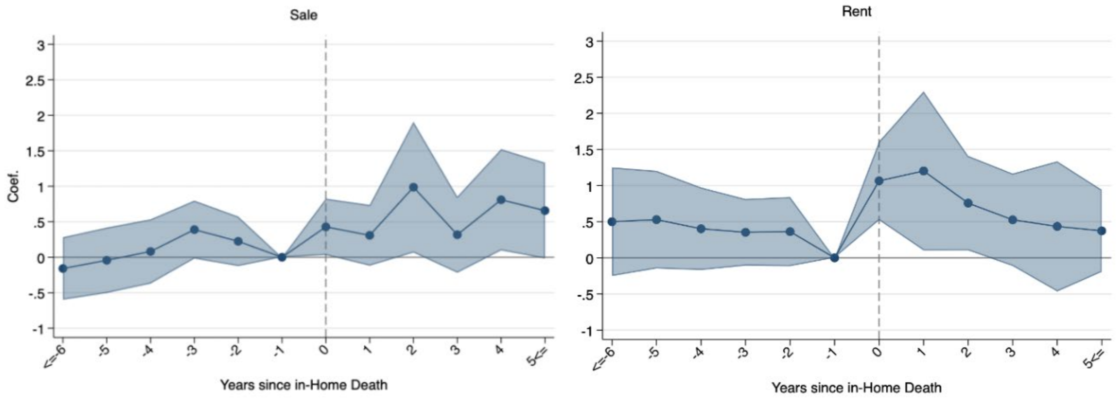

Figure 4.4: Transaction frequencies
Notes: The left panel shows the result for sales prices, and the right panel shows the result for rents. Blue plots are point estimates of treatment effects, with the horizontal axis representing the years from in-home death incidents to property transactions. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

5. Heterogeneity in the Negative Effects of In-home Death: Sale Transactions

In this section, we focus on sale transactions to investigate the heterogeneity of the impact of in-home death from various viewpoints, including trading seasons, property characteristics, regional characteristics, and incident characteristics. Based on the results, we investigate some possible mechanisms of the negative effects of in-home death incidents.

5.1. Trading season

Graevenitz (2018) argues that the impact of disamenities, such as noise, on property prices can be mitigated in a booming market. Building upon this insight, we shift our focus toward understanding how the impact of in-home deaths varies contingent upon circumstances, both on the demand and supply sides.

To begin, we investigate the heterogeneous effect from the viewpoint of a seasonal demand change for sold properties. In Japan, as the business and academic years start in April, housing contract volumes skyrocket in February and March. Alternatively, the number of potential buyers is the largest during these months, implying that, in a peak season, less attractive properties, such as those in buildings where death incidents occurred, have a higher possibility than usual to be matched up with a buyer who is not aware of the death incident in the building or has a higher willingness to pay than other people to live in such a building, thus enabling sellers to sell the property without a discount on the price.

Figure 5.1 displays a comparison between coefficients of the sale prices in the peak seasons (From February to March) and off-seasons (From April to January). During the off-season, we observe a persistent and significant negative impact (red points and ribbons). In contrast, we do not observe such negative effects in the peak seasons (blue points and ribbons). This finding suggests that the negative impact found in the baseline analysis is mainly driven by the contracts made in the off-season. Sellers are more likely to find a buyer with a high willingness to pay to live in the condominium building in which a death incident occurred during the peak seasons than during the off-seasons. Buyers who are in a hurry to purchase a property during the peak seasons are also less likely to explore the *Oshimaland.com* website before entering the contract.

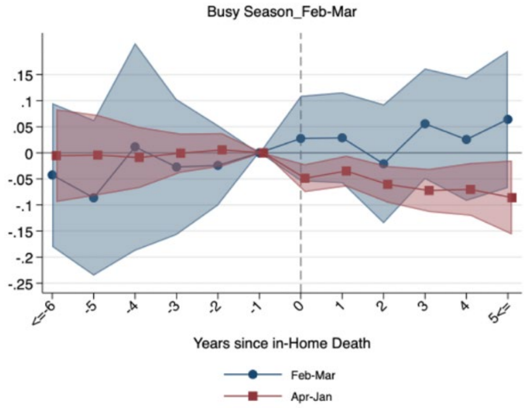

Figure 5.1: Peak season and off-season

Notes: Blue plots are point estimates of treatment effects for the high-season subsample (February and March), and red plots are those for the low-season subsample, with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

5.2. Property characteristics: Number of rooms, Number of floors, and age of building

Tokyo, experiencing a notable concentration of population and economic activity, has witnessed the construction of numerous high-rise and luxury buildings, often referred to as "tower mansions." These buildings typically feature more than 18 to 20 floors and consist primarily of single rooms. Nonetheless, these buildings are highly sought-after places to reside and represent attractive investment opportunities due to their prestige, convenience, and prime locations. In this subsection, we delve into how in-home death impacts such property characteristics, with a specific focus on buildings considered popular, such as single-room properties, properties in tower mansions, and newer properties.

First, we investigate the heterogeneity of impacts in terms of the number of rooms in a property. We hypothesize that the effect of in-home death may be less pronounced for a single-room property than a multiple-room property because the former is often purchased for investment purposes. When property transactions are conducted not solely for residential purposes but also investment purposes, the negative effect of the in-home death on property prices may be further attenuated because the buyers with investment intent may not necessarily intend to reside in the building.

Figure 5.2 presents the coefficient plot and corresponding confidence intervals for single-room properties and for multi-room properties. The impact of in-home death is not statistically significant on the price of single-room properties, whereas it exhibits a negative and significant effect on the price of multi-room properties.

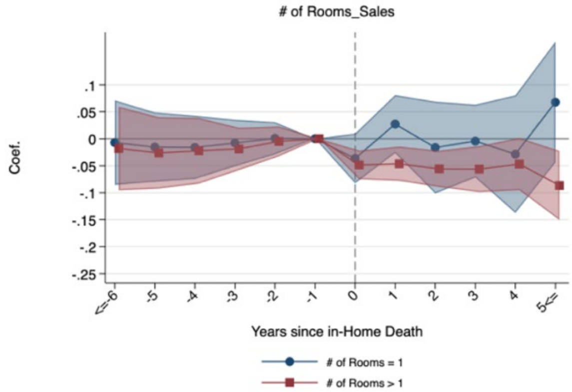

Figure 5.2: Single-room property and multiple-room property
Notes: Blue plots are point estimates of treatment effects for the single-room property subsample, and red plots are those for the multiple-room property subsample, with the horizontal axis representing the years from the in-home death incident to the property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

This outcome aligns with Graevenitz (2018) and supports our hypothesis that the price of single-room properties is less impacted by in-home death than the price of multi-room properties because single-room properties are more likely to be purchased for investment purposes. As shown in the estimation results for rents in condominium buildings (Figure 4.2), owners of single-room properties can lease their properties to renters without reducing the rent following an in-house death. Therefore, the value of a single-room property, calculated as the present value of discounted rental prices, remains the same, as does the willingness to pay by owners for investment purposes. The multi-room properties, in contrast, work differently because their share in the rental housing market is much smaller compared to the sales market, such that the chance for the owners of multi-room properties to find a tenant is small.

To further scrutinize the characteristics of these markets, we conducted an additional sub-sample analysis where buildings with a total number of floors greater than or equal to 18 are defined as tower mansions. Figure 5.3 illustrates the coefficient plot and corresponding confidence intervals for properties in tower mansions and properties in buildings with fewer than 18 floors. The results indicate that the negative impact of in-home death for properties in high-rise buildings is not as pronounced as that for properties in low-rise buildings.

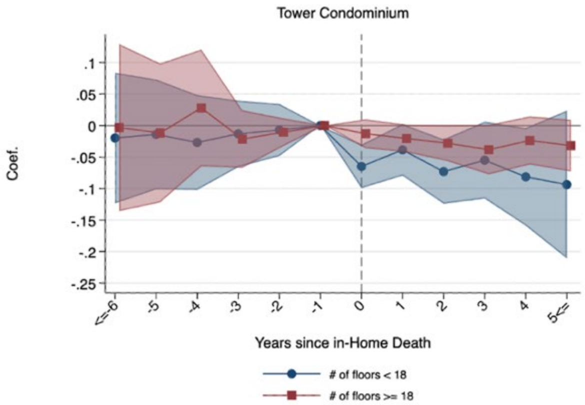

Figure 5.3: Tower condominium (18 or more floors) and not tower condominium
Notes: Blue plots are point estimates of treatment effects for not tower condominium subsample with less than 18 floors, and red plots are those for the tower condominium subsample, with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

Towards the conclusion of this subsection, we present an investigation of whether the building age bears relevance to the magnitude of the impact of in-home death on prices. Figure 5.4 presents the coefficient plots and corresponding confidence intervals for properties in buildings above the median age in the occurrence of in-home deaths and below the median age. The result suggests that the negative impact is more pronounced for older buildings. Anticipating how awareness and preference differ between potential buyers of old and new condominiums is difficult. If we assume that the level of awareness and magnitude of psychological impact is the same across buyers, then a remaining plausible explanation for this differential result is attributed to the supply side. Owners living in the older condominiums have lived there longer and changed lifestyles more substantially since they first moved in compared to owners in newer condominiums. This mismatch between the current lifestyle and property layout lowers their reservation price and increases their probability of moving out, resulting in a larger reduction in transaction prices in older condominium buildings following an in-house death incident.[26]

[26] We lack information about whether the properties were renovated because the renovation variable in the REINS data is blank for most of the records. If we could consider the renovation, the magnitude of the estimated negative impact for properties in older buildings would be larger, given that properties in older buildings are more likely to be renovated.

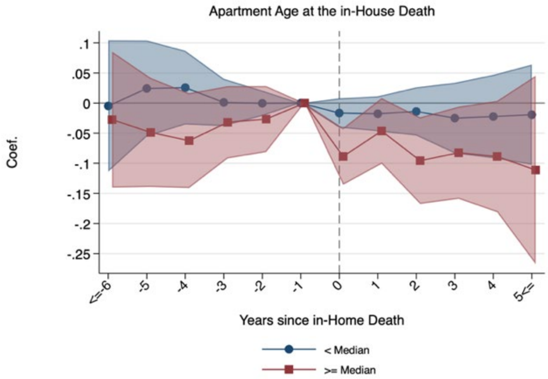

Figure 5.4: Apartment age in the occurrence of in-home deaths
Notes: Blue plots are point estimates of treatment effects for the younger-property-age subsample (lower than the median), and red plots are those for the older-property-age subsample (higher than the median), with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

5.3. Regional characteristics: Vacancy rate and crime rate

This subsection explores the heterogeneous impacts of in-home deaths, shedding light on regional (neighborhood) characteristics of properties. Particularly, we focus on regional variations of vacancy rates, crime rates, and murder rates.[27]

The first heterogeneity analysis in terms of the vacancy rate is intended to investigate how the excess housing supply contributes to the magnitude of price decline following an in-house death incident. Based on a vacancy house rate at the municipality level from the Housing and Land Survey of Japan (MIC, 2018),[28] we split the whole sample into two subsample regions, one with a higher neighborhood vacancy rate above its median and the other with a lower vacancy rate below the median. Our conjecture in this exercise is that the negative impact on price is more severe in a higher vacancy rate area because sellers have to lower offering prices more to find a transaction partner in areas where potential buyers have abundant alternatives.

Figure 5.5 exhibits the coefficient plots and corresponding confidence intervals for properties in the high- and low-vacancy areas. As expected, high-vacancy areas experience a significant reduction in prices immediately after the occurrence of an in-house death within the building. The magnitude of this negative effect persists for more than five years, while the impact becomes statistically insignificant after three years as the confidence intervals widen over the years. Turning to the evolution of the effects in low-vacancy areas, the negative effect is not significant for the first two years, while the effect amplifies and becomes statistically significant after three years from the incident.

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[27] For more discussions on regional heterogeneity, see Appendix F, in which we focus on socioeconomic regional variations.

[28] Housing and Land Survey of Japan is a statistic available only at the municipality level, issued once every five years. The vacancy rate used to split the sample into high and low vacancy rates in the neighborhood comes from an entry in 2018 (MIC: 2018). We chose the year 2018 as our reference year because it lies in the middle of our study period (2012-2020).

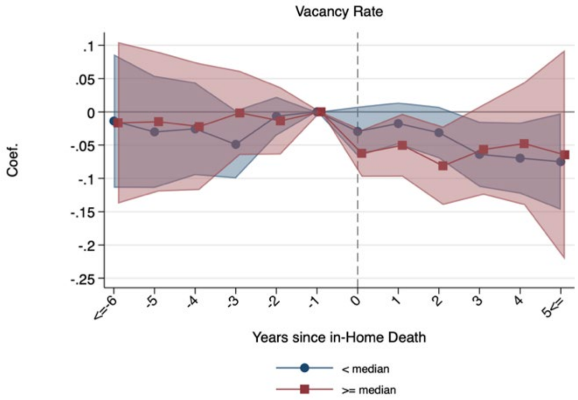


Figure 5.5: High and Low Vacancy Rates in the Neighborhoods

Notes: Blue plots are point estimates of treatment effects for the low-vacancy subsample (lower than the median), and red plots are those for the high-vacancy subsample (higher than the median), with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

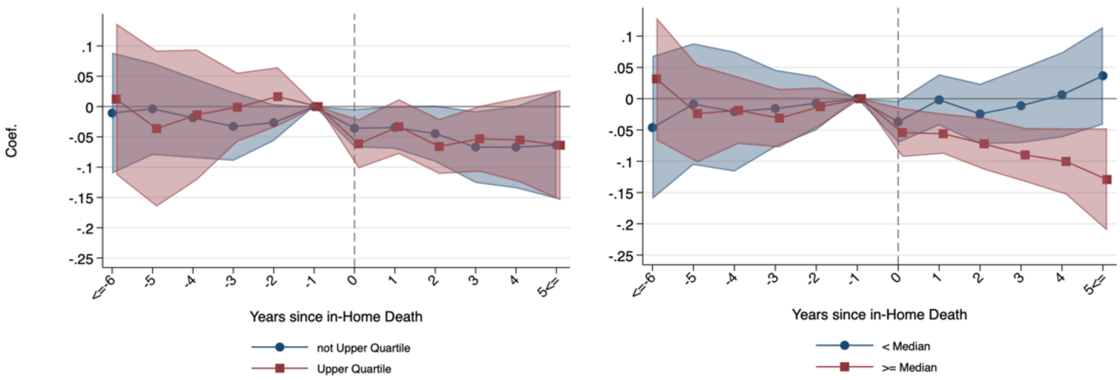
We attribute this interesting evolution of effect in low vacancy areas to the time lag that requires existing residents to move out from the current building after the occurrence of the incident. Recall that our findings on the transaction frequency (Figure 4.4 in subsection 4.4) imply that the replacement of tenants in the rental market takes place immediately after the incident, whereas transactions for sales peak two years after the incident. This finding suggests that owners take more time to find a new place and move out compared to renters. Since areas with low vacancy rates are seller's markets, buyers are forced to buy properties in such areas for somewhat higher prices. A few years after the incident, the transaction price gradually decreased as incumbent residents in the building found new properties and sold their current ones.

Next, we categorize areas by crime rates. This analysis intends to examine whether the impact of in-home death incidents on price differs by the crime rate in the neighborhood. Higher crime rates in a neighborhood could either attenuate or amplify the impact on prices. High crime rates attenuate the negative effect of in-home deaths due to the decreasing marginal effect of an incident. In other words, residents in such areas may be more accustomed to incidents, and potential buyers in the area also anticipate some sort of incident there. Then, the marginal impact of the additional incident is not as significant as the impact in areas with few crimes. However, the impact on the price can be larger in the high crime-rate areas if the potential buyers in those areas are better informed about incidents by searching the *Oshimaland.com* website intensively. Moreover, areas with lower housing demand tend to be buyer's markets and become susceptible to the occurrence of an additional incident, as observed in municipalities with high vacancy rates.

To examine this matter, we use different datasets to construct two crime rate variables. One of the two datasets is the Crimes-in-Tokyo statistics, published by the Tokyo Metropolitan Police Department in 2015. The statistics are available at the district (*cho-cho*) level, while the coverage is limited to Tokyo prefecture with 5,150 districts. Crimes are classified into serious violent crimes (robbery, etc.), violent crimes (assault, intimidation, etc.), burglary theft, non-burglar theft, and other (fraud, etc.). In 2015, an average of 25.7 crimes per year were recorded in districts of Tokyo, with the most common crime category being non-burglary theft (19.8 crimes per year on average). The Crimes-in-Tokyo statistics mainly allow us to see the geographic distribution of petty crimes. We use the index to consider regional characteristics related to public safety within Tokyo. The crime rate is calculated by dividing the count of crimes by the number of households in each district. Unfortunately, the statistics do not include district-level information of particular interest to us, such as the number of murders, the number of in-home incidents versus incidents in public places, and number of fatal versus non-fatal incidents.

The other dataset employed is the in-home death data from *Oshimaland.com*. Yajima and Sadayuki (2023) compare incident counts from the in-home death data based on government statistics and reveal that almost all existing in-home murder incidents are recorded on the website. By assuming that properties of murder sites recorded on *Oshimaland.com* represent the geographic distribution of in-home murder incidents, we construct a municipality-level in-home murder rate by dividing the count of average annual in-home murders by the number of households in each municipality. The murder rates are calculated for municipalities in all four prefectures.

Figure 5.6 shows the coefficient plots and corresponding confidence intervals for properties in the high-crime rate area and low-crime rate area. The result in the left panel (a), employing the Tokyo crime rate, demonstrates a similar evolution of coefficients and statistical significances between subsamples.[29] However, the right panel (b), using the in-home murder rate, exhibits a clear difference in the trend of coefficient plots between subsamples. In particular, the coefficients from the sample with a high murder rate have a strong decreasing trend, and these magnitudes are relatively large compared with other subsample analyses in the previous subsection.



(a) Tokyo-Crime Rate (b) Murder Rate

Figure 5.6: Tokyo-crime rate and murder rate
Notes: Blue plots are point estimates of treatment effects for the (a) low-crime rate (bottom 75%) and (b) low-murder rate (lower than the median) subsample, and red plots are those for the (a) high-crime rate (top 25%) and (b) high-murder rate (higher than the median) subsample, with the horizontal axis representing the years from the in-home death incident to the property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

The result of the murder-rate analysis suggests that the persistent negative impact on sales prices is mainly driven by properties transacted in high murder-rate areas. The result that high-murder areas experience more severe negative effects supports two hypotheses. First, potential buyers looking for properties in high-murder rate areas are more informed about the incidents recorded on the

[29] As Tokyo is a city with a relatively low crime rate, we split the sample at the cutoff of the quantile. The implications of the results remain the same when the sample is divided at the cutoff of the median.

Oshimaland website. Second, high-murder rate areas tend to be buyer's markets due to lower demand, and the price is susceptible to additional negative influences.[30,31]

5.5. Incident characteristics: Incident types, occurrence seasons, and proximity

The effect on property prices may differ depending on the features of the incident. This section delves into heterogeneous impacts concerning the incident characteristics.

First, we scrutinize the negative effects on sale prices by death types. Figure 5.7 shows coefficient plots and corresponding confidence intervals for suicide, murder, and other types of death.[32] The negative effect is more severe in cases of murder than suicide and other types of death. Deaths other than suicide and murder exhibit a statistically significant negative impact only immediately after the incident. These diverse effects can be attributed to differences in the awareness and stigma that people possess toward each type of incident. Murder incidents are often broadcasted by media and known among the public, even those who do not look at the *Oshimaland.com* website. Moreover, the occurrence of murder directly evokes images of crimes, creating a less safe atmosphere and altering the risk perception for residing in the building.

[30] The recent study by Tang and Lee (2023), which examines the impact of move-in of ex-gun offenders on nearby property prices, shows a contradictory result: The negative impact is larger in lower-crime rate areas. This is attributed to the distinct feature between our study and Tang and Lee (2023): the occurrence of in-home death does not mean as much a deterioration of public safety in the neighborhood as move-in of gun offenders. In other words, the move-in of a gun offender alters people's perception of public safety more substantially in the neighborhood with fewer crimes, while people's perception of public safety may change minimally following the occurrence of in-home death because it does not threaten the safety of the living environment in the neighborhood. Another possibility is that the move-in of a gun offender is more publicly acknowledgeable in lower-crime rate areas.

[31] Another important finding from this analysis is that the negative effect in high-murder rate areas is increasing over time. This finding relates to the literature examining the long-run persistence of income inequality across regions due to specific factors that are sought to have direct effects for much shorter term (Ambrus et al., 2020; Bleakley and Lin, 2012; Dell, 2010; Hanlon, 2017). For instance, Ambrus et al. (2020) examine the long-run impact of the Cholera epidemic on housing prices in a neighborhood of nineteenth-century London. They find that prices inside the catchment area fell 15 percent within ten years of the epidemic relative to prices outside the catchment area, and that the price differential doubled 160 years after. They highlight the potential for negative shocks to alter tenant composition over time, which can result in the persistent and amplifying negative effects on neighborhoods. In our context, the result suggests that the historical records of in-home murders posted on websites may contribute to tenant sorting and persistent deterioration of the neighborhood environment.

[32] Of the 3,681 properties for sale (6,183 properties for rent), 369 (804) experienced "murder," 1,207 (1,269) experienced "suicide," and 2,105 (4,114) experienced incidents involving "other" causes. Table C in Appendix C shows the type of death shares in the sale and rental samples. Both in the case of sales and rental properties, "other" death has the largest share (57% in sales, and 67% in rental), and "suicide" is second (33% in sales, and 21% in rental).

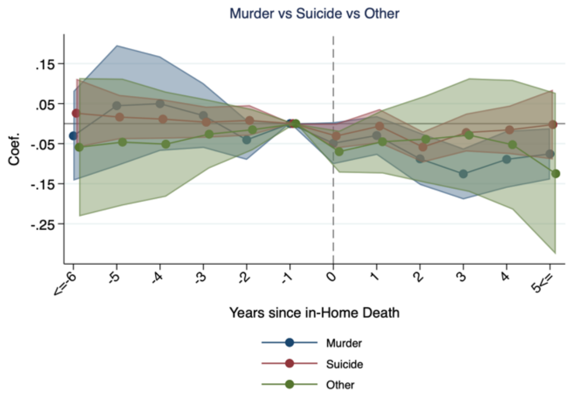


Figure 5.7: By Death Causes
Notes: The blue points are the estimated coefficients on the variable in-home deaths for the subsample of murders, the red points are for suicides, and the green points are for other types of deaths. The ribbons are the corresponding 95% confidence intervals based on the standard errors clustered at the building level.

Next, we investigate the heterogeneous impact by incident according to whether the incident occurred in the summer or not. Because corpses become rotten and emit a foul odor in high temperatures, death events in summer may induce more negative externalities. Figure 5.8 shows the results based on subsamples, one of which is properties in buildings that experienced in-home death incidents from June to September and the other experienced incidents in other seasons. We find a striking difference between the two coefficient evolutions. Although both show negative coefficient estimates, those in summer are larger in their magnitude and more significant. This result indicates that the heavier disamenity of an in-home death can translate into a larger decline in property sale prices.

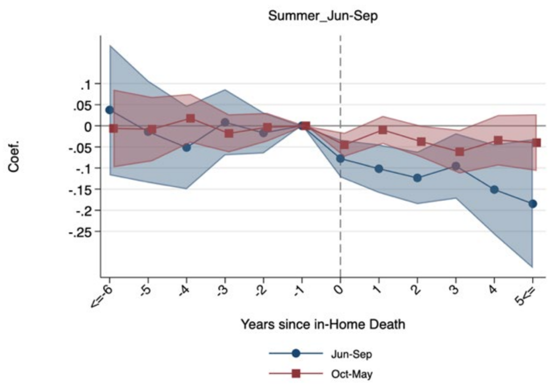


Figure 5.8: Death events that occurred in the summer
Notes: Blue plots are point estimates of treatment effects for the summer death subsample (June–September), and red plots are those for the non-summer death subsample, with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

Lastly, we investigate whether there are larger spillover effects on properties closer to the incident property within the same building by employing the differences in floor levels between in-home death and transacted properties. The sample is divided into a subsample of properties whose floor difference is less than or equal to three (closer properties from the incident property) and another subsample of properties whose floor difference is larger than three (farther properties from the incident property). Observations on the same floor as the incident floor are excluded from the sample.

The results in Figure 5.9 show that the magnitude of the negative coefficients does not diverge between the two subsamples, indicating that there is no systematic tendency for larger negative spillover to closer floors. Contrary to our expectation that closeness to the incident property matters, the result suggests that the magnitude of the negative spillover effect does not depend on closeness to the location of the death incident within the building.[33] Because the *Oshimaland.com* website uses a display format in which flame symbols representing in-home death properties are pinned down on the building (Figure 2.1), potential buyers who see the flame symbols on the website may not pay so much attention to the location of the incident within the building but rather may avoid the building itself.

Finally, although the government guidelines state that property dealers are not required to inform their counterparties about death incidents that occurred in properties other than the ones being transacted, our results suggest that complying with Japan's current property transaction law requires disclosing death incidents within the same building, particularly those recorded in *Oshimaland.com*, regardless of the proximity between the in-home death property and the property being transacted.

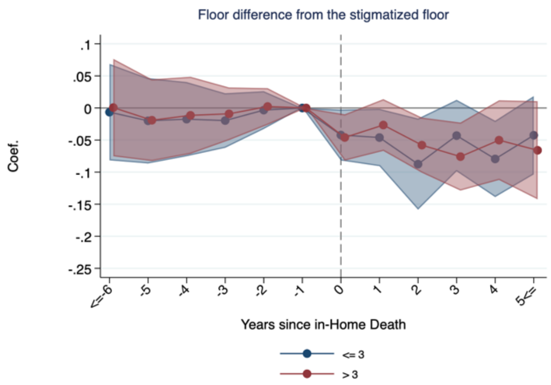


Figure 5.9: Floor Diff. from the Incident Floor
Notes: Blue plots are point estimates of treatment effects for the closer-to-incident subsample (whose floor difference from the incident floor is up to three), and red plots are those for the farther-from-incident subsample (whose floor difference from the incident floor is greater than three), with the horizontal axis representing the years from in-home death incident to property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

6. Conclusion

Utilizing extended datasets on in-home deaths and property transactions, we estimated the impact of a death incident in a property on the prices and rents of properties within the building. We employ the staggered difference-in-differences analysis introduced by Sun and Abraham (2021) to address potential biases stemming from variations in treatment timings and heterogeneous effects across properties. Our estimation confirmed, under various robustness checks, that in-home deaths are associated with a significant reduction in sale prices for properties within the same building. Contrary to the observed impact on prices, our estimation did not reveal the negative impact of a death incident on the rents of other properties within the same building. However, this does not necessarily mean that renters are completely indifferent to such incidents because the estimated impact is a combination of psychological impact and awareness level. In fact, in-home deaths had a significant negative impact on the rent of the property where the incident occurred.

[33] We repeatedly conducted the same exercises with floor difference from 2 to 12, confirming that the results of the constant impact across floor differences were robust. As for the exercises with floor differences of 1 and more than 12, the results are not stable due to an insufficient number of observations in these subsamples, while the implications remain the same.

To better understand the underlying mechanism, we discussed potential explanations for the differential outcomes between sales and rents and performed several analyses. One notable observation is the significant increase in rental transactions immediately following an incident within a building. This phenomenon, coupled with the absence of a negative spillover effect on rent, strongly suggests that renters move into buildings in which a death incident occurred without being aware of the incident before signing their lease contracts. This discrepancy in awareness level between buyers and renters likely contributes to the differential impact on prices and rents.

The Japanese government issued guidelines in 2021 outlining dealers' disclosure requirements regarding in-home death disclosure in response to issues associated with ambiguity in the property transaction law and concerns regarding the increasing occurrence of in-home deaths. The guidelines stipulate no requirement of disclosure for deaths occurring in properties other than the one being transacted. Given that the law mandates disclosure of any information affecting people's decisions, the government's rationale is based on the assumption that people do not consider death incidents in different properties to be a significant influencing factor in their housing decisions. However, this assumption is false according to our findings. Therefore, abiding by the current law in Japan requires property dealers to inform transaction partners about previous death incidents that occurred in the same building, even when these deaths did not take place in the specific property under consideration.

Furthermore, we explored additional sources of heterogeneity within sales transactions to gain deeper insights into the underlying mechanisms of the impact of in-home death. Our findings indicate that the negative impact is more pronounced under particular circumstances. For instance, the impact is more severe when a transaction takes place during the off-season in the real estate market (capturing the effect of low housing demand), when an incident occurs in an area characterized by a higher vacancy rate (capturing the effect of housing oversupply), in an area with a higher murder rate (capturing the residents' awareness of crimes), during the summer season (capturing the seriousness of the death incidents), or in an older building (capturing the attractiveness of the properties). These findings collectively suggest that the impact is amplified in housing markets characterized by lower demand or specific adverse conditions.

Lastly, we acknowledge certain limitations in this research and propose potential avenues for future investigation. This study primarily focuses on relatively large condominium and rental apartment buildings, which are essential for employing the SDiD method due to data constraints. In some extreme cases, the negative impact of a death incident in a particular building might be so significant that no one buys or rents properties in the building, and the owners are compelled to consider demolishing the building altogether. Because housing values of such properties are not observed, the negative impact may be underestimated in this study. Therefore, the exploration of how in-home death incidents relate to housing vacancy and building demolition is important. Additionally, there is a pertinent need to assess the influence of information disseminated through public social media platforms like *Oshimaland.com* on the housing market. While we meticulously extracted and utilized trustworthy instances of in-home deaths for this study, considering the potential influence of false postings on the housing market is essential. If false information were to distort the market, it would necessitate measures to counteract the spread of such misinformation and ensure the integrity of property transactions. Lastly, while our discussion has been premised on the current law in Japan requiring disclosure obligation, whether the obligation of disclosure is essential in the context of in-home deaths is a fundamental consideration. The degree to which each individual cares about death incidents can vary greatly, and some individuals may prefer not to be informed of such an incident even if such an event occurred. Therefore, theoretically, evaluating the role of disclosure rules within the housing market would offer valuable insights into this aspect.

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Appendix

Appendix A: Data cleansing process for *Oshimaland.com*.

In this appendix, we provide a brief explanation of how we cleansed the data from *Oshimaland*.com. This website started in 2005, and their administrative staff collected information on in-home deaths internally. However, they have accepted posting by the public since June 2011. When users post death information, they first indicate the location where the death incident occurred on an online map. The system then automatically records the address of the incident at the building level based on the selected location. Then, users provide detailed information on where the incident occurred, such as the property number and the year/month/date of the occurrence (if they know). In cases when the exact timing is unclear, users have the option to describe approximate dates while acknowledging the ambiguity. The posting form also includes a free entry field where users can provide additional details about the deaths. All of the information is anonymously posted to protect the privacy of users.

Our data set was initially provided by the administrator of the *Oshimaland.com* website, and we organized the data for subsequent analysis. The pioneer study utilizing this data is Yajima and Sadayuki (2022), and Yajima and Sadayuki (2023) used the information on in-home death incidents recorded through 2017, while we use extended information on records through 2020. Therefore, we mainly follow their data cleansing procedure (See the Appendix of Yajima and Sadayuki, 2023). The 2020 in-home deaths dataset comprises a total of 60,995 death records all over Japan, representing all the data collected through the website as of November 19th, 2020. The detailed data cleansing process for each date of occurrence, address, and description of incidents are as follows.

Regarding the date of occurrence, users provided details on the day, month, and year of the incident to the best of their knowledge, typically employing either Japanese Era or Western notation. However, some users provided dates in more ambiguous notation, such as "Spring/YYYY" or "beginning of MM/YYYY." In such instances, we extracted only the verifiable information. Specifically, we extracted the year for the former case and both the month and year for the latter case. Additionally, we excluded data that did not specify the exact month of the incident to match with the REINS data.

Regarding the location of the in-home death, our raw data contained information on the longitude and latitude of each death incident[34]. Using this information, we verified the address, apartment name, and property number by ArcGIS. However, potential bias remains due to users providing incorrect information. Therefore, we only used the data that exactly matched the apartment names in the REINS data.

As for the description of death incidents, we classified the posted information into several categories by keywords. Following the keywords used in Yajima and Sadayuki (2022; 2023), we automatically defined an indicator for each of the death incidents by Stata. After that, we visually verified whether everything was properly classified. In doing so, we removed some information duplicated in the postings.

As noted in the main section, the *Oshimalan*d website allows users to attach additional comments to posted information. Using these comments, we complemented the missing parts as much as possible for the three types of information mentioned above.

[34] This information was not included in the 2017 data. Therefore, Yajima and Sadayuki (2022; 2023) used another geocoding service to retrieve it.

Appendix B: Data matching process for REINS data and *Oshimaland*.

In this appendix, we explain how we matched REINS data with *Oshimaland* data. We matched the data by using the addresses and names of the apartment buildings recorded in each entry. The process is divided into three parts.

Firstly, in terms of the building addresses, the two data points are matched at the street (*cho-cho*) level where the buildings are located. *Cho-cho* is a type of administrative division in Japan that is used for the national census, for instance. The apartment buildings with no recorded addresses at the *cho-cho* level are excluded from this process.

Secondly, we conduct fuzzy matching by using the names of apartment buildings.[35] Before the fuzzy matching process, we removed the noise information contained in the apartment names column of REINS data.[36] We matched the names of apartment buildings in the two data points within the same *cho-cho*. By the fuzzy matching process, the apartment buildings not matched with more than 90% accuracy are omitted.

Finally, we visually verified whether the matched names of apartment buildings were the same or not. The properties in the apartments with correctly matched names are used as our estimation sample.

[35] To conduct fuzzy matching, we use "matchit" command in Stata.

[36] Some name information in REINS data contains noises like "This property is newly built!" to stand out in resident recruitment platforms. We visually checked the noise information and removed text from the apartment names column using Stata.

Appendix C: Spatial distribution of in-home deaths

Appendix Figure C1 shows the overall distribution of death incidents recorded in *Oshimaland.com* in the Tokyo Metropolitan Area.

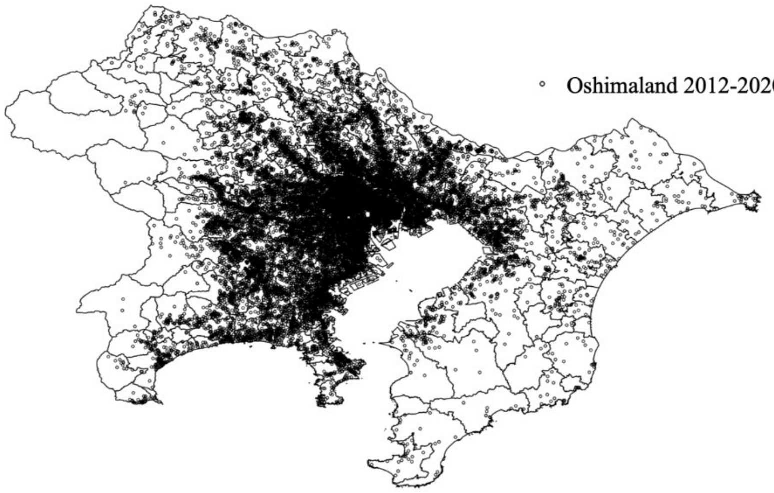


Figure C1: Distribution of recorded in-home deaths in the Tokyo Metropolitan Area
Notes: Polygons represent 212 municipalities in the Tokyo Metropolitan Area. Each circle shows the location of a death incident that occurred between 2012 and 2020 recorded in *Oshimaland.com*.

In addition, in-home death incidents may have a spatially biased distribution. For instance, a death incident may likely be exposed to the public and be recorded on the website more frequently in the high-populated municipality. To delve into this point, we plot the relationship between the number of households and the number of incidents at the municipality level (Figure C2). However, the figure shows a proportional relationship between them, indicating that the recorded incidents on the *Oshimaland* website are not geographically biased from the viewpoint of population distribution.

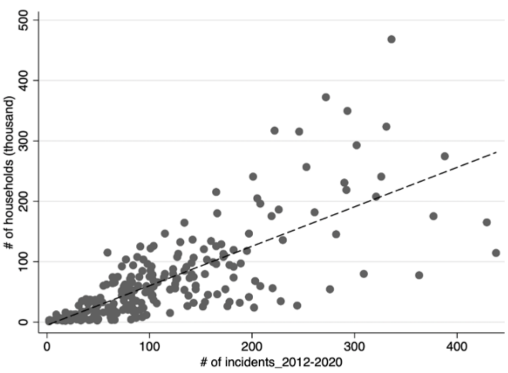


Figure C2: The scatter plot of the number of households and the number of incidents at the municipality level.
Notes: The vertical axis represents the number of households at the municipality level (the unit is one thousand). We refer to the National Census (2010, 2015, 2020) in Japan to calculate the number of households. The horizontal axis is the number of incidents recorded in *Oshimaland* in each municipality that occurred between 2012 and 2020.

	Property for Sale							
	Total		Murder		Suicide		Other	
	# of transactions	mean price (thousand	# of transactions	mean price (thousand	# of transactions	mean price (thousand	# of transactions	mean price (thousand
8years_before	75	34,000	2	16,500	8	45,700	65	33,100
7years_before	133	36,200	5	39,800	25	40,700	103	35,000
6years_before	173	31,000	6	38,400	33	40,400	134	28,300
5years_before	194	39,000	9	28,200	61	55,000	124	31,800
4years_before	256	39,300	18	35,900	77	53,800	161	32,800
3years_before	310	36,100	25	33,800	94	49,600	191	29,800
2years_before	406	39,700	28	35,000	130	51,400	248	34,100
1year_before	500	43,900	48	45,400	146	52,800	306	39,400
0year _after	476	41,600	45	46,000	164	45,300	267	38,600
1years_after	307	41,200	38	46,500	107	45,100	162	37,500
2years_after	248	42,100	22	47,400	92	40,900	134	41,900
3years_after	225	48,100	56	58,700	78	49,900	91	40,000
4years_after	139	47,600	24	59,400	66	48,100	49	41,200
5years_after	116	54,900	28	75,100	54	53,600	34	40,300
6years_after	84	52,800	14	68,300	45	54,600	25	51,100
7years_after	39	39,700	1	42,000	27	38,400	11	42,700
total	3,681	41,400	369	48,700	1,207	48,600	2,105	35,900

	Property for Rent							
	Total		Murder		Suicide		Other	
	# of transactions	mean rent (thousand	# of transactions	mean rent (thousand	# of transactions	mean rent (thousand	# of transactions	mean rent (thousand
8years_before	345	93.78	52	113.13	26	90.12	267	90.36
7years_before	304	88.88	22	123.45	37	136.83	245	78.54
6years_before	354	110.28	14	146.48	59	159.77	281	98.08
5years_before	360	98.83	15	123.5	73	153.16	272	82.9
4years_before	441	98.81	50	71.84	73	193.65	318	81.28
3years_before	572	92.73	87	72.87	139	131.59	346	82.12
2years_before	772	99.5	99	87.03	173	129.41	500	91.61
1year_before	858	95.45	128	78.55	218	127.52	513	86.03
0year _after	881	89.05	133	79.27	168	123.66	582	81.29
1years_after	472	90.62	68	71.93	109	126.12	296	81.83
2years_after	317	94.79	39	123.41	71	112.93	207	83.18
3years_after	240	90.56	43	132.5	50	110.44	147	71.53
4years_after	140	99.03	27	125.95	36	115.89	77	81.71
5years_after	70	122.3	15	109.96	19	156.74	36	109.26
6years_after	47	144.02	12	136.5	12	143.4	23	148.27
7years_after	10	160.46	0		6	98.61	4	253.25
total	6,183	95.68	804	91.59	1,269	132.48	4,114	118.20

Table C: The number of transactions per time-lag from event and types of death

Notes: The table shows the number of estimated properties and their average price/rent by each death type and each elapsed year since the death incidents in the case of sales and rental properties, respectively. Since some death incident is regarded over multiple death categories recorded as murder and suicide, the sums of estimated properties could not equal the sums of properties categorized as each death type. The death type "other" is defined as death incidents other than murder and suicide.

Appendix D: Full results of the baseline model

	Sale		Rent	
	Coef.	S.E.	Coef.	S.E.
Treatment effects (Reference: l = -1)				
l <=-6	-0.0162	0.0396	-0.0075	0.0172
l =-5	-0.0208	0.0326	0.0032	0.0167
l =-4	-0.0194	0.0293	0.0155	0.0102
l =-3	-0.0127	0.0200	0.0070	0.0080
l =-2	-0.0073	0.0136	0.0082	0.0083
l =0	-0.0466	0.0128	-0.0005	0.0063
l =1	-0.0311	0.0140	0.0089	0.0075
l =2	-0.0538	0.0168	0.0188	0.0103
l =3	-0.0538	0.0210	0.0050	0.0123
l =4	-0.0540	0.0248	0.0245	0.0171
l >=5	-0.0629	0.0343	0.0477	0.0189
Control variables				
Floor area	0.0140	0.0006	0.0005	0.0005
Age of building	-0.0095	0.0031	-0.0066	0.0014
Room count categorical dummy (Reference = 5 rooms or more)				
1 room	0.1070	0.0582	-0.8828	0.0356
2 rooms	0.1755	0.0562	-0.6679	0.0353
3 rooms	0.1750	0.0552	-0.4989	0.0375
4 rooms	0.1331	0.0559	-0.3876	0.0503
Floorplan categorical dummy (Reference = other floorplan)				
1R	-0.3375	0.0392	-0.4795	0.0468
1K	-0.3173	0.0354	-0.4377	0.0452
DK	-0.1509	0.0218	-0.3213	0.0428
LK	-0.2902	0.0550	-0.2015	0.1069
LDK	-0.0037	0.0080	-0.132	0.0381
SK			-0.1531	0.0805
SDK	0.2388	0.1356	-0.2292	0.0841
SLDK	-0.0922	0.0667	-0.0703	0.0448
Floor level categorical dummy				
1st ~ 55th floors	YES		YES	
Fixed Effects				
Building FE	YES		YES	
Year FE	YES		YES	
Month FE	YES		YES	
Observations	3,607		6,077	
R-squre	0.976		0.967	

Table D: Main Result
Notes: The table shows the coefficients and t-statistics of the estimation results illustrated in Figure 3.1. L, D, K, S, and 1R stand for Living room, Dining room, Kitchen, Storeroom, and Studio. S.E. columns display the standard errors clustered at the building level.

Appendix E: Robustness checks

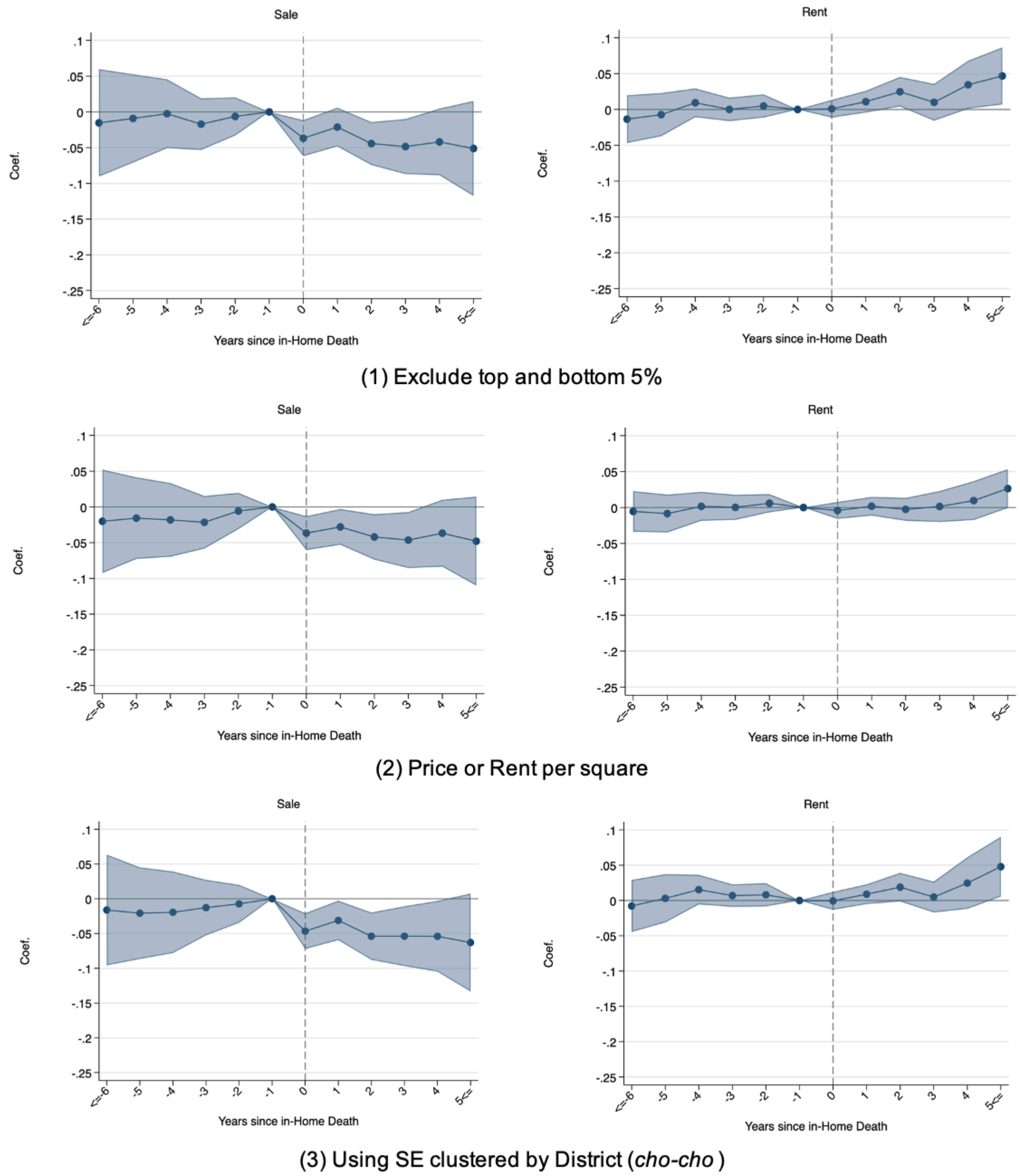
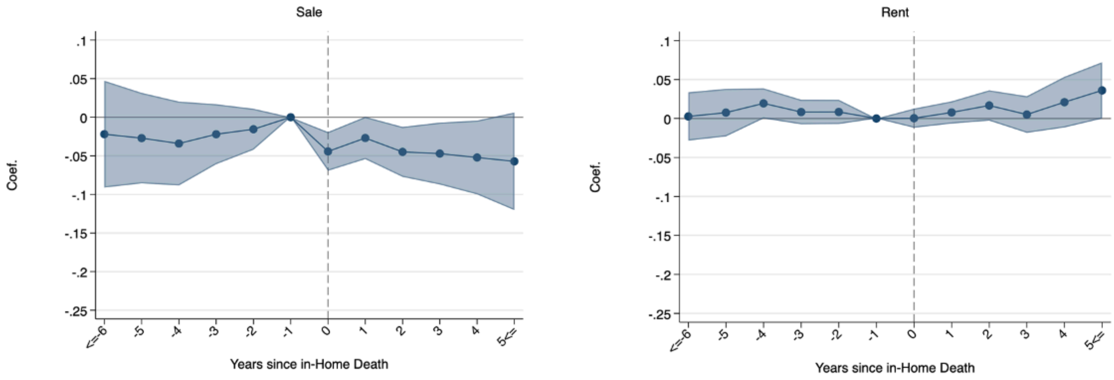
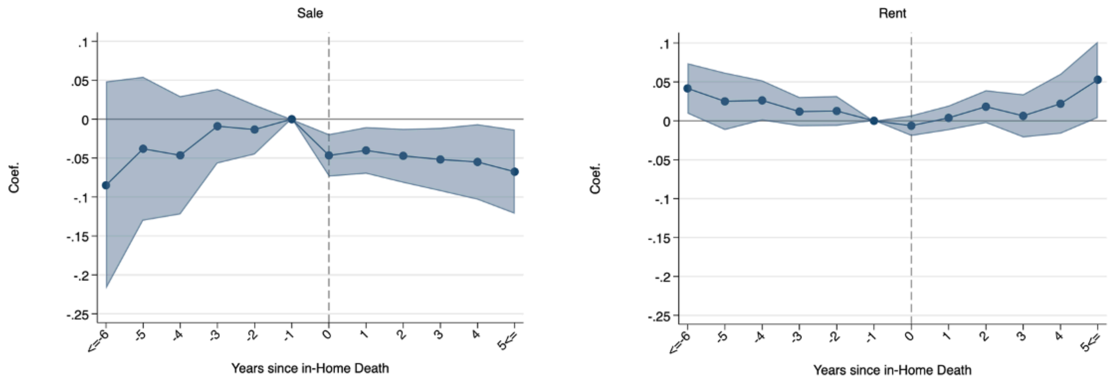


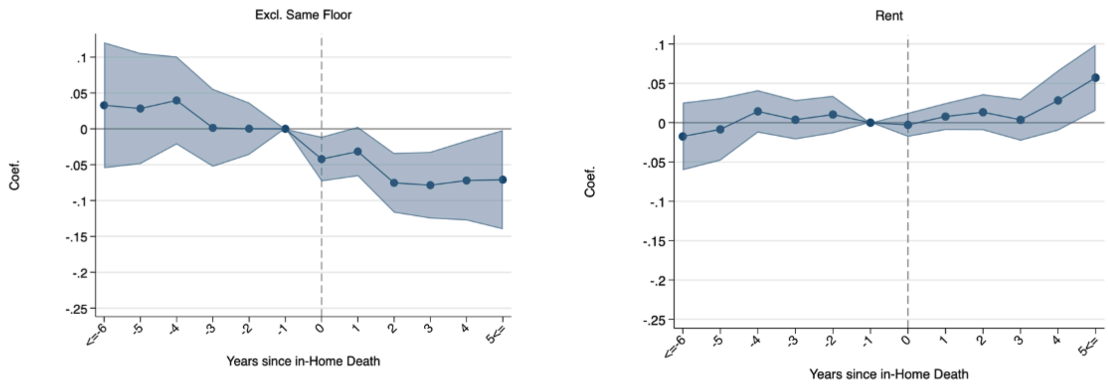
Figure E: Robustness checks



(4) Controlling Year*Municipality trend



(5) in-House Death Year >=2014 and Control Cohort Year >=2019



(6) Exclude Floors of in-Home Deaths

Figure E: Robustness checks (continued)

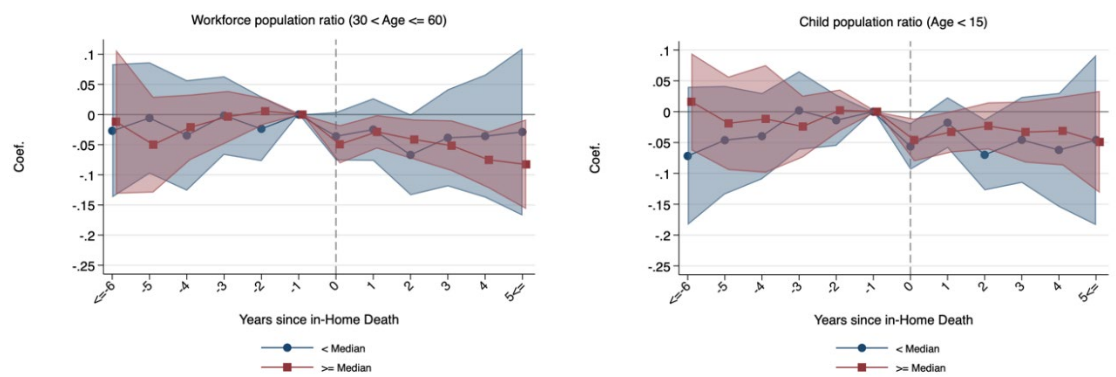
Notes: The left panels show the results of the cases of sales properties. In contrast, the right panels present the effects of death incidents on rental property deals. The blue points are the estimated coefficients on the variable in-home deaths for the housing price/rent. The ribbons are the corresponding 95% confidence intervals. Except for those of (3), the standard errors are clustered at the building level. The standard errors of (3) are clustered at the street (*cho-cho*) level where the apartment buildings are located.

Appendix F: Heterogeneity in Regional Socioeconomic Characteristics

We investigate how the effect of in-home death is attributed to the heterogeneous preferences of the demand side, featuring regional socioeconomic characteristic variations. We conduct two subsample analyses that specifically consider regional characteristics, which can provide insights into the effects of high demand on buildings. The sample is divided based on the workforce population ratio and the child ratio. For the analyses, we utilize district-level demographic statistics, as our property transaction data does not include buyers' demographic information.[37]

We start with the analysis focusing on the workforce ratio. In this analysis, the workforce is defined as the population aged between 30 and 60. Among the Japanese workforce (aged between 15 and 60), individuals aged over 30 are often married and earn a relatively higher income by a seniority rule, which is a popular system among Japanese firms. By contrast, those aged over 65 cannot take out a loan because their retirement age is approaching. Then, the actual demand for residential properties is likely to be high, relative to the supply level, in areas with a large number of people aged between 30 and 60. In such a case, even properties having experienced in-home deaths can find residents with little discount because of the excess demand for properties. Hence, we expect that the negative effect of in-home deaths may be less crucial in those areas with higher workforce population ratios. To investigate this hypothesis, we split the sample into subsamples consisting of properties located in the district (*cho-cho*) with higher and lower workforce resident rates than the median. We expect that the negative impact of in-home death is smaller in higher-workforce resident areas.

Panel (a) in Appendix Figure F exhibits the result. Property prices in the higher-workforce population ratio areas significantly declined after the death incidents, while those in the lower-workforce population ratio areas did not, although we did not find greater coefficient magnitudes for the higher-workforce-ratio subsample. The insignificance of the in-home death variable in the subsample of the areas of the lower workforce population mainly comes from greater standard errors. One reasonable explanation for the wide confidence intervals in the estimation results for this subsample is that there is a huge heterogeneity and variation in demographic and economic characteristics among household heads younger than 30 and those older than 60.



(a) Workforce Population Ratio (b) Child Population Ratio

Figure F: Neighborhood demographics as a proxy of the buyer residents

Notes: Blue plots are point estimates of treatment effects for the (a) low workforce and (b) low child population, and red plots are those for the (a) high workforce and (b) high child population, with the horizontal axis representing the years from the in-home death incident to the property transaction. Light-colored areas are the 95% confidence intervals based on clustered standard errors at the building level.

[37] For the demographic data, we use the Japanese Census in 2015, available at the district (*cho-cho*) level with five-year intervals.

In addition, we consider the child population share in the neighborhood of the transacted properties. We divide the sample into that consisting of properties in a higher child-population-share area (above the median child population share at the street (*cho-cho*)-level) and that in a lower share (below the median). We conjecture that property prices in areas with a high child population share may experience a stronger negative impact from in-home deaths than those in areas with a low child population share area because the former areas may have a higher share of households that can manage to buy properties to reside in. With this exercise, we aim to reveal whether households with families have a stronger preference for better residential amenities. From Panel (b) in Appendix Figure F, however, we observe no clear difference between the coefficient and significance of the death incidents in the same apartment buildings.