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Zheng CHANG

Jing LI
Singapore Management University, lijing@smu.edu.sg

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The impact of in-house unnatural death on property values: Evidence from Hong Kong

Zheng Chang [a,*], Jing Li [b]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, 6/F, Academic 1 Building, Tat Chee Avenue, Kowloon, Hong Kong SAR
[b] School of Economics, Singapore Management University, 90 Stamford Road, 178903, Singapore

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ABSTRACT

The occurrence of in-house unnatural death could negatively affect the value of housing property. This study evaluates the geographic and temporal scope of the impact of unnatural death on property values in Hong Kong. By exploiting the spatial and intertemporal variation of the shock in a difference-in-differences approach, we find significant negative externalities of unnatural death incidence on neighborhood housing values. On average, units in which an unnatural death occurred experience a 25% drop in value following the death. Nearby units on the same floor also show a significant price drop of 4.5%. Prices of units on other floors of the same building decline about 2.6%. Units in other buildings of the same estate observe a price decline of about 1% on average. However, the price for nearby estates within 300 m shows a positive impact of 0.5%, suggesting a very localized sorting mechanism. Temporally, price evolution after death incidence follows a U shape. Housing prices continue to decline up to 4–5 years after deaths and recover gradually afterwards. We also document the heterogeneity of the impact by the type of death incidence (murder, suicide, or accident) and the type of homebuyers (local buyer, investment firm, and other buyers). We find that the negative externalities of death incidence are largely due to a severe stigma effect, rather than channels through the revealed crime risk or the price contagion effect.

1. Introduction

Households choose where to live and which units to buy by assessing a bundle of housing attributes. Aside from commonly observed features, like floor space, number of rooms, and nearby amenities, many intangible features, such as perceived neighborhood crime risk, attitudes toward a certain ethnic group, and psychological perceptions of stigma tagged to a unit, also play a significant role in affecting a household's preference for the unit. Among the latter type of features, information revealed on previous in-house unnatural deaths could substantially reduce the willingness to pay for a unit as well as other units in close proximity. This outcome could be because (1) unnatural deaths, especially those resulting from violent crimes, reveal high crime risks associated with the neighborhood; (2) in-house deaths could generate prolonged externalities associated with the death stigma, having a negative psychological impact on those living in close proximity; and (3) shocks imposed on the price of a particular unit may create contagion effects that affect nearby housing values.

There is extensive literature documenting households' averting behavior against revealed crime risk and/or potential stigma effects that follow the revealed risk. For example, Linden and Rockoff (2008) and Pope (2008) show that house values fall by 2.3–4% following the move-in of a registered sex offender in close proximity. Congdon-Hohman (2013) and Dealy et al. (2017) find that house prices drop substantially following the discovery of a methamphetamine lab and a long-lasting stigma effect remains even after the decontamination of those labs. However, few studies thus far have considered the direct impact of unnatural deaths on nearby property prices, even though such deaths occur at high frequency, are often connected to crime or suicide, and generate substantial neighborhood disruptions. In particular, deaths from violent crimes trigger strong emotional disturbance and disperse fears about possible murders in the community. In addition, unnatural deaths from suicide might have a strong physiological impact on a neighborhood especially one in which there are strong beliefs in ghosts and the afterlife.

So (2007) analyzes the externalities of unnatural death on properties values by using seven large-scale housing estates in Hong Kong from 1991 to 2006. Although he finds negative effects of unnatural death on property values, his hedonic regression method is likely to yield biased results, as unnatural deaths are likely to correlate with unobservable

* Corresponding author.
E-mail addresses: zchang@cityu.edu.hk (Z. Chang), lijing@smu.edu.sg (J. Li).

factors of housing estates. Bhattacharya et al. (2017) adopt a difference-in-differences (DID) approach to estimate the negative effect of haunted houses on nearby houses within major large-scale estates in Hong Kong. The authors also find negative externalities of unnatural deaths, and some of their main findings are consistent with our estimation in this study. However, their estimation largely focuses on short-run effects. They also ignore multiple treatment issues, which could underestimate the real effect. Our study overcomes these weaknesses and provides a more comprehensive understanding of the geographic and intertemporal scope and mechanism of housing externalities caused by unnatural death incidence. Given the similarities between our study and Bhattacharya et al. (2017), we provide a detailed comparison between these two studies in appendix Table A1.

Specifically, our study examines (1) the geographic scope of the long-run impact of unnatural death within and beyond housing estates; (2) how the market response following unnatural deaths evolves temporally; and (3) how unnatural deaths resulting from different types of death and different types of homebuyers lead to different extent of housing market responses. Aside from these main questions, this study also explores whether housing price variations are likely caused by the following three channels: risk awareness, the stigma effect, or the price contagion effect.

The analysis relies on comprehensive data on housing transactions and unnatural deaths in Hong Kong spanning the period 2001 to 2015. The data contain detailed information on housing units and location characteristics as well as households' characteristics. Linked with publicly released information on the incidence of in-house unnatural deaths, we are able to explore the housing market outcomes in response to the occurrence of unnatural deaths from various perspectives. The geographic scope of the data allows us to explore the extent to which the impact varies with spatial features captured by residential density. The long time horizon of the data allows us to explore the temporal pattern of the market responses over an extended period.

We adopt various specifications in a difference-in-differences setting that explores both intertemporal and geographic variations in the shock to identify its impact. One potential threat to the identification of the causal impact is the endogeneity of the shock. For example, if the death incidence is more likely to occur in a neighborhood that is deteriorating over time, the fall of house prices following the shock could reflect the deviating trend between the treatment and control neighborhoods. We argue that the occurrence of unnatural deaths is not a consequence of high-risk individuals sorting into more vulnerable neighborhoods. In particular, we control for building fixed effects in our empirical analysis and show that the geographic scope of the impact is contained within a small cluster of buildings. It is difficult to believe that high-risk individuals would sort into a particular floor level given the thinness of the housing market. This is in line with Bayer et al. (2008) in identifying the peer effect on labor market outcomes.

We obtain the following findings: housing values drop about 25% for units with deaths, 4.5% for other units on the same floor, 2.6% for other floor units in the same building, and 1% for units in other buildings of the same estate. However, the average house price of units in other estates within 300 m increases 0.5%. For units with deaths, the price decline is sustained across the whole study period. The price impact on units in other geographic scopes follows a U shape and starts to reverse after 4–5 years of a death. The impact is significantly different by type of death, and type of homebuyer. Lastly, we explore the mechanism of the price variation caused by the unnatural death incidence, and find that the impact is largely from the stigma effect rather than other channels.

The evidence documented in this study contributes to the literature in a number of ways. First, it quantifies the social impact of a direct and striking signal of social disturbance—unnatural deaths of local residents. These incidences cause uneasiness about living in the neighborhood, especially for those deaths resulting from murder and suicide. Death incidence leads to spatially concentrated responses but long-lasting temporal impacts. Given the durable nature of housing, the long-run supply of housing tends to be perfectly inelastic when facing reduced demand. In this case, market response generates sharp equilibrium price drops even after a long time horizon (Glaeser and Gyourko, 2005). With proper controls, an accurate measure of the long-run effect is essential for a better understanding of the aggregate social cost following the occurrence of in-house unnatural death.

Second, our findings complement the literature on housing externalities/spillovers. Housing prices may be affected by nearby properties through urban revitalization (Rossi-Hansberg et al., 2010; Hornbeck and Keniston, 2017), cessation of rental control (Autor et al., 2014), crime risk (Linden and Rockoff, 2008), forced sales (Campbell et al., 2011), and so forth. The difference between our study and others is that we emphasize the psychological impact on nearby property value. Although the role of psychology in affecting the behavior of investors has been well studied in the past 2 decades, most studies have focused on high-liquid assets, such as stocks (Shiller, 2003; Thaler, 2006). Even though housing is one of the most important asset classes, research on psychological impact on the housing market remains rare. Our study aims to fill the gap in this field.

Third, this study is related to the literature identifying the hedonic price function for local (dis)amenities, such as school quality, pollution, crime, and property taxes, by exploiting a quasi-experimental design (Black, 1999; Lynch and Rasmussen, 2001; Bui and Mayer, 2003; Chay and Greenstone, 2005). One major obstacle in identifying such hedonic prices is that variation in these location-specific features may be correlated with unobservable factors that also affect housing prices. In this case, the estimated hedonic prices in a simple cross-sectional setting reflect the impact of both the key feature of interest and other unobserved factors, which leads to either upward or downward bias. This study explores a plausible exogenous shock to the housing market in identifying the impact of unnatural deaths on housing market outcomes in a difference-in-differences setting. The evidence indicates that this factor explains a significant variation in housing prices within the geographic and temporal scope of the shock.

The rest of this paper is organized as follows. Section 2 introduces the housing market structure and psychological background in Hong Kong. Section 3 describes the data and summary statistics. Section 4 performs a number of examinations on the effect of unnatural death incidence on property values. Section 5 offers a number of robustness checks to verify our empirical results. Section 6 explores the mechanism of the death incidence on housing prices. Section 7 concludes.

2. Hong Kong's housing market and psychological background

2.1. Housing market in Hong Kong

Hong Kong was ranked the most expensive housing market from 2011 to 2017 by the annual Demographia International Housing Affordability Survey.[1] These high housing prices are largely determined by the city's housing supply shortage relative to demand. In 2016, about 7.3 million people lived within a 1100-square kilometer territory. Geographically, the city is surrounded by the South China Sea from the east, south, and west. The north of the city borders Shenzhen, one of the mega cities in mainland China. As 80% of Hong Kong is mountainous with natural parks, its developed area accounts for only 24% of the territory, and the residential land use accounts for about 7% of the land (Planning Department of Hong Kong, 2016). Moreover, the city's land supply is driven largely by economic and political considerations rather than housing market prices (Chiu, 2007). The geographical constraint and inelastic land supply certainly contribute to the city's expensive housing (Glaeser et al., 2005; Saiz, 2010).

To protect the interests of low-income residents, the Hong Kong

[1] The reports of the annual Demographia International Housing Affordability Survey can be found in the following link: http://www.demographia.com/dhi.pdf.

government established a public housing system in the 1950s. At present, the public housing system in Hong Kong accommodates more than 2 million local residents, and provides about 50% of the housing stock. Although most public housing projects are located in suburban districts, they reduce the development space for private housing and likely crowd out private development (Sinai and Waldfogel, 2005), which in turn further drives up private housing prices.

Housing demand in Hong Kong, one of the financial hubs of East Asia, remains high. As an immigration society, the city accommodates multinational residents. In the past decade, the Hong Kong government has launched various policies to attract high-skilled professionals, investors, and students from mainland China to work, live, and study in Hong Kong.[2] These new immigrants drive up housing prices, since immigrants are not eligible for public housing. For example, near 30,000 investors were approved to receive permanent residency in Hong Kong through the Capital Investment Entrant Scheme (CIES) from 2003 to 2015, with an investment of more than 6.5 million HK dollars (HKD) (the threshold was increased to 10 million HKD in 2010). The vast majority (90%) of investors are from mainland China. Through the CIES, the Hong Kong government has raised more than 270 billion HKD (about 35 billion US dollars) investment, although the immigration scheme was suspended in 2015. Even though there is no empirical study to estimate the impact of the CIES on Hong Kong's housing price, the capital inflow through the CIES is likely to push up local housing prices. The housing price index rose from about 100 in 2007 to more than 300 at the end of 2016.

Given the expensive housing price, households have to make careful housing decisions. Many empirical studies have shown the relationship between tangible factors (e.g., housing characteristics, local amenities, and accessibility) and housing price. Those tangible factors are certainly important for homebuyers. However, intangible factors are also important in Hong Kong's housing market. Although different ethnic groups live in Hong Kong today, 89% of the population speaks Cantonese (Hong Kong Census, 2016). Those local residents have a strong belief in Feng Shui when making housing decisions.

2.2. Psychological background of unnatural deaths in Hong Kong

Superstitious beliefs are rooted in many societies and cultures, and the concept of an afterlife is a popular one across cultures. In many societies, death is taboo.[3] Influenced by Taoism, traditional Chinese believe that people who died as a result of violence or unnatural events can become "ghosts" who can disturb successive occupants through various means (Poo, 2004). Housing units in which unnatural deaths have occurred are called "haunted units," which are regarded as bad Feng Shui, and are unsuitable for habitation.[4]

In Hong Kong, Feng Shui is arguably one of the most important considerations for housing decisions, especially of local residents. Almost every local household consults a Feng Shui master before purchasing a house. Although there is no scientific evidence to support Feng Shui theory, scholars in psychology have pointed out that superstitious believes are useful coping mechanisms for misfortunate and uncertainty in life, especially during harsh times (Vyse, 1997; Zhang et al., 2013). Intangible psychological effects influence a buyer's willingness to pay, which has certain implications for housing markets. Not surprisingly, units with good Feng Shui tend to enjoy premium and vice versa. Non-local housing buyers in Hong Kong are indirectly affected by Feng Shui culture, because units with bad Feng Shui might be illiquid in the housing market.

A few empirical studies have estimated the effects of Feng Shui on property values in Hong Kong, Taiwan, and Singapore. These studies have shown that housing units with good Feng Shui tend to enjoy a price premium, and vice versa (Chau, 2001; Lin, 2007; Agarwal et al., 2014). However, most empirical studies in this area have two problems. First, there is no clear quantitative definition for good or bad Feng Shui. Researchers need to separate the effect of Feng Shui from the tangible capitalization effect of local amenities/disamenities. For example, housing units facing a river can be regarded as having good Feng Shui. However, those units are likely to have a price premium owing to the capitalization of the good view, even without Feng Shui considerations. Second, the Feng Shui attributes (regarded as local amenities or disamenities) are likely to be correlated with unobserved factors within the hedonic pricing framework (Epple, 1987). For example, lucky and unlucky building/floor/unit numbers are associated with good/bad Feng Shui.[5] Many buildings in Hong Kong do not have building/floor/unit numbers ending with 4, which is considered bad luck in Feng Shui. An effective approach to estimate the causal effect of intangible effects, such as Feng Shui, on housing values would be to identify an exogenous change in Feng Shui factors in a neighborhood and its effect on housing prices.

The study of death incidence on property value provides an opportunity to examine the intangible psychological effect of personal beliefs on property values. Unlike other Feng Shui attributes, an unnatural death is likely to be exogenous to housing units. Although we have not come across any empirical research to examine the effect of unnatural death on housing prices, news on unnatural deaths is quite popular among social media in Hong Kong. Murders and suicides within housing units are more likely to be reported, and the prices of those haunted units are usually 20–40% lower than the market values of similar ones.

To understand the effect of unnatural death incidence on property value, we interview two local housing agents in Hong Kong. Generally, housing units in which unnatural deaths have occurred, such as murder, suicide, and accidents, are considered haunted, but deaths due to disease are not considered in the same category. As the housing price is affected by the degree of violence involved in those deaths, murders and suicides tend to have larger effects on housing prices than accidents do. Households can acquire related information on haunted units through housing agents, building managers, and even neighborhood residents. As the information on haunted units is relatively easy to collect, non-local households generally do not have an information disadvantage with regard to acquiring haunted unit information compared to local households.[6]

3. Data sources and descriptive statistics

Our analysis relies on two main data sources. The first dataset comprises housing transaction data from EPRC.ltd, the largest data vendor in Hong Kong. There are several type of residential properties in EPRC's dataset, including estates, single buildings, village houses, and public housing. Estates, as defined by the EPRC, are housing projects comprising

[2] Immigration policies and related statistics can be found through the annual reports of immigration department of Hong Kong: http://www.immd.gov.hk/eng/press/press-publications.html. Chang (2017) documents the impact of mainland Chinese students on neighborhood rental price in Hong Kong.

[3] In many Western countries, unnatural deaths also affect housing choice. Bhattacharya et al. (2017) provide a good overview on this.

[4] Feng Shui is an ancient Chinese philosophical system of harmonizing human beings with their living environments; the theory was widely used for site selection and building design by ancient Chinese (Bruun, 2008).

[5] In China, 6 and 8 are considered lucky numbers, as they are homophonic to luck and prosperity. The number 4 is pronounced in the same way as "dead" in Chinese and is considered an unlucky number.

[6] There is no law requiring agents to disclose unnatural death cases to homebuyers. However, there is a legal precedent to do so after a housing agent was penalized by a court in order to compensate for all the losses of the homebuyer after hiding information on unnatural death. Thus, the incentive for strategic lying by agents is relatively low (see https://legalref.judiciary.hk/lrs/common/search/search_result_detail_frame.jsp?DIS=43673&QS=%2B&TP=JU).

Table 1
Annual numbers of unnatural deaths in Hong Kong,[a] 2001–2015.

Geographic Regions	Hong Kong Island	Kowloon	New Territories	Total
	(1)	(2)	(3)	(4)
2001	14	19	20	53
2002	11	14	20	45
2003	22	20	36	78
2004	15	15	19	49
2005	17	8	20	45
2006	10	9	20	39
2007	11	13	23	47
2008	18	17	32	67
2009	21	10	27	58
2010	18	17	32	67
2011	10	7	17	34
2012	21	12	36	69
2013	32	29	39	100
2014	27	23	46	96
2015	21	17	49	87
Total	268	230	436	934

[a] This table doesn't include death incidence due to diseases.

at least two building towers. Single buildings are smaller in terms of scale and number of units than estates are. Estates and single buildings are the main components of Hong Kong's private housing market. There are around 970 estates and 30,000 single buildings recorded by the EPRC, but the estates cover about two-thirds of private housing transactions. The village houses are small-scale properties built by farmers in suburban areas with generally 2–3 floors. Compared to private housing units, public housing units that are sold have to satisfy various government regulations, in which case the transaction price cannot be purely market driven.

Our study focuses only on housing transactions within estates, which are the most liquid property in Hong Kong's private housing market. The EPRC data report detailed the unit address (street, property name, floor, and unit number), transaction price and date, gross floor area (GFA), orientation, number of living rooms and bedrooms, and name of homebuyer. We classify homebuyers into three categories: local buyers, firms, and others.[7] To control for inflation, we convert the nominal sale price into a real price measured based on the price level in December 2015. We drop observations without variables for price, unit size, and floor number, and those with sales price and unit size (GFA) below 1% or above 99% of those levels in the data.

The data on the incidence of unnatural death are mainly from two public websites and one private real estate consulting firm.[8] These websites have more than 8000 death records in total, covering all type of properties (office, commercial, public housing, etc.) from 2001 to 2015.[9] The information on each death includes the date, name of estate, and a brief description. After merging the unnatural death events from the two public resources and excluding duplicates, we identify 934 unnatural death cases (excluding disease) in a total of 368 estates. Table 1 summarizes the annual numbers of deaths among Hong Kong's three regions.[10] We match the data on unnatural deaths with housing transaction data from the EPRC. Using GIS software, we identify the spatial distribution of estates in which unnatural deaths occurred in Hong Kong, as shown in Fig. 1.

One caveat of the data on death incidence is that not all records have complete information on the specific unit number of a death. All 934 cases can be identified at the estate level, but only 705 cases can be identified at the building tower level, 418 cases at the floor level, and 250 cases at the unit level, as shown in Table 2.[11] Across the groups of incidence reported at these four levels, roughly 2–5% are murder cases, 84–90% are suicides, 7–11% are accidents, and the rest resulted from the unclassified category. Notice that the deaths from murders are disproportionately more likely to identify housing unit numbers. This could be due to relatively wide media coverage following the murder case.

Given the nature of the data, we utilize different samples when exploring different geographic scopes of the market response. When the focus is on the immediate spillover effects on the closest neighbor(s) on the same floor, the effect is identified based on the sample with housing unit number reported. When we extend the analysis to examine the average impact on other floors, the sample with floor level identified is utilized. When the geographic scope is further extended to other buildings or estates, we use the sample with buildings or estates identified, respectively. The details of the specification are explain later.

Another important feature of the data is that there are often multiple shocks imposed on the same building or estate. Table 3 reports the frequency of deaths for a building or an estate by using a sample with death incidence identified at the building tower level (705 deaths in total). Column 1 shows that about 46% of the estates in the data have one death, 19% of the estates have two deaths, 16% have three deaths, and 20% have more than three deaths. Even at a narrower scope, at the building tower level, 2.5% of the towers in the sample have at least twice the death shocks during the sample period (Column 2). Columns (3) and (4) summarize the number of estates and towers beyond the haunted estates and within 300 m of their boundary. We only consider the boundary estates without any death incidence. The scale of boundary estate is significantly smaller than the haunted estates. On average, estates in which deaths have occurred have 10.42 building towers (2814/270), while boundary estates have 3.28 building towers (637/194).

Finally, Table 4 defines variables and summarizes statistics based on the geographic scope of housing transactions related to the haunted units, including haunted units themselves, other units in the same floor, other floors in the same building, other buildings in the same estates, and other estates within 300 m. Variables include the unit transaction price, unit characteristics (GFA, unit age, and floor number), several event dummies, type of death (murder, suicide, and accident), and type of homebuyers (local, firm, and other).[12]

4. Estimating the effect of unnatural death on housing values

To identify the impact of unnatural deaths, we follow the literature on the hedonic method and examine the extent to which this disamenity has been capitalized in housing values (Rosen, 1974). A typical concern when interpreting the hedonic coefficient is omitted variable bias. If an unobserved unit or neighborhood feature is correlated with the variable of interest, the ordinary least square estimates of the hedonic coefficient will be biased (Bartik, 1987; Epple, 1987). A large number of studies have taken various approaches, such as difference-in-differences and regression discontinuity design, to address omitted variable bias in uncovering the capitalization rate of school quality, crime, population,

[7] Local residents in Hong Kong speak Cantonese and use traditional Chinese characteristics. Mainland Chinese speak Mandarin and use simplified Chinese characteristics. We can easily identify local buyers based on the names of homebuyers using programming languages. The names of homebuyers end with .co or .ltd are classified as firms.

[8] The two websites recording the unnatural death incidences are http://www.property.hk/unlucky/and https://www.squarefoot.com.hk/haunted/. We signed a confidential agreement not to disclose the company name.

[9] Our study starts from 2001, as one of the largest public websites (http://www.property.hk/unlucy/) was founded in July 2000. Our study ends in 2015, as the data from the private consulting firm end in 2015.

[10] Geographically, Hong Kong has three regions: Hong Kong Island and Kowloon are the urban areas, and the New Territories is the suburban area.

[11] The publicly sourced data do not identify the specific unit in which the death occurred. The identified 250 cases at the unit level are from the private consulting firm mentioned above.

[12] The dataset includes the number of living rooms and bedrooms. As we control the unit size, we do not add the number of living rooms and bedrooms in the regression.

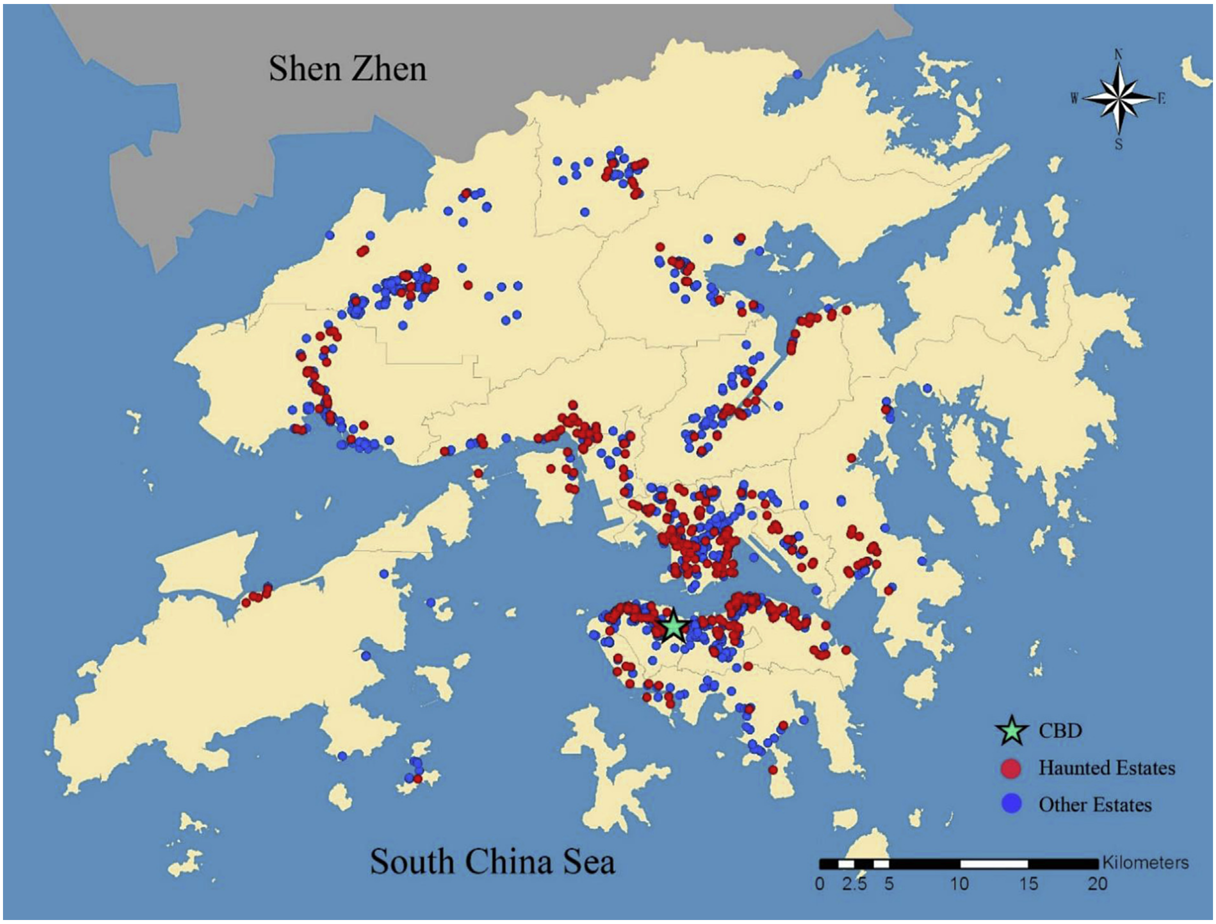

Fig. 1. Spatial distribution of death incidence in Hong Kong, 2001–2015.

Table 2
Numbers and types of unnatural deaths by identifiable scope.

Identifiable Scope	Deaths identified at the estate level	Deaths identified at the tower level	Deaths identified at the floor level	Deaths identified at the unit level
	(1)	(2)	(3)	(4)
Murder	17 (1.82%)	17 (2.41%)	16 (3.83%)	14 (5.6%)
Suicide	835 (89.4%)	625 (88.65%)	351 (83.97%)	211 (84.4%)
Accident	70 (7.49%)	53 (7.52%)	46 (11%)	22 (8.8%)
Unclassified	12 (1.28%)	10 (1.42%)	5 (1.2%)	3 (1.2%)
Total	934	705	418	250

Table 3
Numbers of estates/towers and numbers of deaths [a].

Within Estates and Beyond	Estate	Tower	Other estates within 300-m boundary	Other towers within 300-m boundary
	(1)	(2)	(3)	(4)
No deaths	0	2185 (79.74%)	194	637
One death	124 (45.93%)	490 (17.88%)	–	–
Two deaths	51 (18.8%)	51 (1.86%)	–	–
Three deaths	42 (15.56%)	12 (0.44%)	–	–
Four (or more) deaths	53 (19.63%)	2 (0.07%)		
Total	270	2814	194	637

[a] The table reports the numbers of deaths which can be identified at the tower level. 705 deaths (refer to Table 2) occur within 270 estates and 2814 building towers.

and property taxes (Colwell et al., 2000; Davis, 2004; Figlio and Lucas, 2004; Gibbons, 2004; Linden and Rockoff, 2008). The core idea is to access the response of property values to an arguably exogenous change in these location-specific factors.

Similar logic applies when evaluating the impact of unnatural death. For example, deaths from murder may be more likely to occur in neighborhoods with high crime risk, and housing in these places tends to have low values. The incidence of suicide could be negatively correlated with the wealth status of the family, in which case, the total willingness to pay for the unit would be low. If this is the case, a simple cross-sectional comparison of the housing price following the incidence of death might lead to downward bias of the estimated coefficients. Indeed, as shown in Table A2, while controlling for neighborhood fixed effects, regressing the number of unnatural deaths that have occurred in an estate on the logarithm of the average price per square feet of units within the estate through a negative binomial regression yields a significantly negative coefficient of −0.683 (Column 1). The corresponding coefficient is −0.362 if the same number of unnatural deaths is regressed on the logarithm of transaction price as another proxy of household wealth status (Column 2). This result implies that there is strong negative correlation between the incidence of unnatural death and other unobserved neighborhood characteristics.

To address the concerns on omitted variable bias, we adopt a difference-in-differences strategy by exploiting the cross-sectional and intertemporal variation in the incidence of death across the entire housing market in Hong Kong. Table A3 demonstrates the pre-event parallel price trends among treaded and control groups. The cross-

Table 4
Variable definitions and summary statistics [a].

Variable	Description	Own unit[b]	Other units on the same floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
		(1) Mean(SD)[g]	(2) Mean(SD)	(3) Mean(SD)	(4) Mean(SD)	(5) Mean(SD)
Price_Gfa	Unit price, HKD/square foot	5374.59(2489.617)	5563.631(2560.697)	5731.26(2700.281)	5459.595(2570.395)	6704.574(3246.555)
Total_Price	Total price per unit, HKD million	4.3408(4.1876)	4.1603(3.3557)	4.3608(3.4123)	3.9115(2.8064)	5.2623(4.2757)
GFA	Gross floor area, square foot	740.7258(303.4179)	697.7618(249.7702)	716.7722(253.394)	690.549(218.2652)	729.9423(257.3883)
Age	Age of unit in years	13.1548(9.561)	13.5061(9.9301)	12.6431(10.1456)	16.6645(9.4153)	11.0539(10.8564)
Floor	Floor number	20.8645(11.2031)	21.3512(11.7332)	22.9189(15.0903)	18.5738(12.3725)	18.9705(12.596)
After	Binary, 1 = transaction after the death incidence, 0 otherwise	0.5419(0.499)	0.4186(0.4935)	0.4436(0.4968)	0.4166(0.493)	0.3457(0.4756)
After_Event	Binary, 1 = transaction after the death and before the first transaction of haunted units, 0 otherwise	0	0.2187(0.4135)	0.3077(0.4615)	0.3349(0.472)	0.2904(0.454)
After_Tran	Binary, 1 = transaction after the first transaction of haunted units, 0 otherwise	0.5419(0.499)	0.1999(0.4)	0.1359(0.3427)	0.0816(0.2738)	0.0553(0.2286)
Murder	Binary, 1 = transaction associated with murder, 0 otherwise	0.0645(0.2461)	0.0595(0.2367)	0.047(0.2116)	0.0226(0.1486)	0.0036(0.0598)
Suicide	Binary, 1 = transaction associated with suicide, 0 otherwise	0.8323(0.3742)	0.8499(0.3572)	0.8221(0.3824)	0.8941(0.3078)	0.9186(0.2734)
Accident	Binary, 1 = transaction associated with accident, 0 otherwise	0.0968(0.2961)	0.0832(0.2763)	0.1218(0.3271)	0.0663(0.2488)	0.0772(0.267)
Local	Binary, 1 = transaction associated with local buyers, 0 otherwise	0.8194(0.3853)	0.8742(0.3317)	0.8621(0.3448)	0.8785(0.3267)	0.8258(0.3793)
Firm	Binary, 1 = transaction associated with firm buyers, 0 otherwise	0.1065(0.3089)	0.0583(0.2344)	0.0651(0.2467)	0.0603(0.238)	0.0708(0.2565)
Other	Binary, 1 = transaction associated with other buyers, 0 otherwise	0.0742(0.2625)	0.0674(0.2509)	0.0727(0.2597)	0.0612(0.2398)	0.1034(0.3045)
Observation		310	1646	92639	2195966	800757

[a] Year and month dummies as well as building tower dummies are not included in the summary statistics.
[b] Own unit refers the unit receiving the unnatural death.
[c] Other units on the same floor exclude the haunted units.
[d] Other floors in the same building exclude the floor occurring unnatural death.
[e] Other buildings in the same estate exclude the towers occurring the unnatural death.
[f] Other estates within 300 m refer boundary estates without any death incidence.
[g] SD refers standard deviations.

sectional and intertemporal variation in the incidence of the unnatural death allows us to explore the impact while controlling for building fixed effects and year-by-month fixed effects. Specifically, we adopt the following specification to implement the identification strategy:

$$P_{it} = a_0 + a_1 Shock_{st} + a_2 X_{it} + \mu_j + \tau_t + \varepsilon_{it}, \tag{1}$$

where P_{it} is the log total price of unit i transacted at time t. $Shock_{st}$ is a dummy variable that takes a value of 1 if the unit is sold after the death within a geographic scope of s, and otherwise takes a value of 0. X_{it} is a vector of unit characteristics, including the natural logarithm of unit size (GFA), unit age (Age), and floor number (Floor). μ_j is a building tower fixed effect to capture specific time-invariant building characteristics,

Table 5
Effect of death incidence on housing values by identifiable scope [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event	−0.2538*	−0.0451***	−0.0263***	−0.0111***	0.0046***
	(0.1297)	(0.0158)	(0.0082)	(0.0007)	(0.0012)
Unit Characteristics[g]	YES	YES	YES	YES	YES
Tower Fixed Effects	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES
R Squared	0.9952	0.9787	0.9697	0.9689	0.9755
Observations	310	1646	92639	2195966	800757

[a] The table summarizes our baseline results for housing externalities of unnatural death at different identifiable scopes. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

and τ_t is the year-by-month fixed effect. ε_{it} is the error term. The standard errors are clustered at the building tower level.

To explore the geographic scope of the spillover effect, we vary the index s in a set of regressions to include only the unit itself first, then other units on the same floor, other floors in the same building, other buildings in the same estate, and other estates within 300 m. The varying magnitude of the estimated a_1 helps us to understand the extent to which the impact of unnatural death disperses spatially. As shown in Column 1 of Table 5, units in which unnatural deaths occurred experience a 25% drop in value following the incidence. Nearby units on the same floor also receive a significant price drop, of 4.5%, as shown in Column 2. Columns 3–5 show that the magnitude of the spillover effect drops steadily as the geographic scope expands across the set of definitions, until it reverses to a positive impact at the 0.46% level for other estates within 300 m. This result suggests that potential homebuyers might deliberately choose to avoid estates that have units in which unnatural deaths have occurred, and instead search for housing in other estates in relatively close proximity.

As indicated earlier, only a small subset of all deaths report the specific housing unit number in which the incidence occurred. Hence, the identification of the own-unit impact solely relies on this small sample of the data (310 transactions with unit numbers identified and that have received the shock at a certain point in time during the sample period). The impact of the unnatural death on other units of the same floor is identified by including other unit transactions on the same floor as the identified death unit (1646 observations). With regard to identifying the impact on units on other floors in the same building, we expand the sample to include deaths that can be identified at the floor level. Doing so increases the sample size to 92,639 observations. Similarly, Column 4, which presents the impact on other buildings in the same estate, further expands the sample to include those deaths that can be identified only at the building level. Column 5 further includes those deaths that can be identified only at the estate level.

Next, we delve deeper into the challenge associated with multiple treatment that occurs in this same set of geographic scopes. Although we find multiple death incidence at both the tower and estate levels (shown in Table 3), each death is likely to be independent of one another. Through the case description on each death, nearly all deaths are due to social, economic, or psychological reasons rather than poor quality or maintenance of housing properties. We run simple OLS regressions to examine the relationship between a dummy on whether a unit with a death and unit attributes at different levels, and we find that unit attributes do not explain whether a death event occurs. The results are shown in Appendix Table A4.

The initial set of analysis simply treats each death as an independent occurrence and estimates an average treatment effect across all deaths. However, the impact of a sequence of shocks imposed on the same estate might vary in magnitude. We further specify the model to capture this multiple treatment effect. Table 6 shows that the effects of death incidence on other floors in the same building (column 3) tend to increase for estates without multiple shocks on building towers. Table 7 shows that the average effect of death incidence tends to decline as estates receive more death shocks.

Another focus of the study is to explore the temporal scope of the spillover effect. The idea is that the impact of the shock at the very beginning is potentially large owing to immediate psychological responses. However, over time, the impact might be diluted when the death has been forgotten. A better understanding of the long-term impact of the incidence is importance for accurately assessing welfare losses following the death. To capture this temporal pattern, we run a similar set of the regressions controlling the time lag following the death. Table 8 shows that the impact is dramatically sustained for units that have received a death shock. The drop in price started immediately following the shock, but persisted even many years after the incidence. For units in other scopes, the price evolution takes a U shape, and the price continuously declines for 4–5 years.

Next, we explore the heterogeneity of the effect of death incidence by type of death and type of homebuyer. As documented in the previous section, the effect of death incidence on housing price might vary by the

Table 7
Effect of death incidence on housing values by number of deaths [a].

Identifiable Scope[b]	Other Units on the Same Floor[c]	Other Floors in the Same Building[d]	Other Buildings in the Same Estate[e]	Other Estates within 300 m[f]
	(1)	(2)	(3)	(4)
Estates with one death shock	−0.0853 (0.0876)	−0.0884*** (0.0286)	−0.0567*** (0.0119)	0.0115*** (0.0041)
Estates with two death shocks	−0.0567 (0.0612)	−0.0563*** (0.0195)	−0.0504*** (0.007)	−0.0057 (0.0034)
Estates with three (or more) death shocks	−0.0291 (0.017)	−0.0105 (0.0067)	−0.0092*** (0.0007)	−0.0047*** (0.0012)

[a] This table summarizes the results of three regressions based on the number of unnatural deaths within estates. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level. All regressions control the unit characteristics, tower fixed effects and time fixed effects.
[b] We don't run the unit effect as the sample size is relatively small in each regression.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.

Table 6
Effect of death incidence on housing values without multiple shocks at the tower level [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event	−0.2396 (0.1749)	−0.0587*** (0.0197)	−0.0418*** (0.0109)	−0.0121*** (0.0008)	0.0058*** (0.0015)
Unit Characteristics[g]	YES	YES	YES	YES	YES
Tower Fixed Effects	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES
R Squared	0.996	0.9785	0.9685	0.9638	0.9755
Observations	242	1255	68866	1691872	654280

[a] The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table 8
Temporal effect of death incidence on housing values [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After1 × Event	−0.3117**	−0.0324*	−0.013**	−0.0054***	0.01***
	(0.1341)	(0.0171)	(0.0064)	(0.0008)	(0.0017)
After2 × Event	−0.2153	−0.0491***	−0.0235***	−0.0134***	0.0093***
	(0.251)	(0.0183)	(0.0081)	(0.0009)	(0.0019)
After3 × Event	−0.2466	−0.0251	−0.0305***	−0.0207***	0.0056**
	(0.182)	(0.0222)	(0.0099)	(0.0012)	(0.0027)
After4 × Event	−0.1935	−0.0538**	−0.0306***	−0.0216***	0.0007
	(0.1797)	(0.0238)	(0.0107)	(0.0013)	(0.0022)
After5 × Event	−0.3118	−0.0588**	−0.0235**	−0.0164***	−0.0003
	(0.2405)	(0.0249)	(0.0119)	(0.0013)	(0.0024)
After6 × Event	−0.2952	−0.0563**	−0.0211	−0.0111***	−0.0008
	(0.2291)	(0.0265)	(0.0129)	(0.0011)	(0.0026)
After7 × Event	–	−0.0521*	−0.0161	−0.0025**	−0.0005
	–	(0.0268)	(0.0135)	(0.0011)	(0.0032)
After8 × Event	–	−0.0344	−0.0112	0.0044***	−0.003
	–	(0.031)	(0.0139)	(0.001)	(0.003)
After9 × Event	–	−0.0387	−0.0035	0.0102***	(0.0047)
	–	(0.0345)	(0.0147)	(0.0012)	(0.0043)
After=>10 × Event	–	−0.0188	(0.0091)	0.0099***	−0.0004
	–	(0.0351)	0.0172	(0.0017)	(0.004)
Unit characteristics[g]	YES	YES	YES	YES	YES
Tower fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R squared	0.9956	0.9788	0.9699	0.9691	0.9762
Observations	310	1646	92639	2195966	800757

[a] The table shows the results of temporal effect of death incidence on different identifiable scopes. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence. As we don't have enough samples to capture all temporal variations after controlling the tower and time fixed effects, our estimation stops at year 6 (After=>6) at the unit level, while other scopes stop at year 10 (After=>10).
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

degree of violence involved. We should observe a large price decline due to deaths with deep psychological impact. Table 9 reports those results. We find that the impact is strongest for murder cases and is not present for accidents. Suicides seem to have the strongest spillover impact to the neighborhood. There may be concern that murder and suicide cases are well reported on social media, which can affect the price variation. However, wide media coverage can be regarded as evidence of deep psychological impact of murders and suicides.

Lastly, we examine the price variation by type of homebuyer. Different groups of buyers may have different levels of psychological recognition with respect to Feng Shui beliefs. Table 10 shows that local buyers are the most sensitive group to death incidence. Investment firms are also quite sensitive to the negative shocks of death incidence, especially for units within the same building towers. However, for other non-local buyers, including mainland Chinese homebuyers, the impact of death incidence on property values is relatively small, except for units in which the death shocks occurred.[13] As the sorting mechanism may exist for less superstitious buyers, these buyers sort into buying “haunted” units or live close to them. Given this, we estimate the upper envelope of the bidding functions of all types of buyers. The price differentials among all these buyers in the study refer to the possibility of the stigma effects triggered by the superstitious belief. In other words, because superstition matters in bidding for the “haunted” housing units, those holding stronger beliefs sort away from these units. This behavior generates a lower price for the haunted units in the hedonic regression (upper envelope of the bidding functions).

5. Robustness checks

As we can only identify 250 death incidences at the unit level, concern may arise about the difference between the 250 cases and other death incidences that cannot be identified at the unit level. In this section, we present three further robustness checks. The first one is the regression on housing estates corresponding to those 250 death incidences, and the results are shown in Table 11.

We find similar housing externalities in the different geographic scopes when we focus on estates in which the death incidence can be identified at the unit level. This finding indicates that other estates with death incidence identified at tower and estate levels share similar housing externalities within and across housing estates. Another concern is that the current unit- and floor-level estimation could be overestimated, since nearly all murder cases can be identified at the unit level. We run another regression by excluding murder cases, and the results are shown in Table 12.

The results show that the unit and floor effects are slightly lower than in the full sample regression, but the effects on other spatial scopes are nearly identical. Again, the overall patterns of spatial decay remain the same. Lastly, we add back disease cases as a robustness check. There are 140 disease cases, but most of them can be identified only at the building and estate levels. The results are shown in Table 13.

After including the disease cases, the results for different types of death are nearly identical to those estimated before. However, all coefficients on the disease are relatively small and insignificant. This result

[13] We run an F-test to examine whether the coefficients between local buyers and other buyers are different. The F-test is very significant from columns (2) to (4), indicating that other buyers are not sensitive to the housing externalities of unnatural death. However, at the unit level (the first column), the F-test is significant only at 13%, and therefore, we cannot reject the hypothesis that other buyers also care about unnatural death if they live in the haunted units.

Table 9
Effect of death incidence on housing values by type of deaths [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event × Murder	−0.6083***	−0.1066*	−0.0514	−0.0009	0.0057
	(0.1833)	(0.0638)	(0.0373)	(0.0044)	(0.0038)
After × Event × Suicide	−0.2406*	−0.0419**	−0.0259***	−0.0114***	0.0048***
	(0.127)	(0.0167)	(0.0087)	(0.0008)	(0.0012)
After × Event × Accident	−0.1107	−0.0371	−0.0121	−0.0068***	0.002
	(0.2111)	(0.0268)	(0.0216)	(0.0023)	(0.0031)
Unit characteristics[g]	YES	YES	YES	YES	YES
Tower fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R squared	0.9959	0.9788	0.9698	0.9689	0.9755
Observations	310	1646	92639	2195966	800757

[a] The table shows the results of death incidence by type of deaths. The dependent variable is the log unit total price (lnTotal_Price). The three main independent variables are the type of death interacted with time and event dummies. We don't include the unclassified type of death in the regression. Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table 10
Effect of death incidence on housing values by type of homebuyers [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event × Locals	−0.261**	−0.0465***	−0.0288***	−0.0125***	0.0005
	(0.1292)	(0.0162)	(0.0082)	(0.0008)	(0.0012)
After × Event × Firms	−0.3079	−0.0723***	−0.0181*	−0.0024	0.0284***
	(0.2196)	(0.0275)	(0.0095)	(0.002)	(0.0034)
After × Event × Others	−0.2284	−0.0153	−0.0062	0.0005	0.0206***
	(0.1641)	(0.0215)	(0.0092)	(0.0015)	(0.0034)
Unit characteristics[g]	YES	YES	YES	YES	YES
Tower fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R squared	0.9952	0.9788	0.9698	0.969	0.9755
Observations	310	1646	92639	2195966	800757

[a] The table shows the results of death incidence by type of homebuyers. The dependent variable is the log unit total price (lnTotal_Price). The three main independent variables are the type of homebuyers interacted with time and event dummies. Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

is consistent with the view that disease does not account for haunted housing, and the negative effect on nearby units should be small.

6. Mechanism of death incidence on housing price

Section 4 shows the housing externalities of the unnatural death incidence, and it seems that the stigma effect is likely to be the main channel of housing externalities. This section further explores the price mechanism of death shocks by ruling out other channels: the crime risk effect and price contagion effect.

Linden and Rockoff (2008) and Pope (2008) both documented the crime risk of sexual offenders on housing values. Households have less willingness to pay for units closer to sexual offenders, because these households are concerned about crime risk. Our study involves certain type of crimes (2% murder and 90% suicide), but both have very different natures to the sexual offender type. Sexual offenders can conduct their crimes multiple times, but both murders and suicides are one-time events, as criminals are either die or are sent to jail. In addition, suicide is a personal action, and usually presents no direct harm or threat to other households.

The previous section (Table 2A) shows that households living in a poor neighborhood are more likely to experience deaths. This risk is likely to be the result of poverty or other social and economic reasons, and is not at all related to death incidence per se. In another words, one death does not trigger or increase the possibility of another death in the same estates. Deaths within the same neighborhood should be independent of each other. Intuitively, after controlling for household income level, the number of deaths across estates should largely depend on the scale of estates. We should observe more deaths in large-scale estates, which can be indicated by the number of units, average unit size (GFA), and time on the market (building age). As deaths are a rare event (relative to number of households), we apply a Poisson model to examine the relationship between the numbers of unnatural deaths and estate scales. Table A5 gives the variable definitions and summarizes the statistics for the following Poisson regression. All the independent variables use log form, and thus, the coefficient can be interpreted as elasticity. The regression controls the neighborhood fixed effect and standard deviations are clustered by neighborhoods. The results are summarized in Table 14.

Table 11
Effects within estates covering 250 identified unit death shocks [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event	−0.2538*	−0.0451***	−0.0188***	−0.0111***	0.0028**
	(0.1297)	(0.0158)	(0.0071)	(0.0007)	(0.0012)
Unit Characteristics[g]	YES	YES	YES	YES	YES
Tower Fixed Effects	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES
R Squared	0.9952	0.9787	0.9704	0.9696	0.9778
Observations	310	1646	79772	1956788	555875

[a] The table shows the results of death incidence within estates, where haunted units occur. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table 12
Effect of death incidence on housing values without murder cases [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event	−0.2228*	−0.0404**	−0.0238***	−0.0111***	0.0046***
	(0.1254)	(0.0159)	(0.0083)	(0.0007)	(0.0012)
Unit Characteristics[g]	YES	YES	YES	YES	YES
Tower Fixed Effects	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES
R Squared	0.9959	0.9788	0.9691	0.9688	0.9755
Observations	290	1548	88286	2146385	797883

[a] The table shows the results of death incidence on housing values by excluding the murder cases. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table 13
Effect of death incidence on housing values including disease [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After × Event × Murder	−0.6083***	−0.1056*	−0.0514	−0.0005	0.0057
	(0.1839)	(0.0636)	(0.0373)	(0.0042)	(0.0041)
After × Event × Suicide	−0.2406*	−0.0419**	−0.0259***	−0.0113***	0.005***
	(0.1274)	(0.0166)	(0.0087)	(0.0008)	(0.0012)
After × Event × Accident	−0.1107	−0.0367 (0.0268)	−0.0119 (0.0216)	−0.0071*** (0.0023)	0.0043 (0.0028)
	(0.2118)				
After × Event × Disease	−0.0257	0.0354	−0.0106	0.0028	−0.0013
	(0.7384)	(0.0525)	(0.0112)	(0.0022)	(0.0017)
Unit characteristics[g]	YES	YES	YES	YES	YES
Tower fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R squared	0.996	0.979	0.97	0.9694	0.9767
Observations	312	1655	94682	2454027	956761

[a] The table shows the results of death incidence by type of deaths including 140 disease cases. The dependent variable is the log unit total price (lnTotal_Price). We don't include the unclassified type of death in the regression. Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table 14
Numbers of deaths with respect to the scale of estates [a].

Dependent Variable	Count numbers	Count numbers	Count numbers	Count numbers	Count numbers
	(1)	(2)	(3)	(4)	(5)
Log(number of units in each estate)[b]	0.9919***	1.0017***	0.996***	1.002***	1.0014***
	(0.0487)	(0.0452)	(0.0499)	(0.0481)	(0.0482)
Log(age of estate)[c]	–	0.9198***	0.9967***	0.9284***	0.9339***
	–	(0.1126)	(0.1361)	(0.1966)	(0.1986)
Log(average unit size in each estate)[d]	–	–	0.3142	0.3651	0.5702
	–	–	(0.2463)	(0.246)	(0.4935)
Log(average unit price/sf in each estate)[e]	–	–	–	−0.2361	–
	–	–	–	(0.3887)	–
Log(average total unit price in each estate)[f]	–	–	–	–	−0.2092
	–	–	–	–	(0.384)
Neighborhood fixed effect	YES	YES	YES	YES	YES
Pseudo R2	0.5137	0.5417	0.5402	0.5404	0.5404
Observation	973	959	834	834	834
Deviance goodness-of-fit	801.197	688.8493	614.5643	613.9971	614.1031
Prob > chi2[g]	0.9013	1	0.9951	0.9987	0.9987

[a] The table shows the results of Poisson regressions to illustrate the relationship between the number of deaths within each estate and the scale of estate. The dependent variable is count number of death incidence within each estate. The independent variables include number of unit, age and average unit size of estate, in which can indicate the scale of estate.

[b] The number of units in each estate is from the Centaline Property, which is one of the largest housing vendor in Hong Kong.

[c] The age of estate is accounted by the year of 2015 (2015 – construction year). The construction year of each estate is from the Centaline Property.

[d] The average unit size of each estate is accounted based on the transacted units from 2001 to 2015.

[e] The average price of each estate is accounted based on the price of transacted units from 2001 to 2015.

[f] The average unit total price of each estate is accounted based on the unit total price of transacted units from 2001 to 2015.

[g] The Prob > chi2 demonstrates a perfect fit for the Poisson regression.

Columns (1)–(3) report the elasticity of the number of deaths and scale of estates. We find that the elasticities of the number of deaths with respect to the number of units and age of estates are both close to 1, and the results are very robust. The coefficient on the average unit size of estate is also positive, although not significant. In columns (4) and (5), we add the log(price) and log(total price) to indicate the average housing value and household wealth level, respectively. Both coefficients are negative, although not significant. Table 14 also reports the deviance of goodness-of-fit and all models appear to be a perfect fit to Poisson regression. One assumption of the Poisson model is that each event is independent given the same interval of time. The regression results seem to support that death incidences within a neighborhood are independent, and thus, we can largely rule out the crime risk perception channel.

Next, we explore whether the price effect by death incidence is triggered through the price contagion channel, as the haunted units are sold with an average discount of 25%. This channel is highlighted by Campbell et al. (2011), who estimated the housing price externalities caused by foreclosure sale in the state of Massachusetts in the United States. On average, foreclosure units experience a price drop of 27%, and the housing price for units within 0.05 miles also declines 1%. In our study, units with deaths have the largest and most sustained price drop. If the prices of other units are affected through the channel of price contagion, we should observe a significant price decline after the first transaction of haunted units. To examine the effect of price contagion, we create two new dummies: event dummy (after_event) and transaction dummy (after_tran) to separate the effects of death incidence and the first sale of haunted units. The regression results are reported in Table 15.

We find that all coefficients on the event dummies are very significant, indicating that other units are significantly affected by a death. By comparison, the coefficients on the transaction dummy are relatively small and not significant, except for other buildings in the same estate shown in column (4). However, Table 8 (column 4) shows that price tends to decline for 4 years after the death. As the first transaction of haunted units occurs 2.63 years after the death on average, the results shown in column (4) cannot provide much evidence to support the price contagion channel. Instead, the result demonstrates that the stigma effect is the main channel for the housing externalities.

7. Conclusion

In-house unnatural deaths are a common phenomenon within neighborhoods. In Hong Kong, nearly 6000 unnatural deaths were reported from 2001 to 2015.[14] This study documents the impact of unnatural death incidence on housing values. Using various difference-in-differences analyses, we find that haunted units lost more than 25% in value over a 15-year time window (2001–2015). Other units are also affected, but the magnitude depends on the geographic scope. The price evolution of other affected units appears to be U shaped, and the price starts to reverse 4–5 years after a death. Furthermore, the effect of death impact varies by type of death, and type of homebuyer. We confirm that the housing externalities of unnatural death incidence are mainly through the stigma effect, rather than other channels.

Our study complements the existing literature on housing externalities with several distinct features. First, we aid understanding of the role of psychology on housing values. Although many studies emphasize the role of psychological/behavior impact on asset values, most of these studies focus on highly liquid assets, such as stocks. Even though housing is one of the most important asset classes, research on the impact of psychological/behavior on the housing market is still limited. Our study finds that psychological recognition through cultural beliefs has a profound impact on neighborhood values. Second, our examination focuses on long-term effects, rather than short-term horizons of 1–2 years. As housing prices in other units continuously decline for 4–5 years, the short-term estimation is unlikely to be accurate. Table A6 summarizes the difference-in-differences results by employing different time windows, and confirms that short-term estimation underestimates the price decline and welfare losses. Third, our study performs multiple dimensional examinations to understand the effect of death incidence on neighborhood values through spatial, temporal, and heterogeneous analysis, thereby helping to understand the stigma effect of death incidence on housing values from broader perspectives.

The implications of this study should not be limited to Hong Kong and other Chinese societies where Feng Shui culture is prevalent. In fact,

[14] The two public websites report more than 8000 unnatural death incidences from 2001 to 2015, but there are many duplicates.

Table 15
Stigma effect VS price contagion [a].

Identifiable Scope	Own unit[b]	Other units on the same Floor[c]	Other floors in the same building[d]	Other buildings in the same estate[e]	Other estates within 300 m[f]
	(1)	(2)	(3)	(4)	(5)
After _Event	–	−0.0566***	−0.0289***	−0.0119***	0.0052***
	–	(0.0164)	(0.0081)	(0.0008)	(0.0012)
After_Transaction	−0.2538*	−0.0171	−0.0168	−0.0072***	0.0013
	(0.1297)	(0.02)	(0.012)	(0.0011)	(0.003)
Unit characteristics[g]	YES	YES	YES	YES	YES
Tower fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R squared	0.9952	0.9789	0.9698	0.9689	0.9755
Observations	310	1646	92639	2195966	800757

[a] The table shows the results of stigma effect vs price contagion. The dependent variable is the log unit total price (lnTotal_Price). The two main independent variables are explained in Table 4. Standard errors are clustered at the building tower level.
[b] Own unit refers the unit receiving the death incidence.
[c] The floor effect regression excludes haunted units.
[d] The building effect regression excludes floors receiving death incidence.
[e] The externalities within the same estates exclude the building towers receiving death incidence.
[f] The boundary estates don't have any death incidence.
[g] Unit characteristics include log(GFA), log(Age), and log(Floor).

death is a taboo subject in many societies, including many Western countries, such as the US and UK (Walter, 1991), and death incidence is likely to affect a household's willingness to pay for housing in many place around the world. As in-house unnatural death incidence is not an uncommon phenomenon (compared to crime), its impact on housing values should not be neglected. More broadly, our study illustrates the importance of psychological/behavioral impact on housing price of tradition and cultural beliefs. We hope that further research can reveal the physiological/behavioral effects on households' willingness to pay in housing markets, which would certainly deepen our understanding of housing externalities and asset pricing.

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Appendix

At the revise and resubmit stage of this paper, we came to know a paper by Bhattacharya et al. (2017) that studies a similar question in the same setting. Despite variations in sample size and measures taken to account for the geographic and temporal scope, we obtained similar main results. The consistency reassures the replicability of our main findings. To further mark the differences between our paper and Bhattacharya et al. (2017), we show a detailed comparison in Table A1.

Table A1
Comparison of our paper with Bhattacharya's paper.

		This Paper	Bhattacharya et al. (2017)
Data Source	(1)Housing Transaction Data	974 estates	214 out of 7352 estates (2.9%)
	(2)Haunted Housing Data	2 public websites (http://www.property.hk/unlucky/https://www.squarefoot.com.hk/haunted/) and information provided by a private consulting firm	4 public websites (http://www.property.hk/unlucky/https://www.squarefoot.com.hk/haunted/, www.hk-compass.com/badfile.php, www.spacious.hk/en/hong-hong/resources/tragic-events)
	(3)Sample period	From 2001 to 2015	From 2000 to 2015
	(4)# of Death Event	934 unnatural death with 250 cases with specific housing units identified	898 unnatural death with 165 cases with specific housing units identified
Empirical Analysis	(5) Time scope	Long run effect	Short run effect
	(6) Spatial Scope	Housing Externalities Units beyond the same estate	Asset Pricing Units within the same estate
	(7) Temporal Scope	DID	DID
	(8) Multiple treatment	Yes	No
	(9) Heterogeneous	Death type and buyer type	Death type
	(10) Mechanism	Stigma, Crime Risk, Price Contagion	Quality versus Firesale

Specifically, we highlight the difference between these two papers in two broad aspects: data and empirical analysis. Related to data, we found four major differences:

First, the transaction data employed in both exercises come from the same source, EPRC.ltd, the largest data vendor in Hong Kong. From this data, we have obtained 974 estates for our analysis. Bhattacharya et al. (2017) indicated that they chose 214 estates out of 7352 estates in total –only large estates with more than 1000 units. Based on a follow-up call with EPRC.ltd, our sample of 974 estates is more consistent with EPRC's records. We didn't restrict our sample to large estate.

Second, data on the incidence of unnatural death come from partially different sources for these two papers. Our data come from two public websites[1] and one private real estate consulting firm.[2] The public websites complement each other in providing the information related to in-house death in Hong Kong.[3] However, the public sourced data do not identify the specific unit in which the death occurred – 75% identified at the tower level and 45% identified at the floor level. The data obtained from the private consulting firm provides a few additional records of deaths but largely agree with the general information provided in the two public websites. More importantly, it helps to identify 250 units in which the death occurred. This detailed information allows us to separately identify the impact on the unit itself and other nearby units on the same floor. The data in Bhattacharya et al. (2017) are from four public websites. Two overlaps with our sources and the other two are www.hk-compass.com/badfile.php and www.spacious.hk/en/hong-hong/resources/tragic-events. We have double checked and confirmed that information provided in these two additional sites won't improve the number of identified units based on what has already been captured in our public and private combined dataset.

Third, the sample period and total number of observations are slightly different. Our final sample is from 2001 to 2015. It starts from 2001 as one of the largest public website (http://www.property.hk/unlucky/) was founded in July 2000 and records in the initial few months seem not very complete. It ends in 2015 as the data from the private consulting firm end in 2015. Bhattacharya et al. (2017) use data from 2000 to 2015. Given that the Bhattacharya et al. (2017) select on large estates while we use all identified estates, we have larger number of observations even with a sample period that is one year less than that in Bhattacharya et al. (2017).

Fourth, Bhattacharya et al. (2017) has identified 898 unnatural death in total and 165 cases with specific housing units identified. We have identified 934 unnatural death with 250 cases with unit identified. This information on the specific death unit is from the private consulting firm mentioned above. Bhattacharya et al. (2017) didn't reveal the source of the information for the 165 unit identified cases in their most recent version. (This information is not provided in the public websites indicated in the paper).

Related to empirical analysis, we summarize the differences from six perspectives. First, we focus on the long run impact of the unnatural death since the negative shocks could have long term impact on housing values given the asymmetric nature of real properties (Glaeser and Gyourko, 2005). Bhattacharya et al. (2017) largely measures the short run effect.

Second, we examines a broader geographic scope of the impact of unnatural death. We separate the impact into own unit effect, impact on nearby units on the same floor, impact on units on other floors of the same building, impact on units in other buildings of the same estate, and impact on units outside the estate but within 300 m radius. Bhattacharya et al. (2017) has focused on the effect within the estates, without extending the analysis to other nearby estates.

Third, we examine the temporal pattern of the impact for an extended period of time.

Fourth, there are cases with multiple death treatment within an estate. We have separately identified these estates and find the marginal impact of unnatural death tends to decline as more shock within the sample building and the same estates occurs (see Tables 6 and 7). Bhattacharya et al. (2017) didn't take this into consideration when designing their empirical specifications.

Fifth, we consider heterogeneity along two dimensions: death type and buyer type. Bhattacharya et al. (2017) considers only death type.

Lastly, we consider three channels through which the impact may come to play: the stigma effect, potential crime risk, and the price contagion effect. Bhattacharya et al. (2017) approaches the question from ther perspective of quality channel versus fire sale effect.

Table A2
Numbers of deaths and average housing price of estates [a].

Dependent Variable	Count numbers	Count numbers
	(1)	(2)
log(average price per square foot)[b]	−0.6834** (0.2873)	
log(average total unit price)[c]		−0.362* (0.1879)
Neighborhood fixed effect	YES	YES
Pseudo R2	0.1762	0.1769
Observation	834	834

[a] The table shows the results of negative binomial regressions to illustrate the relationship between the number of deaths and the average housing price of estate. The dependent variable is count number of death incidence within each estate. As many estates don't have transaction price information, the number of estates is 834 in this table. Standard errors are in parentheses.

[b] The average price of each estate is accounted based on the price of transacted units from 2001 to 2015.

[c] The average unit total price of each estate is accounted based on the unit total price of transacted units from 2001 to 2015.

Table A3
The pre-trend examination between treated and other control groups[a].

Identifiable Scope	Tower - Linear	Tower -Quadratic	Tower - Cubic	Estate -Linear	Estate - Quadratic	Estate - Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Linear time trend × death dummy	−3.33e-06	−8.1e-04**	−2.4e-04	7.25e-06	6.6e-04*	2.3e-04
	(0.0001)	(3.5e-04)	(5.6e-04)	(9.65e-05)	(3.4e-04)	(5.6e-04)
Quadratic time trend × death dummy	–	5.15e-06***	−3.4e-06	–	4.27e-06**	−9.08e-06
	–	(1.91e-06)	(6.84e-06)	–	(1.88e-06)	(6.81e-06)
Cubic time trend × death dummy	–	–	3.43e-08	–	–	5.35e-08**
	–	–	(2.56e-08)	–	–	(2.53e-08)
Unit Characteristics[b]	YES	YES	YES	YES	YES	YES
Tower Fixed Effects	YES	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES	YES
R Squared	0.9695	0.9696	0.9696	0.9716	0.9716	0.9716
Observations	331515	331515	331515	382237	382237	382237

[a] The table shows the pre-trend examination between treated and control groups at tower and estate levels. We thank for the suggestion form a referee for the following steps: first, drop observations once a death occur at the tower level. Second, randomly drop observations from no death towers in equal shares to the death tower each period (in the same year and month) to keep the composition of the two samples the same. Third, interact a time trend (linear, quadratic, and cubic) with the dummy for the death sample. Again, the dependent variable is the log unit total price (lnTotal_Price). The main independent variable is the interaction term (time trend x

death event). We find all coefficients are all close to 0, although the quadratic regression in column (2) and (4) are significant. Standard errors are clustered at the building tower level.

[b] Unit characteristics include log(GFA), log(Age), and log(Floor).

Table A4
Unit attributes and death incidence [a].

Identifiable Scope	Units on the same floor	Units in the same building	Units in the same estate	Units in the estate and beyond
	(1)	(2)	(3)	(4)
log (Gfa)	0.0548	0.0007	8.6e-05	7.1e-05
	(0.0999)	(0.0021)	(2.6–04)	(2.2e-04)
log(Floor)	–	0.0007	8.9e-05	7.7e-05
	–	(0.0005)	(5.8e-05)	(5e-05)
log(Age of Estate) [b]	–	–	1.7e-05	1e-05
	–	–	(2.9e-04)	(2.4e-04)
Tower Fixed Effects	YES	YES	YES	YES
R Squared	0.0965	0.0045	0.0085	0.0086
Observations	1060	34563	292814	346103

[a] The table shows the OLS regression results to demonstrate the relationship between the unit attributes and whether a unit receives a death at different levels by controlling the building tower fixed effect. The dependent variable is the dummy on whether a unit has a death or not. Independent variables are major unit attributes. Standard errors are in parentheses.

[b] The age of estate is accounted by the year of 2015 (2015 – construction year).

Table A5
Variable definitions and summary statistics for Poisson regression [a].

	Description	Observations	Mean	SD
Unit[b]	Number of units in each estate	973	743.26	1340.48
Age[c]	Age of estate (Year)	974	25.66	12.75
Gfa[d]	Average gross floor area of units (sqft)	834	993.7	648.02
Price/sf[e]	Average price per sqft of units (HKD per sqft)	834	6754.56	3933.971
Total_Price[f]	Average total unit price (HKD million)	834	8.32	10.88

[a] The table summarizes variables for Poisson regression. SD refers to standard deviation.

[b] The number of units in each estate is from the Centaline Property, which is one of the largest housing vendor in Hong Kong.

[c] The age of estate is accounted by the year of 2015 (2015 – construction year). The construction year of each estate is from the Centaline Property.

[d] The average unit size of each estate is accounted based on the transacted units from 2001 to 2015.

[e] The average price of each estate is accounted based on the price of transacted units from 2001 to 2015.

[f] The average unit total price of each estate is accounted based on the unit total price of transacted units from 2001 to 2015.

Table A6
Effect of death incidence on housing values by different time windows [a].

Identifiable Scope[b]	Other Units on the Same Floor[c]	Other Floors in the Same Building[d]	Other Buildings in the Same Estate[e]	Other Estates within 300 m[f]
	(1)	(2)	(3)	(4)
1 year DID	–	0.0002	−0.0037***	0.0078***
	–	(0.0039)	(0.0007)	(0.0019)
2 years DID	−0.0115	−0.0064	−0.0082***	0.0052***
	(0.0332)	(0.0059)	(0.0009)	(0.0019)
3 years DID	−0.0431*	−0.0147**	−0.0145***	0.0058***
	(0.0261)	(0.0065)	(0.0011)	(0.002)
Full year DID	−0.0451***	−0.0263***	−0.0111***	0.0046***
	(0.0158)	(0.0082)	(0.0007)	(0.0012)

[a] This table summarizes the results of four regressions based on the different time windows. The dependent variable is the log unit total price (lnTotal_Price). Standard errors are clustered at the building tower level. All regressions control the unit characteristics, tower fixed effects and time fixed effects.

[b] We don't run the unit effect as the sample size is relatively small in each regression.

[c] The floor effect regression excludes haunted units. We don't have enough samples to run the regression within 1 year time window on the floor level.

[d] The building effect regression excludes floors receiving death incidence.

[e] The externalities within the same estates exclude the building towers receiving death incidence.

[f] The boundary estates don't have any death incidence.

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