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Published in:
Sustainability (Switzerland)

Published: 01/12/2024

Document Version:
Final Published version, also known as Publisher's PDF, Publisher's Final version or Version of Record

Published version (DOI):
10.3390/su162410809

Publication details:
Asadieh, B., & Neisch, P. M. (2024). From the City to the Suburb: City Dynamics in the Time of a Polycrisis. *Sustainability (Switzerland)*, *16*(24), Article 10809. https://doi.org/10.3390/su162410809

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From the City to the Suburb: City Dynamics in the Time of a Polycrisis

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Abstract: External events and crises significantly influence urban development. This study primarily aimed to investigate the impact of the COVID-19 pandemic on city development dynamics through structural change and spatiotemporal analysis, focusing on the Hong Kong SAR as a case study. The analysis revealed disruptions across the office, residential, and retail property sectors during late 2019 and early 2020. The findings emphasize the "Polycrisis" concept, where overlapping social, economic, and health crises amplify impacts. The office sector demonstrated greater vulnerability, particularly in higher grade offices in and near central business districts. In contrast, the residential sector showed greater resilience overall, with smaller, centrally located units being more vulnerable, while larger, peripheral units exhibited a stronger resilience. The retail market responded distinctively, with peripheral areas experiencing a greater impact than the city core, reflecting pandemic-related restrictions. In general, the findings show that the recovery from the crises is slow and might affect future land use and urban planning norms. Additionally, population trends highlighted a shift toward suburban living, with recent rising densities in peripheral districts and population declines in central areas. This study's insights contribute to policymaking, urban planning, and discussions on understanding the evolving city dynamics.

Keywords: decentralization; urban planning; migration; COVID-19; polycrisis

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Citation: Asadieh, B.; Neisch, P.M. From the City to the Suburb: City Dynamics in the Time of a Polycrisis. *Sustainability* **2024**, *16*, 10809. https://doi.org/10.3390/su162410809

Academic Editor: Hong Tang

Received: 15 October 2024
Revised: 2 December 2024
Accepted: 4 December 2024
Published: 10 December 2024

1. Introduction

Cities are complex systems that grow from within and around their peripheries. However, the traditional balanced development of central areas and suburbs shifted to city centers due to decreased reliance on cars and increased engagement in active travel [1]. The transformation of cities has long been controversial owing to the dynamic nature of city development, especially in response to external crises. One of the underlying changes in urban dynamics that has recently gained considerable importance is the impact of the pandemic on residential areas and land use [2,3]. Pandemics affect the planning and configuration of cities to solve urban deficiencies [4]. Likewise, the COVID-19 pandemic altered the urban structure and created challenges regarding the future of urban development [1,5] and health policies [6]. Changes in the use of local spaces and business districts, mobility, and movement patterns are examples of these shifts [7].

The imposed isolation during the pandemic increased physical distances, contrasting with the contemporary centralization trend that typically aimed to decrease the distance and time [8,9]. The demand for consumption amenities and short-term lodging options decreased during the pandemic, resulting in declining housing rental prices in urban areas [10,11]. In addition, the large-scale availability of working from home due to preventive measures created an awareness of suburban areas as primary or secondary residences. Consequently, the need for the proximity of dwellings to workplaces decreased, and the housing demand moved from highly populated neighborhoods to the suburbs in search of bigger and better dwellings [12–14]. Metropolitan areas with high densities experienced the most significant changes in de-densification, as they depended on the pre-pandemic density of the region [15].

The expected changes varied from decentralization to a return to centralization. For instance, in the early post-pandemic period, it was assumed that the large scale of WFH could potentially decrease office rents, increase the quantity of housing in suburbs, and impact population movements [16,17]. Nygaard and Parkinson [18] distinguished it from the traditional sprawling effect and assumed it was becoming the "new normal". On the other hand, Couclelis [19] asserts that despite the deficiencies of the current forms of cities, there will be no significant differences between the post- and pre-pandemic structures in the long term. For example, a temporary outmigration in Sydney as an effect of the pandemic shock on urban dynamics was controlled by housing policies [18].

Both decentralization and centralization can be beneficial for the citizens. While dispersed economic activity offers opportunities for neglected areas, such as a better healthcare system [20], it may come at the expense of urban agglomeration economies and pose challenges for local governments [21]. Moreover, despite the downsides of density, the effective distribution of health and public services in the most densely populated cities in the world, such as Singapore, Hong Kong, and Seoul, has helped to manage the pandemic [22]. Therefore, resistance or mitigation due to the effect of exogenous drivers might result from the agglomeration economics that can legitimate the return to central areas, offering more amenities, interactions, and social status [18]. Although cities are showing signs of recovery for this reason, the future remains uncertain in determining the ability of cities to recover post-pandemic [15]. Beck and Hensher [23] assert that recovery has been reduced and might affect future land use and transportation norms.

Regarding the impact of the COVID-19 pandemic on decentralization, scholars tracked shifts in individuals' behaviors. Ilham and Fonzone [24] reviewed residential relocation trends, revealing increased teleworking, reduced daily travel, and increased time spent indoors, which can subsequently lead to decentralization. In the United States, studies showed a significant "Donut Effect", where household, business, and real estate demands shifted from densely populated central business districts to suburban areas. This pandemic-induced trend increased the property demand and prices in suburban and rural zones while reducing real estate values within metropolitan centers, reflecting a broader decentralization pattern [25,26]. Moreover, the growing adoption of remote work in Canada was correlated with increased urban sprawl, highlighting a shift in urban planning and transportation dynamics that prioritized accommodating decentralization [27].

In Australia, property prices and the rental demand in commercial districts weakened, contrasting with a strengthened residential market in suburban areas during the pandemic's peak period. This pattern underscores a growing distinction in demand between commercial and residential spaces [7,18]. More broadly across Australia, the pandemic challenged contemporary urbanization trends, prompting discussions concerning de-urbanization, re-centering cities, and establishing new urban areas [28]. In Beijing, the pandemic highlighted decentralization trends, accelerating suburbanization among higher income home relocators while slowing it for younger, middle-income groups, leading to a more balanced population distribution [29]. Decentralization trends were further evidenced by broader international observations, including in Ireland, Germany, Portugal, France, Austria, Denmark, Finland, Hungary, Norway, Estonia, Spain, the United Kingdom, and the United States, where shifts in the housing demand moved it away from city centers. These shifts were influenced by COVID-19 restrictions and access to high-speed internet, fostering relocation to suburban or rural zones while maintaining connectivity to urban amenities [30].

Regarding methods, scholars have used various approaches to portray the possible changes in city structure concerning the decentralization of the population, including tracking postal code changes [25], bid rent theory [14,21], tracking vacancy rates and rental prices [7], and tracking shifts in residential and workplace preferences [9]. Additionally, researchers have used scenario-based models to predict the urban structure's future and found a higher possibility of the population returning to the central city [1]. However, a scenario-based model mainly depends on the defined equations, such as the prevalence of working from home and its acceptance. Other scenario-based studies [31,32] also show that telework influences relocation patterns, potentially reducing megacity pressure and leading to job shifts to central districts, increased commuting distances (despite decreased commuting times), and fluctuating real estate prices (peripheral increases, central decreases).

The persistence of the inclination toward suburban areas and its extent were utterly discussed during the pandemic since many employees were expected to continue working remotely even after the pandemic [33]. Therefore, it is anticipated that there will be significant changes in the housing demand dynamic and the allocation of economic activity within urban and suburban areas [32,34]. While not every pandemic-driven change in the urban structure is expected to last, historical evidence shows that consistent outmigration trends, similar to those in the recent pandemic, may result in long-term behavioral adjustments affecting urban development [18]. However, the review study conducted by Balemi and Füss [35] shows that the real estate market's response to the pandemic shock was diverse in different places due to its heterogeneous nature.

While previous studies have examined decentralization trends in various countries, they often fail to account for contexts like Hong Kong, where geopolitical and spatial constraints necessitate intra-city rather than inter-city decentralization. Moreover, its previous experience with a similar health crisis in 2003 during the SARS outbreak [36] makes it a distinctive context to explore. At that time, housing prices were on a five-year downward trend, making it challenging to isolate the pandemic's impact [37]. In contrast, the COVID-19 pandemic occurred after a decade-long increase in market prices. Research indicates that Hong Kong's housing market exhibited lower instability during the COVID-19 pandemic compared to the SARS outbreak in 2003 [36]. In this research, we aimed to understand the city dynamics based on the pandemic-driven changes in office, residential, and retail properties in Hong Kong.

This study examines the city dynamics based on the pandemic-driven changes in office, residential, and retail properties and explores the recent population changes. It contributes to the existing literature on housing and decentralization, such as that by Gupta and Mittal [21] and Yiu and Cheung [14], by employing distinct methodologies, including Structural Breakpoint Analysis and Spatial Hot Spot Analysis. While real estate trends reveal the market's response to external shocks, the accompanying shifts in population dynamics highlight the interconnectedness of housing preferences and urban spatial patterns. Understanding these demographic trends further contextualizes the changes in real estate markets observed by Lu and Wang [36]. In this research, we aimed to investigate the following questions:

1. Did the COVID-19 pandemic impact the structural dynamics of Hong Kong's real estate market across different sectors?
2. To what extent do rental prices and vacancy rates corresponding to residential, office, and retail properties reflect the trends caused by the COVID-19 pandemic?
3. Does the population density of residential properties confirm a relocation trend from urban to suburban areas?

The following sections cover the methods used in this research, the results of the data analysis, and the discussion that elaborates on the interpretation of the results. Finally, we conclude with the findings.

2. Materials and Methods

To explore the research questions, we used the publicly accessible real estate and population data retrieved in November 2024 from the official Hong Kong SAR government's online sources. The districts' categorization differed in scale depending on their availability. Hierarchically, the Hong Kong SAR is divided into 9 Primary Planning Units (PPUs), 51 Secondary Planning Units (SPUs), and 282 Tertiary Planning Units (TPUs). However, the official data from the Rating and Valuation (R.V.) department are based on TPUs covering specific areas. In this sense, the Hong Kong SAR comprises three major regions

(Figure 1) and 18 sub-districts (Figure 2). Six sub-districts have been identified as office sub-districts by the R.V. department (Figure 3), while data on residential and retail rates are categorized under the three major areas. The known central business district for office properties is Central, the retail market is in the Kowloon area, and the dense residential areas are Hong Kong and Kowloon.

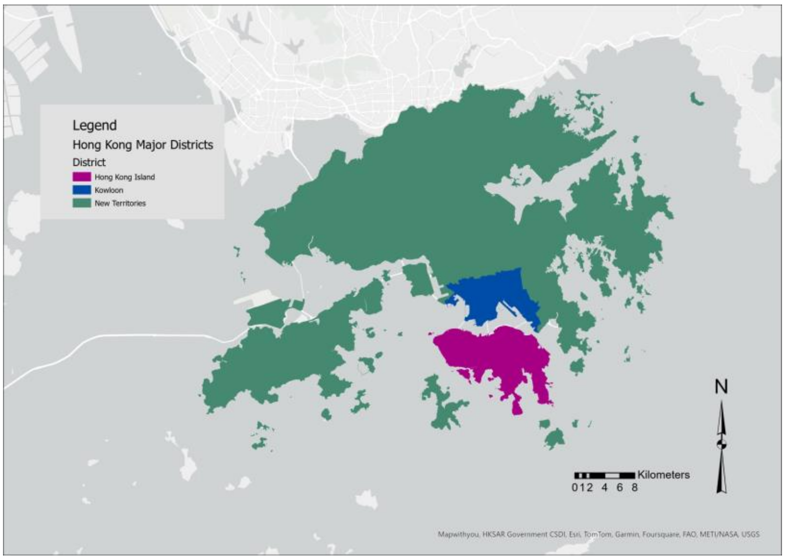

Figure 1. Major districts of Hong Kong SAR.

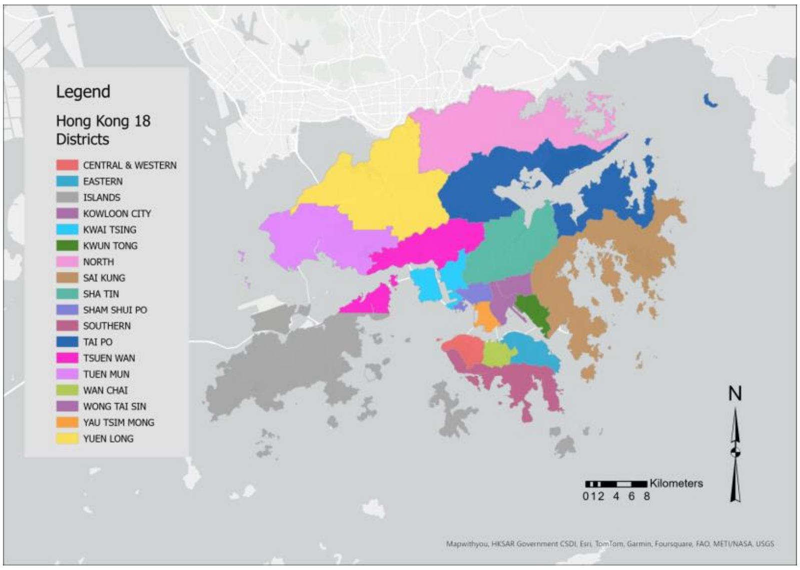

Figure 2. Sub-districts of Hong Kong SAR.

The real estate data included rental and price rates associated with residential, office, and retail properties that were categorized based on the district areas. In addition, we used the vacancy rate data to check whether the possible price and population changes could happen due to external immigration. The available format and time span for the data were monthly from January 1999 to August 2024 for the rental rates and yearly from 1985 to 2023 for the vacancies when we retrieved the data. Because of the extensive missing information in the land value data, we focused on rental rates for real estate analysis. The population data were annual and on a sub-district scale from 2001 to 2023. We turned the population into density by dividing it by the district area to better interpret the results.

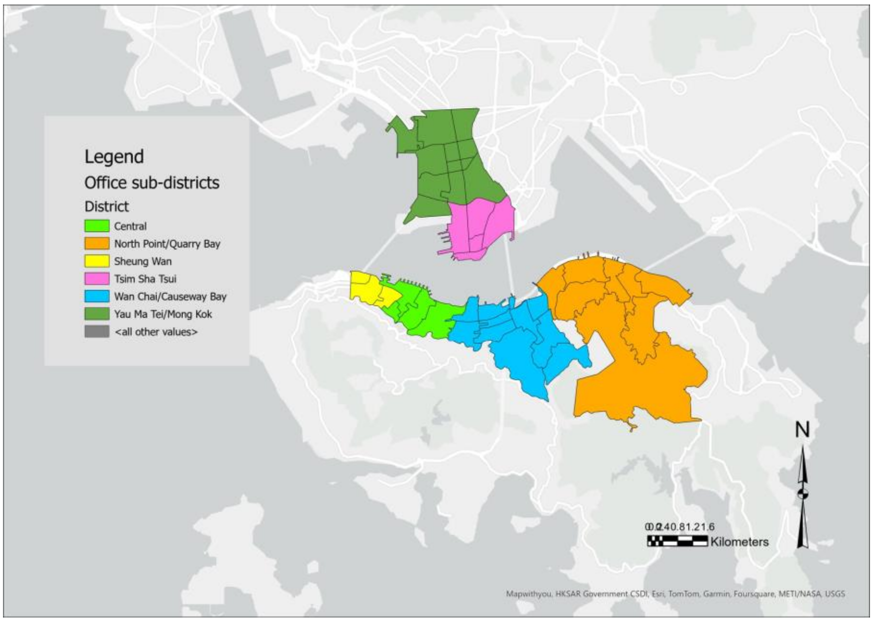

Figure 3. Office sub-districts determined by the Hong Kong SAR's Rating and Valuation department.

The technical notes released by the government of the Hong Kong SAR [38] have distinguished office grades and residential classes. From the descriptions, it can be understood that the quality of the offices decreases with the grades. Therefore, Grade A offices are considered modern with higher quality, spacious plans and better air quality. Grade B offices have an ordinary design and average quality, while Grade C offices have basic quality. For the residential categories, there are five classifications of sizes, A, B, C, D, and E, representing areas of less than 40 m^2, 40 m^2 to 69.9 m^2, 70 m^2 to 99.9 m^2, 100 m^2 to 159.9 m^2, and 160 m^2 or above, respectively. The retail data did not have categorizations other than the districts.

To examine pre- and post-COVID-19 trends, our approach consisted of two primary analyses: real estate analysis and population analysis. Changes in real estate are generally cyclical; however, in response to external forces, structural changes can occur, disrupting these patterns. These structural changes, which alter underlying economic fundamentals, can be reflected by the turning points [39]. Change points may be known or unknown [40]. Various methods can test whether changes significantly differ from the past pattern to statistically detect and determine turning points in time series. While the Chow [41] and CUSUM [42] tests are suitable for single breakpoint detection, the Bai–Perron test [43] is more effective, especially for our dataset, due to its ability to detect multiple breakpoints across a long time span. Furthermore, using the Bai and Perron test eliminates the bias of choosing specific dates, allowing for unbiased breakpoint detection across the entire dataset.

We also examined trends in the population density and descriptive projections. Since the directions of population movements are unknown, given the limitations of total population data, our analysis was limited to tests that detect spatiotemporal trends. The Mann–Kendall trend test [44] is a non-parametric statistical test for assessing monotonous upward or downward trends in time series without assuming a specific data distribution. The Getis-Ord Gi* statistic [45,46] is a spatial autocorrelation statistic that detects clustering or dispersion patterns in spatial data. It is beneficial in identifying local hot or cold spots where high or low values of a variable cluster together. Both methods have been used in investigating temporal data trends related to, but not limited to, the population [47–49], meteorology [50,51], and public health [52].

The data included a few missing data at random. Since the breakpoint statistical analysis required continuous data over the entire time span, we imputed the missing values using the Kalman smoothing algorithm implemented in the "imputeTS" package, specially written for univariate time series to maintain data continuity [53]. This method is beneficial for dynamic systems while accounting for noise and uncertainty. Importantly, imputing these few missing values was unlikely to impact the results, as the analysis was intended to capture temporal patterns characterized by inherent fluctuations and seasonality. Thus, addressing these minor gaps ensures robustness in our analysis without introducing significant bias. However, rental data for Grade E residential properties in the New Territories were only available starting in January 2019. In this case, we limited the analysis to the available timeframe without employing imputation. The population data did not have missing data, and the analyses were conducted without any imputations. Below, we outline the methodology and statistical tests applied for real estate and population analysis.

2.1. Real Estate Data Analysis Process

The Bai and Perron method is based on segmented regressions of a standard linear regression model assuming an m number of breaks ($m + 1$ segments) in the data through minimizing the sum of squares. We employed linear models to explore the fitted lines:

$$y_t = {x'}_t\beta + {z'}_t\delta_j + u_t \tag{1}$$

where

$j = 1, \ldots, m + 1$.
$t = (T_{j-1} + 1, \ldots, T_j)$, $T_0 = 0$, and $T_{m+1} = T$.
y_t is the response variable (the rates) at time t.
x_t and z_t are explanatory variables.
β and δ_j are the coefficients.
u_t represents the error term.

The indices $T_1, \ldots, T_m$ determine unknown breakpoints that partition the time series into distinct segments. The primary objective was to estimate regression coefficients in the presence of these breakpoints. Moreover, the structural breakpoints (change points) were estimated using the sum of least squares method. The formulation for determining breakpoints can be expressed as

$$(T_1^*, \ldots,\ T_1^*) = argmin_{T_1,\ldots\ ,T_m} S(T_1,\ \ldots\ ,\ T_m) \tag{2}$$

The analysis process was conducted using the "Strucchange" package in the R system to date structural changes with unknown timing and multiplicity [54]. The package uses the Bai and Perron approach to detect the breakpoints.

2.2. Population Trend Analysis Process

This section includes two tests conducted on the data.

2.2.1. Mann–Kendall Trend Test

This test is for temporal data with a length of n from $x_1, x_2, \ldots, x_n$.

$$\text{S} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}\left(x_j - x_i\right) \tag{3}$$

$$Var(s) = \frac{1}{18}\left(n(n-1)(2n+5) - \sum_{p=1}^{g} t_p(t_p - 1)(2t_p + 5)\right) \tag{4}$$

where n is the time series length and x_i and x_j represent variable values at time points i and j, respectively. The sign function sgn(*) returns the sign of its argument:

$$\text{sgn}\left(x_j - x_i\right) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \tag{5}$$

where n is the number of data points, g is the number of tied groups, and t_p is the number of tied values in the p-th group. The Mann–Kendall statistic runs on the z-scores of the space–time hot spot analysis for the selected cube variable.

Calculate the Z-statistic, which is a standardized measure, using the formula

$$Z = \frac{S}{\sqrt{Var(s)}} \tag{6}$$

The Z-statistic follows a standard normal distribution under the null hypothesis of no trend.

2.2.2. Getis–Ord Gi* Statistic

This method involves calculating a local *Gi** statistic for each spatial unit and assessing the significance of these local statistics. The process involves computing local sums ($W_i\ X_i$) and local means (W_i) for each spatial unit i, where W_i is the spatial weight for unit i and X_i is the variable of interest. The *Gi** statistic for each spatial unit uses the following formula:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{7}$$

where W_{ij} is the spatial weight between units i and j, X_j is the variable's value for unit j, X^- is the mean of all values, S is the standard deviation of all values, and n is the number of spatial units.

$$\overline{X} = \frac{\sum_{j=1}^{n} x_i}{n} \tag{8}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{9}$$

To conduct the temporal analysis, we used ArcGIS Pro software version 3.0.1. After creating the table with the temporal data associated with the districts, we created the space–time cube utilizing this table. The "Emerging Hot Spot Analysis" tool was used to conduct the assessment. The K-nearest method was chosen to conceptualize spatial relationships as it defines neighborhoods based on proximity and avoids arbitrary distances (n = 2).

3. Results

3.1. Real Estate Results

The Bai and Perron analysis identified several structural breakpoints across the office, residential, and retail real estate sectors in Hong Kong. Tables 1–4 summarize these breakpoints and the changes in slopes observed before and after each breakpoint. Due to the excessive number of graphs, we have only presented the Grade A offices to demonstrate the analysis process (Figure 4). The frequency of breakpoints is presented in Figure 5. The analysis revealed four main breakpoint clusters across the datasets for office, residential, and retail properties:

A. Early 2000s to 2004: this period included economic recovery post-Asian financial crisis (1997) and the SARS outbreak (2003), which likely influenced early breakpoints for office, residential, and retail properties.

B. 2008–2009: the global financial crisis of 2008 is a notable breakpoint across all property types, reflecting the recession's impact on the property demand and pricing in Hong Kong.

C. The mid-2010s (2013–2015): this period saw a recovery phase, with moderate growth in most real estate sectors, likely driven by economic stabilization and robust property demand.

D. End of 2019 to early 2020: breakpoints at the end of 2019 align with social unrest in Hong Kong, while those in early 2020 reflect the impact of COVID-19's first wave and subsequent lockdown measures.

Table 1. Bai and Perron analysis results for office units.

Class	District *	F	Previous Breakpoints				Latest Breakpoint			Slopes	
			B1	B2	B3	B4	2.50%	Break	97.5%	Pre	Post
Grade A	Sheung Wan	228.2	2005 (4)	2009 (2)	2013 (8)	2019 (2)	2019 (1)	2019 (2)	2019 (5)	7.07	−4.69
	Central	399.7	2004 (9)	2008 (12)	2013 (1)	2020 (04)	2020 (3)	2020 (4)	2020 (5)	5.03	−4.51
	Wan Chai	446.1	2004 (12)	2009 (1)	2014 (1)	2019 (11)	2019 (10)	2019 (11)	2019 (12)	3.07	−3.55
	North Point	152.4	2004 (1)	2009 (1)	2014 (11)	2020 (8)	2020 (1)	2020 (5)	2020 (10)	1.80	−0.65
	TST	355.2	2004 (10)	2009 (1)	2013 (2)	2020 (3)	2020 (2)	2020 (3)	2020 (5)	−0.87	1.28
	Mong Kok	147.5	2005 (1)	2013 (9)	2018 (1)	-	2017 (2)	2018 (1)	2018 (3)	−1.41	−4.97
Grade B	Sheung Wan	224.2	2004 (8)	2008 (11)	2018 (11)	-	2018 (10)	2018 (11)	2018 (12)	3.01	−1.35
	Central	215.7	2004 (8)	2009 (1)	2014 (2)	2020 (2)	2020 (1)	2020 (2)	2020 (4)	3.31	−1.31
	Wan Chai	329.3	2004 (8)	2008 (12)	2015 (9)	2020 (3)	2020 (2)	2020 (3)	2020 (6)	1.07	−0.51
	North Point	150.1	2004 (8)	2009 (1)	2015 (10)	2019 (11)	2019 (9)	2019 (11)	2020 (3)	1.87	−0.45
	TST	284.6	2003 (5)	2008 (12)	2015 (9)	2019 (12)	2019 (11)	2019 (12)	2020 (6)	0.97	−0.45
	Mong Kok	277.3	2003 (4)	2008 (12)	2015 (8)	2020 (4)	2020 (2)	2020 (4)	2020 (6)	0.67	1.07
Grade C	Sheung Wan	322.8	2004 (7)	2008 (12)	2015 (2)	2019 (9)	2019 (8)	2019 (9)	2020 (3)	0.91	−0.52
	Central	295.5	2004 (7)	2008 (12)	2013 (7)	2019 (9)	2019 (8)	2019 (9)	2020 (1)	1.70	−0.57
	Wan Chai	253.1	2003 (11)	2008 (11)	2015 (8)	2020 (3)	2020 (2)	2020 (3)	2020 (7)	1.12	0.03
	North Point	265.8	2004 (5)	2008 (11)	2013 (1)	2019 (9)	2019 (8)	2019 (9)	2019 (12)	1.19	−0.04
	TST	214.5	2003 (9)	2008 (12)	2015 (9)	2020 (1)	2019 (10)	2020 (1)	2020 (4)	0.58	0.35
	Mong Kok	293.9	2003 (7)	2008 (11)	2015 (12)	2019 (11)	2019 (10)	2019 (11)	2020 (6)	1.60	0.09

* Sheung Wan, Central, Wanchai/Causeway Bay, North Point/Querry Bay, Tsim Sha Tsui, Yau Ma Tei/Mong Kok.

Table 2. Bai and Perron analysis results for residential units.

Class	District *	F	Previous Breakpoints				Latest Breakpoint			Slopes	
			B1	B2	B3	B4	2.50%	Break	97.5%	Pre	Post
Class A	Hong Kong	172.2	2004 (5)	2008 (10)	2016 (1)	2019 (11)	2019 (10)	2019 (11)	2019 (12)	2.73	0.36
	Kowloon	411.8	2004 (4)	2008 (10)	2015 (10)	2019 (12)	2019 (11)	2019 (12)	2020 (3)	1.84	0.91
	NTs	402.6	2003 (4)	2008 (11)	2015 (10)	2019 (9)	2019 (8)	2019 (9)	2020 (2)	1.53	0.38
Class B	Hong Kong	186.8	2003 (3)	2008 (10)	2015 (11)	2019 (9)	2019 (8)	2019 (9)	2019 (10)	1.88	−0.39
	Kowloon	411.8	2003 (12)	2008 (10)	2015 (11)	2019 (9)	2019 (8)	2019 (9)	2019 (11)	1.61	0.31
	NTs	277.9	2003 (2)	2008 (11)	2015 (11)	2019 (9)	2019 (8)	2019 (9)	2019 (12)	1.24	0.11
Class C	Hong Kong	148.5	2002 (11)	2008 (10)	2012 (8)	2019 (9)	2019 (8)	2019 (9)	2020 (1)	1.29	0.05
	Kowloon	138.8	2004 (3)	2011 (9)	2015 (9)	2019 (8)	2019 (7)	2019 (8)	2019 (12)	1.41	0.01
	NTs	221.3	2003 (4)	2008 (10)	2015 (10)	2019 (9)	2019 (8)	2019 (9)	2020 (1)	1.04	0.02
Class D	Hong Kong	200.1	2003 (5)	2008 (11)	2013 (1)	2019 (10)	2019 (9)	2019 (10)	2020 (1)	0.78	0.21
	Kowloon	71.8	2003 (7)	2008 (11)	2019 (6)	-	2019 (5)	2019 (6)	2019 (11)	1.05	0.07
	NTs	148.4	2003 (4)	2008 (10)	2013 (2)	2019 (10)	2019 (8)	2019 (10)	2021 (7)	0.38	−0.10
Class E	Hong Kong	283.0	2003 (6)	2008 (11)	2013 (2)	2019 (11)	2019 (8)	2019 (11)	2020 (1)	0.01	0.45
	Kowloon	37.1	2007 (7)	-	-	-	2007 (5)	2007 (7)	2007 (12)	−0.05	0.71
	NTs	39.6	missing	missing	missing	2023 (1)	2022 (12)	2023 (1)	2023 (4)	−0.11	0.47

* NTs: New Territories.

Table 3. Bai and Perron analysis results for retail units.

Class	District *	F	Previous Breakpoints				Latest Breakpoint			Slopes	
			B1	B2	B3	B4	2.50%	Break	97.5%	Pre	Post
Rental	Hong Kong	579.9	2003 (3)	2008 (11)	2014 (9)	2019 (11)	2019 (9)	2019 (11)	2020 (1)	−0.76	−0.52
	Kowloon	451.7	2002 (12)	2011 (7)	2015 (9)	2019 (12)	2019 (11)	2019 (12)	2020 (2)	1.58	0.68
	NTs	281.0	2003 (6)	2012 (2)	2019 (10)	-	2019 (9)	2019 (10)	2020 (6)	2.51	−0.24

* NTs: New Territories.

Table 4. Bai and Perron analysis results for vacancy rates and ratios (%) of offices and residential units.

Type	District	F	Previous Breakpoints				Slopes	
			B1	**B2**	**B3**	**B4**	**Pre**	**Post**
Office	Grade A	38.384	1997	2015	-	-	−9.18	113.49
	Grade B	45.726	1990	2004	2014	-	−5.15	28.98
	Grade C	99.241	1990	1996	2003	2013	−11.98	4.76
Office (%)	Grade A	21.947	1997	2014	-	-	−0.39	1.04
	Grade B	24	1990	2004	-	-	0.25	0.39
	Grade C	52.302	1990	1996	2012	-	−0.88	0.33
Residential	Class A	20.248	1998	2011	-	-	−0.64	0.77
	Class B	217.22	2006	-	-	-	1.42	−0.40
	Class C	83.977	1996	2002	2015	-	−0.17	0.51
	Class D	20.903	1999	-	-	-	0.08	0.04
	Class E	NA	NA	-	-	-	NA	0.07
Residential (%)	Class A	11.978	1991	1998	2012	-	−0.17	0.15
	Class B	114.6	2006	-	-	-	0.17	−0.10
	Class C	94.653	1996	2002	2015	-	−0.26	0.28
	Class D	21.045	1999	-	-	-	0.01	−0.04
	Class E	21.045	2001	-	-	-	0.00	0.00

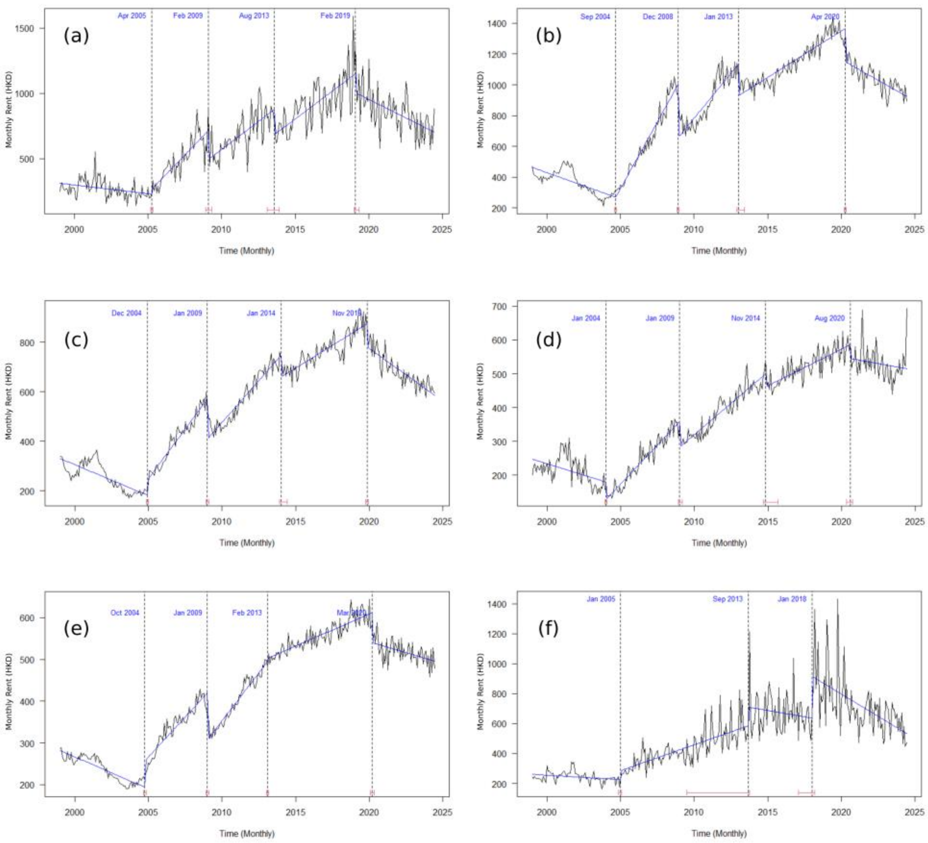

Figure 4. Breakpoint graphs for Grade A offices: (**a**) Sheung Wan, (**b**) Central, (**c**) Wan Chai/Causeway Bay, (**d**) North Point/Querry Bay, (**e**) Tsim Sha Tsui, (**f**) Yau Ma Tei/Mong Kok. The red lines show the margins of each break point.

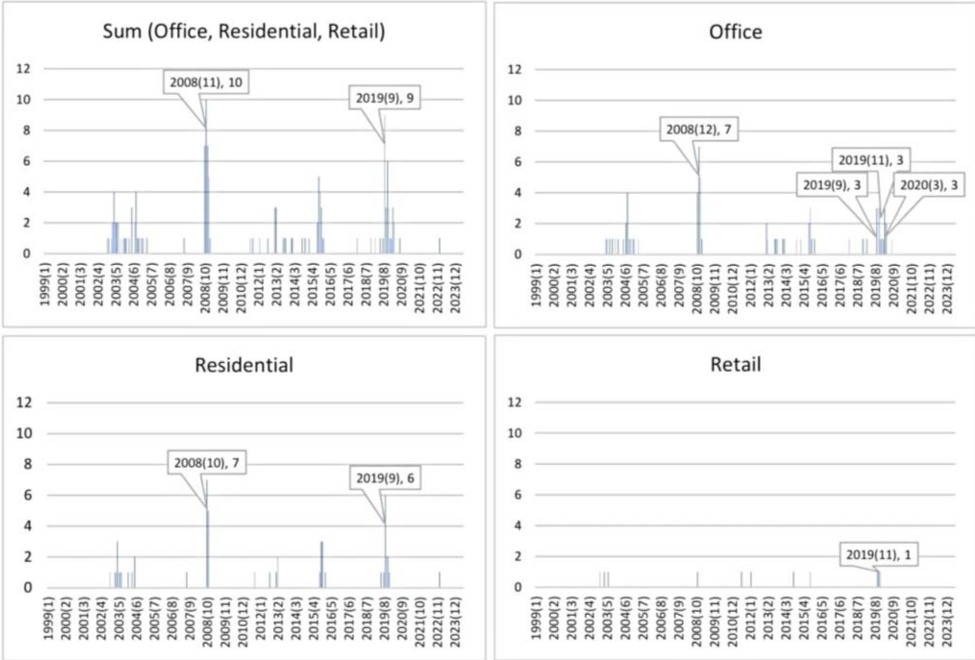

Figure 5. Frequency of breakpoints in office, residential, and retail sectors, and the summation of these sectors.

Since our research focuses on the recent changes in temporal trends, we present the latest cluster of the breakpoints. Regarding the office units, a significant cluster of breakpoints occurred in late 2019 and early 2020, with Grade A offices showing the highest slope changes. Grade B and C offices also experienced changes, but to a lesser extent, indicating varying responses across office grades. Regarding districts, Sheung Wan and Central, as central business districts, showed the most substantial trend shifts. North Point and Tsim Sha Tsui demonstrated the most stability, with North Point experiencing minimal decline and Tsim Sha Tsui showing slight growth post-breakpoint. Wan Chai and Mong Kok had moderate positive pre-slopes but saw notable declines post-breakpoint, though less severe than in Sheung Wan and Central.

The residential sector showed structural breakpoints, primarily around late 2019. Despite a sharp drop in rental rates during the breaks, rental patterns maintained positive slopes post-breakpoint, indicating sustained demand across all areas. Classes A and B, representing smaller units, experienced the most significant slope changes, reflecting greater vulnerability. Likewise, Class C declined to a lesser extent, while Class D exhibited a higher stability. In contrast, Class E shifted from decline to growth, suggesting recovery or resilience for larger residential units. Concerning the districts, Hong Kong Island experienced the steepest post-breakpoint decline, while Kowloon experienced a milder decrease, indicating greater resilience. The New Territories showed the least change, indicating steadier growth and stability.

Retail property breakpoints emerged primarily in late 2019, with distinct rental trends across districts. The New Territories showed the most significant decline in growth post-breakpoint, with an evident shift from a sharp rental increase to a decline, followed by Kowloon's deceleration, though the trend was still positive. In Hong Kong, the rate of rental decline slowed after the latest breakpoint, indicating a stabilization trend. Vacancy rates did not show a significant break associated with the latest crisis.

3.2. Population Trend Results

This section presents the spatiotemporal analysis results. Table 5 and Figure 6 show the analysis results of emerging hot spots and their patterns. Additionally, Figures 7 and 8 show the trends in population changes based on recent years. The spatiotemporal analysis of the population showed a predominantly upward trend across most districts except Hong Kong Island. Hot spot analysis identified significant clusters of high population growth, distributed mainly across the New Territories. Conversely, a cold spot, exhibiting a statistically significant downward trend, was identified in the Hong Kong Island region. Emerging hot spot analysis, as the analysis of the recent trends, confirmed the persistence and intensification of growth in the Kowloon region and the diminishing cold spot in the suburban areas.

Table 5. Results of the emerging hot spot analysis.

District	Pattern	Hot %	Cold %	Mean	STD	Z-Score	*p* Value
Wong Tai Sin	Intensifying Hot Spot	100.0	0.0	22.93	0.75	5.02	0.000
Kowloon City	Intensifying Hot Spot	100.0	0.0	20.24	1.47	4.81	0.000
Kwun Tong	Intensifying Hot Spot	100.0	0.0	27.76	2.23	5.02	0.000
Sai Kung	Consecutive Hot Spot	52.2	0.0	1.87	0.20	4.86	0.000
North	Diminishing Cold Spot	0.0	95.7	1.13	0.07	3.27	0.001
Central and Western	No Pattern Detected	0.0	0.0	11.04	0.46	3.59	0.000
Wan Chai	No Pattern Detected	0.0	0.0	8.71	0.60	−0.42	0.673
Eastern	No Pattern Detected	0.0	0.0	17.02	0.88	−1.90	0.057
Tuen Mun	Diminishing Cold Spot	0.0	95.7	3.09	0.07	4.49	0.000
Yuen Long	Diminishing Cold Spot	0.0	95.7	2.16	0.28	4.49	0.000
Southern	No Pattern Detected	0.0	0.0	3.78	0.13	−1.90	0.057
Islands	Diminishing Cold Spot	0.0	95.7	0.43	0.09	3.96	0.000
Sham Shui Po	Intensifying Hot Spot	95.7	0.0	20.83	2.00	5.49	0.000
Yau Tsim Mong	Intensifying Hot Spot	95.7	0.0	23.61	1.77	5.49	0.000
Kwai Tsing	No Pattern Detected	0.0	0.0	11.12	0.40	5.07	0.000
Tsuen Wan	No Pattern Detected	0.0	0.0	2.59	0.16	5.07	0.000
Tai Po	Diminishing Cold Spot	0.0	95.7	1.18	0.05	3.27	0.001
Sha Tin	No Pattern Detected	4.3	0.0	4.99	0.22	3.96	0.000

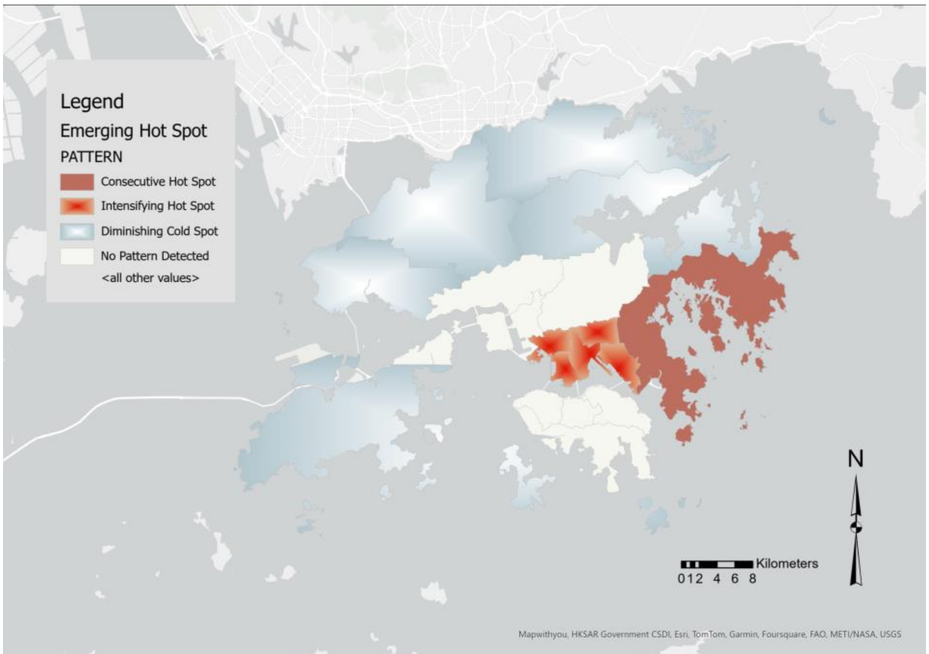

Figure 6. Results of emerging hot spot analysis.

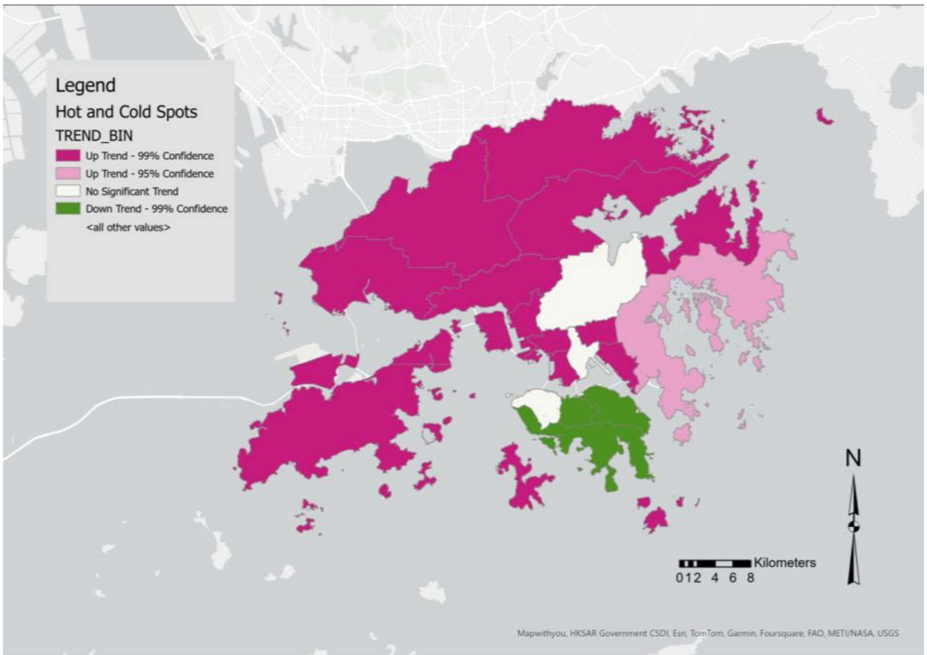

Figure 7. Hot and cold spot analysis results.

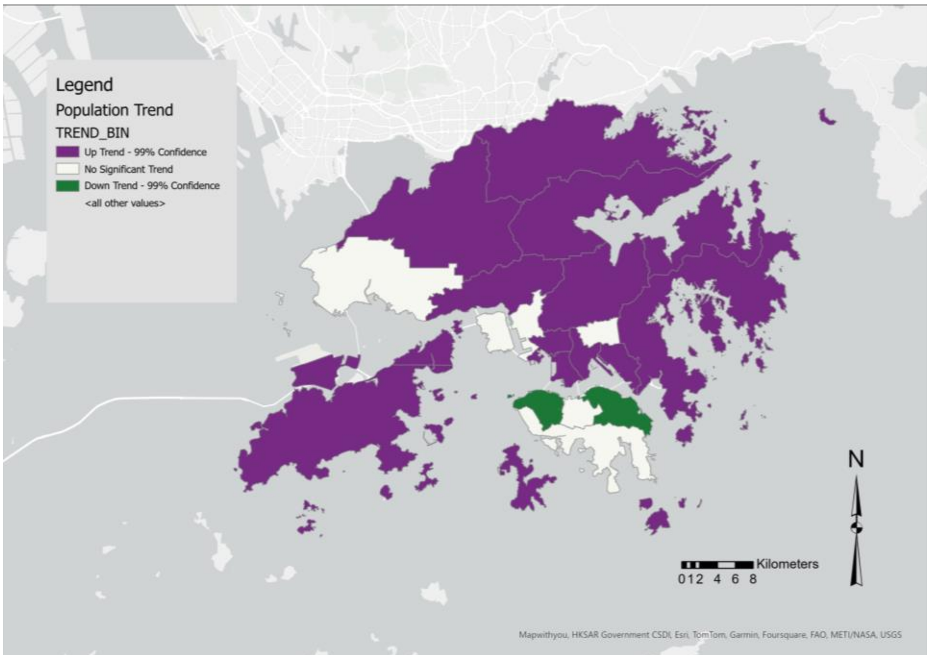

Figure 8. Population trend results.

4. Discussion

This section discusses the analysis results to draw conclusions on the changes in real estate and population dynamics. The structural change analysis identified multiple breakpoints across Hong Kong's real estate sectors, indicating significant shifts in rental rates over time. While these breakpoints are consistent with past and recent external events, this discussion focuses on the breakpoints linked to the recent crisis. Additionally, the spatiotemporal analysis highlighted dynamic population changes in Hong Kong, revealing emerging trends in urban dynamics.

4.1. Real Estate

The recent shock is comparable to the financial crisis of 2008 from the magnitude and market response perspective by examining the frequency of breakpoints. However, the broader dispersion of the breakpoints and the unique post-break slopes of the property market indicate a more intricate interplay of change drivers. The results show breakpoint clusters in late 2019 and early 2020, coinciding with social unrest and the COVID-19 pandemic in Hong Kong. Moreover, the findings show the diverse reactions of real estate sectors to external disruptions, illustrating how these events can change demand patterns across different property types and locations. This aligns with previous findings demonstrating real estate markets' diverse and location-specific responses to pandemic shocks [35]. Among the sectors, the office market experienced the most noticeable structural change and a higher external crisis vulnerability than the residential and retail markets. Rental growth shifted from positive to negative, suggesting declining demand and increased caution among businesses, particularly in central business districts. This reduced demand in central business districts is consistent with international trends observed in previous studies [7,18].

A closer look at the breakpoint cluster shows that the office sector responded immediately to the pandemic in early 2020 and social unrest in late 2019. A meaningful pattern was not apparent when considering the breakpoints in 2019 and 2020 according to different grades of offices and the district categories. However, the crisis's severe impact was associated with higher grades and being closer to the commercial business districts. In contrast, smaller businesses and offices in less central districts were less affected than in high-demand areas like Central and Sheung Wan. Despite the traditional expectation of higher resilience among higher grade companies [55], our findings suggest a more complex scenario influenced by multiple factors. This complicated interplay of the external shocks and the clustering of breakpoints around late 2019 and early 2020 exemplifies the concept of a "Polycrisis", which is a notion used to approach the complex web of interconnected challenges and changes, including those of an environmental, economic, political, geopolitical, social, health, and technological nature, that mutually influence and amplify each other [56–58].

This concept can explain the compounded challenges observed across Hong Kong's real estate market, as different sectors faced simultaneous, escalating pressures. In this case study, a polycrisis might be a combination of coincidental social, economic, and public health crises that amplify effects on sectors dependent on business stability. A similar discussion can also be had on the impact of the SARS outbreak, where the housing market was already experiencing a decreasing trend [37]. Additionally, the contrasting trend during the COVID-19 pandemic with rising prices pre-pandemic strengthens the significance of our findings in illustrating the specific impact of the pandemic on this up-trend. The shorter period down-trend of the housing market pre-outbreak and the lack of resilience experience during the SARS outbreak compared to the more extended, pre-pandemic up-trend and the socio-political drivers have resulted in different responses in the property market. Therefore, a deeper understanding of polycrises and the interplay of change drivers should be further explored to strengthen policies for creating resilient cities.

For the residential sector, the breakpoints clustered around late 2019, reflecting notable disruptions in market dynamics. Despite these disruptions, the overall positive trend of the residential sector post-break suggests notable resilience compared to the office sector. Such higher resilience has also been observed by comparing the effect of the SARS and COVID-19 pandemics on the housing market [36]. Concerning historical pandemics, such as plague and cholera, our findings align with the previous influence of health crises on the property market, in which rental rates and land prices decline and transactions drop significantly [35]. Variations in demand across unit classes and districts highlight the distinct impact of the crisis on rental rates. Smaller units were found to be more vulnerable, while larger units demonstrated signs of recovery and resilience. District-related trends further emphasize the diversity of these shifts, with areas like Hong Kong

Island experiencing sharper declines, while the regions of Kowloon and the New Territories showed moderate responses, indicating better stability.

Retail property breakpoints were clustered primarily in late 2019, with distinct rental trends across districts. As a peripheral region, the New Territories showed the greatest decline in growth post-break with an evident shift from a sharp rental increase to a decline, followed by Kowloon's deceleration, though the trend was still positive. In Hong Kong, the rate of rental decline slowed after the latest breakpoint, indicating a stabilization trend. This response contrasts with the results of the office and residential sectors, which might justify the reduced consumer traffic and tourism. Vacancy rates across retail and other property types remained relatively unaffected by recent crises, suggesting that shifts in rental patterns were driven by demand-side factors rather than changes in the overall supply. The constant up-trend of pre-pandemic vacancies, especially for the office sector, may rationalize the vulnerability of the offices. However, based on the differences between pre- and post-slopes in the real estate sectors, the authors contend and agree with the assertion made by Beck and Hensher [21] that the recovery from the crises is slow and might affect future land use and urban planning norms.

4.2. Population

The districts on Hong Kong Island exhibited a declining trend in population density, while the peripheral districts experienced diminishing cold spots, indicating an increase in density, particularly in recent years. This shift aligns with findings from studies reporting a rising demand for suburban areas [25,26]. However, the causality needs to be investigated, as our analysis did not examine the change drivers. The shift in housing preferences from dense urban districts to suburban areas could be attributed to the attractive characteristics of peripheral regions or the challenges associated with living in densely populated areas, which push or pull residents toward less dense zones [59]. Similarly, the increased teleworking during the pandemic was a significant reason for decentralization [24]. However, urban-to-rural relocations had started before the COVID-19 pandemic [60]. Therefore, the pandemic can be seen as an accelerator factor concerning the ongoing trends rather than a change driver. Consequently, the pandemic's long-term impact on urban density and whether people will return to central business district areas remains uncertain, depending on future re-urbanization policies [1,5,18].

Both decentralization and centralization involve trade-offs for residents and governments [21]. While decentralization-related migration has been linked to higher life satisfaction than centralization [61], unregulated suburbanization can result in challenges such as increased reliance on private cars, the conversion of agricultural land to urban use, and inefficient land use due to single-purpose zoning [62]. It is also noteworthy that, while there is a partial resemblance, the overall spatial pattern does not definitively show a "donut effect", which implies rapid growth in the outer rings of a city while the central areas experience a decline [25]. The distribution of clusters appears more inconsistent than a clearly defined ring. Therefore, while weak signs of a donut effect might be present, it is not a strong or perfectly defined example. This might stem from the complex interplay of geographical constraints, as the rings are not evenly located, and commercial business districts are on the southern side. In general, the population trends, particularly the rise in demand for suburban areas and declining density in central districts, highlight the need for practical policies to address decentralization and its implications.

4.3. Policy Recommendations

These findings contribute to policymaking decisions concerning city development dynamics, which are shifting towards decentralizing central business districts based on our findings. To prevent the immediate shocks caused by external events, policymakers should promote the development of flexible and hybrid spaces, particularly in decentralized locations, to reduce the dependency on high-demand central business districts. Retail strategies will also benefit from these mixed-use developments that foster economic activity and resilience. Shifting population dynamics require policies that invest in infrastructure and accessibility in peripheral districts. Supporting digital infrastructure and hybrid retail models can enable businesses to navigate demand volatility effectively. Moreover, these areas should be upgraded to reflect the reasons contributing to the relocations. Further research is required to investigate the relocation drivers.

Moreover, embracing a polycrisis preparedness framework is essential. Recognizing the interconnected nature of crises, such as those of economic, social, and public health origins, is vital for developing adaptive strategies [56–58,63]. Urban development should also align with future-ready models, including telework-friendly designs, ensuring long-term adaptability to evolving societal and economic trends [64]. In addition, the insights from this study can be applied to other high-density cities facing similar challenges. Cities with distinct characteristics but comparable challenges in managing population density, infrastructure, and economic resilience may benefit from adopting the insights in their urban development strategies. Tailoring these findings to local contexts could help shape more adaptable, future-ready urban policies. Although the observed patterns inform the proposed policies, certain limitations in this study's scope and data must be acknowledged. Addressing these gaps is essential for refining the conclusions and ensuring the robustness of policy interventions.

4.4. Limitations

While the Bai–Perron test effectively identifies the timing of structural breaks, it does not reveal their underlying causes. Further investigation is necessary to understand the drivers behind these market and population dynamic shifts. Moreover, the research was conducted shortly after the COVID-19 pandemic, capturing only the immediate responses to the crisis. A more extended analysis of long-term market behaviors and population trends is essential for drawing targeted policy implications. Lastly, the lack of land value data and directional population changes leads to ambiguity in interpreting the results, which could limit the precision of the findings. Therefore, the uncertainty regarding the pandemic-driven changes should be addressed when generalizing the results, similarly to previous studies [15,23].

5. Conclusions

This study explored the evolving real estate and population dynamics of Hong Kong in response to the recent COVID-19 pandemic. However, the results showed significant structural changes pertaining to a more complex context, where the intensified impacts of coincidental social, economic, and public health crises affected the real estate market, exemplifying the concept of a "Polycrisis". The overlapping crises placed additional pressure on the rental rates, which amplified responses. The office sector exhibited extreme vulnerability, with higher grade offices and those closer to central business districts being more impacted than peripheral areas. However, the residential sector demonstrated resilience, with variations across the districts and unit sizes reflecting diverse demand patterns. Smaller and central units were found to be more vulnerable, while peripheral and larger units demonstrated signs of recovery and resilience.

Contrastingly, the retail market showed a different response, where peripheral areas were affected more than the city core, aligning with the preventive measures and restriction of various activities during the pandemic. In general, the findings show that the recovery from the crises is slow and might affect future land use and urban planning norms. These shifts were accompanied by population changes, with declining densities in central districts and rising demand in peripheral areas. The analysis of population trends highlighted a shift toward decentralization, with peripheral districts experiencing increased population density, suggesting a growing preference for suburban living. This trend, accelerated by the pandemic, underscores the long-term implications for urban planning and real estate development. However, the shift was not uniform, and the overall spatial distribution of population changes did not fully align with the "donut effect", indicating that further exploration of causal factors and policy implications is needed.

This research contributes to a deeper understanding of how external crises influence urban dynamics, offering valuable insights for policymakers and urban planners to develop strategies that promote resilience in both the real estate sector and population distribution. Future studies should investigate and explore the long-term effects of external crises on urban trends from a polycrisis perspective. While this research offers valuable insights, further investigations regarding the drivers of structural breaks, long-term market behaviors, and population dynamics are necessary to refine policy implications. Future studies should also integrate broader factors, including land values and migration patterns, to deepen our understanding of these transformative urban processes. By fostering resilient and adaptable urban systems, compact cities like Hong Kong can better manage the impacts of future crisis shocks.

Author Contributions: Conceptualization, B.A. and P.M.N.; methodology, B.A.; software, B.A.; validation, B.A. and P.M.N.; formal analysis, B.A.; data curation, B.A.; writing—original draft preparation, B.A.; writing—review and editing, B.A. and P.M.N.; visualization, B.A.; supervision, P.M.N.; project administration, B.A.; funding acquisition, P.M.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been supported by the CityU Strategic Research Grant 7005654 and Start-Up Grant 7200700.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

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