

Article

Gender and Age Disparities in Public Health Crisis Disruptions to Cross-Border Mobility: A Causal Analysis of Daily Flows Between Shenzhen and Hong Kong

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Abstract

Cross-border mobility (CBM) is highly sensitive to policy shocks during public health crises, yet its behavioral and demographic dynamics remain poorly understood. CBM disruptions can be conceptualized as differentiated responses to non-pharmaceutical interventions (NPIs) across demographic groups in integrated cross-border systems. Focusing on the Shenzhen–Hong Kong cross-border mobility corridor, causal evidence shows that NPIs generate both immediate and uneven mobility contractions. These responses are structured along gender and age lines: younger individuals and males exhibit more elastic and rapid behavioral adjustments, whereas females demonstrate greater stability and faster recovery. In contrast, older adults show limited initial responsiveness but prolonged recovery, indicating persistent structural constraints. These findings identify vulnerable populations and provide empirical evidence for designing targeted, equitable border management and transportation policies in highly integrated regions during future public health crises.

Keywords: COVID-19; non-pharmaceutical interventions; cross-border mobility; spatial disparities; interrupted time series

1. Introduction

Border regions are dynamic interfaces that hold the potential for both discord and collaboration [1]. The movement of people across these borders is pivotal for fostering interaction and cooperation. Pandemics, such as the COVID-19 outbreak, have significantly disrupted this movement, with profound implications for border regions [2,3]. It is essential to understand how such emergencies impact daily cross-border mobility (CBM) to manage the spread of infectious diseases while avoiding conflicts and isolation. This understanding is not only crucial for the COVID-19 pandemic but also for preparing for future public health emergencies.

In the early stages of pandemics, non-pharmaceutical interventions (NPIs), including border closures, quarantine measures, and health screenings, have been recognized as effective tools in controlling the transmission of viruses [4–6]. These interventions, while vital for public health, have also led to social disparities [7]. For example, older adults seeking medical treatment or visiting family across borders, as well as individuals of working and studying age, have experienced considerable disruptions [8]. As we enter the



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post-pandemic era, it is imperative to assess the impact of NPIs on CBM to effectively manage public health emergencies and minimize social disruptions across various demographic groups. The development of more adaptive cross-border mobility management strategies is crucial for enhancing preparedness for future emergencies, balancing public health imperatives with socio-spatial equity [9].

Pandemics have historically influenced cross-border mobility [10], yet the COVID-19 pandemic's impact on global movement has been unprecedented in scale and speed. Extensive research has explored the nexus between non-pharmaceutical interventions (NPIs) and individual mobility during pandemics, revealing a positive correlation between NPI implementation and reduced population mobility during initial outbreak periods [11–13]. However, these studies, predominantly focusing on intercity or intracity mobility [14–16], have often overlooked cross-border mobility (CBM), which, unlike intercity mobility within a single administrative system, is shaped by border controls and institutional barriers and is thus particularly sensitive to border policies. Moreover, CBM studies have concentrated on cross-country movements, such as those within the European Union (EU) [17–19], while neglecting cross-border regions within a single country with distinct systems, like the Hong Kong–Shenzhen cross-boundary (HSCB).

Before the COVID-19 pandemic, economic cooperation between Shenzhen and Hong Kong had been intensifying, leading to increased population flow. Daily cross-border tourist visits rose from an average of 284,600 in 1999 to 667,000 in 2017 [20]. The promotion of unrestricted movement between Shenzhen and Hong Kong has been a significant concern, particularly in the context of the Guangdong–Hong Kong–Macao Greater Bay Area Development Plan, which aims to enhance regional integration across borders [21]. Therefore, examining the effects of NPI policies on different population groups in the HSCB area is crucial. It provides insights into the complexities of border policy implementation during public health crises and ensures equitable policy execution.

The aim of this study is thus to analyze the causal effect of NPI policies on CBM during the first wave of the COVID-19 pandemic, while also accounting for the variability in effects across different population groups. It is worth noting that while some studies have examined the impact of NPI policies on the spread of the virus and their effects on mobility, they have mainly relied on cross-sectional data and lack causal inference analysis [13,22–24]. In contrast, this article utilizes longitudinal anonymous mobile phone location big data in the region to conduct an interrupted time series (ITS) quasi-experimental analysis. This analysis explores the causal effects of major policies issued by Shenzhen and Hong Kong in the early stages of the pandemic on CBM, as well as the heterogeneity of individuals, including the following questions: (1) What are the causal effects of major NPI policies on CBM in the Shenzhen–Hong Kong region during the initial stages of COVID-19 prevention and control? (2) How does the impact of NPI policies on CBM vary based on demographic factors such as gender and age, and what factors contribute to these variations? (3) To what extent do the implemented policies produce differential impacts across demographic groups, and which groups are most affected?

This study contributes to a broader understanding of border dynamics and mobility patterns under exceptional circumstances, such as pandemics. The findings not only inform our understanding of crisis response in border regions but also illuminate the complex interplay between policy interventions, mobility patterns, and socio-demographic factors in cross-border contexts during periods of disruption. This knowledge is crucial for developing more resilient, adaptive, and equitable border management strategies that can effectively respond to various challenges.

The rest of this paper is structured as follows. Section 2 reviews the existing literature. Section 3 describes research area, dataset and the ITS design. Section 4 shows the

results of ITS models and compares effects of NPI policies on CBM between Hong Kong and Shenzhen. Finally, Section 5 concludes the paper and discusses the limitations of the research.

2. Literature Review

2.1. Factors Affecting Cross-Border Mobility (CBM)

Cross-border mobility (CBM) encompasses a wide range of spatiotemporal characteristics and driving factors [25,26]. These movements are categorized based on duration, including daily, periodic, seasonal, and migratory forms, and by distance, spanning from neighborhood to cross-city, cross-country, and cross-border movements [27,28]. Distinct from intercity mobility that occurs within a single administrative system, CBM crosses different political and institutional boundaries and is therefore shaped by border-specific factors such as entry controls and immigration procedures. This distinction makes CBM particularly sensitive to border policies during public health crises, warranting attention as a research object in its own right. From a medium to long-term perspective, the shaping of CBM is significantly influenced by push–pull factors, covering macroscale socioeconomic conditions and microscale individual decision-making factors [29,30]. Push factors encompass a range of unfavorable conditions in the origin region, such as subpar living standards, stagnant economic growth, accelerated population increase, elevated unemployment levels, and insufficient social security provisions. Conversely, pull factors in the destination region include attractive attributes like superior living standards, vibrant economic development, controlled population growth, minimal unemployment rates, comprehensive social welfare systems, and enhanced educational opportunities.

Mau & Mewes [25] proposed a comprehensive framework to examine the determinants of cross-border activities within the European Union, considering both macro-level national characteristics and micro-level individual demographic factors. Their findings revealed that at the macro level, factors such as smaller country size, higher levels of economic development and globalization, and a larger proportion of foreign-born population positively influence cross-border mobility. At the micro level, individual characteristics like age, gender, immigrant background, and foreign nationality were found to be associated with higher levels of European cross-border mobility. In addition, CBM is also affected by various factors related to cross-border interactions, such as commuting costs, infrastructure and transportation improvements, border systems, and family living standards [31].

From a short-term and daily perspective, the dynamic characteristics of CBM and its determining factors exhibit more immediacy and diversity. According to Levitt and Schiller [32], this mobility pattern is particularly pronounced between neighboring countries. The main motivations behind short-term cross-border flows include work, education, leisure, shopping, family visits, and social activities [33–36]. For instance, Spierings and van der Velde [37] found that daily cross-border shopping behavior is significantly influenced by economic factors such as exchange rate fluctuations and price differences. They studied the Dutch–German Rhine–Waal Euroregion and discovered that Dutch consumers were more likely to shop across the border when the exchange rate was favorable and when German prices were lower for certain products. Similarly, Gerber [38] discovered that cross-border commuting is heavily impacted by factors such as transportation infrastructure and border control efficiency, based on a study of cross-border workers in the Benelux region.

As research deepens, CBM studies have gradually formed three main focus areas: border dynamics, cross-border identity formation, and cross-border equity issues among distinct population groups. First, the study of border dynamics has been paid attention to explore the changes in border forms, the complexity of border roles, and the filtering of border differences [39]. It has been observed that border forms are evolving from being a

mere continuous line defining national territory and sovereignty to complex, networked, and mobile filtering systems [40]. Within this evolving border forms, borders take on a dual role, simultaneously embodying elements of protection and isolation, opportunity and danger, and contact and conflict, as well as cooperation and competition [41]. These transformations are further influenced by development level disparities on both sides of the border, contributing to the creation of varying degrees of permeability [42].

Second, the changes in border forms and roles also lead to shifts in identity among residents on both sides of the border. This, in turn, underscores the significance of discussing cross-border identity in the context of CBM. Research indicates that CBM contributes to the formation of diverse, mutable, changeable, and blended regional identities [43]. This evolving sense of local identity shapes the “reimagined borders” held by border residents and influences the transit modes of cross-border populations [44,45]. The study of place identity among cross-border populations also plays a crucial role in shaping immigration policies and border control strategies [46].

Third, the dynamics of cross-border populations and their place identity differ across borders, ultimately shaping their perspectives on cross-border equity. It is especially crucial to focus on the equity issues faced by vulnerable or marginalized individuals. Thus, it is important to broaden the scope of border studies beyond merely examining border forms and functions to paying greater attention to the cross-border sense of identity arising from border differences and the participation of ordinary people in cross-border daily life [47]. To be specific, studies have shown that the CBM of older people is closely linked to social welfare policies such as medical insurance and access to social housing, as well as family-related reasons like caregiving for grandchildren [48]. Similarly, children’s CBM is influenced by disparities in educational resources across regions and family planning policies [21]. The CBM of women can be constrained by their familial responsibilities, limiting their ability to engage in cross-border movement [49]. Additionally, women are more vulnerable to the effects of disparities in transportation infrastructure compared to men [50]. Moreover, women face more obstacles and insecurity within the cross-border job market [51]. Therefore, the variations within the cross-border population should not be disregarded, and addressing how to guide cross-border population mobility to achieve fairness becomes a significant and imperative issue.

In the context of the Guangdong–Hong Kong–Macao Greater Bay Area (GBA), cross-border population mobility exhibits some unique characteristics and influencing factors. Lin and Tse found that cross-border population mobility between Hong Kong and Mainland China involves multiple groups, including shoppers, workers, property buyers, and retirees, who engage in bidirectional movement for various reasons [42]. These individuals leverage the differences between the two regions to access cheaper goods and services, better opportunities, and improved quality of life. They emphasize that cross-border mobility serves as a strategy for people to cope with regional inequalities and the uneven impacts of globalization. Furthermore, Tam and Zhai explored the cross-border tourism spatial dynamics in the GBA and discovered that with the acceleration of regional integration, cross-border tourism flows have become increasingly frequent, serving as a significant driving force for regional economic development and social integration [52]. Simultaneously, Cao et al. pointed out that the improvement of transportation infrastructure and the construction of a cross-border transportation system have played a crucial role in promoting the free flow of people, goods, and information [53]. In summary, cross-border mobility becomes an important means for people to cope with unbalanced development and seek better life opportunities.

However, the outbreak of the COVID-19 pandemic has presented new challenges and opportunities for CBM research. The pandemic has not only disrupted regular cross-

border mobility patterns but also highlighted the need for a deeper understanding of how CBM dynamics change under the influence of sudden public health events. This has prompted researchers to pay more attention to finer scales and daily perspectives under abnormal conditions. Specifically, NPI policies, such as border closures, emerged as the primary strategies to curb the spread of the virus, effectively transforming national and regional borders into insurmountable barriers. This phenomenon, referred to as “COVID fencing” by Medeiros et al. [54], underscores the systematic closure of national borders to restrict people’s mobility. Notably, however, these pandemic-related NPI policies were often inadequately prepared for cross-border populations, resulting in significant disruptions in their daily movements.

2.2. Impact of NPI Policies on CBM During the COVID-19 Pandemic

Existing research delves into the impact of border closures and other NPI policies on the spread of COVID-19, cross-border transmission of the virus, population movements, public transportation, and daily life in border areas [55,56]. It aims to understand how these measures affect CBM and identifies potential solutions to mitigate their negative consequences. The focus is on analyzing the challenges faced by individuals living in border regions, the disruption of cross-border economies and social systems, and the disparities in access to healthcare and essential services [13,23,24]. By examining these aspects, researchers hope to develop strategies and policies that balance public health concerns with the need for CBM.

Much of the existing research on border closures and their impacts primarily focus on the borders between countries, particularly within the EU [19,57]. These studies revealed that, due to a lack of coordination and the prioritization of national interests, border closures are often viewed as isolating and conflicting within cross-border regions. However, our understanding of non-EU areas, particularly those with unique cross-border systems within a country, remains limited. The case of the Shenzhen–Hong Kong border, located within the Guangdong–Hong Kong–Macau Greater Bay Area in southern China, offers a unique and important context.

During the pandemic in the Greater Bay Area, a limited number of studies employed descriptive analysis to compare the impact of NPI policies on CBM between the Greater Bay Area and other regions. For instance, Zhong et al. [58] compared the changes in population movement, daily population flow fluctuations, and long- and short-distance population movement levels before and after lockdown in the Guangdong–Hong Kong–Macao Greater Bay Area and the San Francisco Bay Area, using NPI measures as a research context. Another study by Hakim et al. [59] conducted descriptive analysis to examine the relationship between NPIs and community mobility in Australia, Japan, Hong Kong, and Singapore. Their findings suggest that these policies resulted in reduced community mobility in Australia, Japan, and Singapore, but not in Hong Kong.

Within the Greater Bay Area, some researchers have utilized various methods to investigate the relationship between NPI policies and domestic population movement, focusing on their impact on different income groups. For example, Chan et al. [60] used Granger causality analysis to investigate the potential connection between the number of COVID-19 cases, government austerity policies, and community mobility in Hong Kong. Their findings suggested that the community’s response to the epidemic preceded the implementation of government policies, and strict control measures effectively reduced the number of confirmed COVID-19 cases. In a separate study, Pan et al. [61] utilized mobile big data to investigate the impact of the COVID-19 on different income and immigrant groups in the three core cities of Shenzhen, Guangzhou, and Foshan. The study reveals that socially disadvantaged groups have limited access to advanced preventive measures

to avoid infection. In general, these studies provide an important basis for understanding population mobility during the pandemic, but research on specific cross-border contexts such as the Shenzhen–Hong Kong border remains limited.

2.3. Research Gaps

In summary, while there has been research examining CBM from short-term to long-term conditions, as well as the impact of NPI policies on intercity or intracity mobility during the COVID-19 pandemic, several research gaps require further investigation. Firstly, existing studies have touched upon the effects of NPI policies on mobility but have not specifically explored the Shenzhen–Hong Kong cross-border context [58,59]. Limited research exists regarding cross-border populations traversing between Hong Kong and Shenzhen during the pandemic. This gap highlights the lack of a fundamental understanding of the characteristics of these individuals, whether they represent a uniform composition or a diverse range of groups. Moreover, most existing cross-border studies are set in the European Union, involving movement between sovereign states with comparable institutional arrangements. The Shenzhen–Hong Kong case, by contrast, involves an intra-national border under the “one country, two systems” framework, connecting two jurisdictions that differ in their legal, administrative, and public-health regimes but without national sovereignty between them. Its border-control logic, the composition of its cross-border populations, and its pandemic policy responses therefore differ markedly from the EU context, underscoring the necessity of examining the Shenzhen–Hong Kong case as a distinct cross-border system.

Secondly, it is worth noting that most of existing studies are cross-sectional comparisons that lack causal inference analysis. This limitation makes it challenging to establish a clear cause-and-effect relationship between NPI policies and cross-border population movements. Although Chan et al. [60] used Granger causality analysis to explore potential correlations, there is a need for more robust longitudinal and causal research to confirm these relationships.

Thirdly, while current research has shed light on the social inequality issues exacerbated by NPI policies [57,62,63], there is limited examination of the differential impact of the same NPI policies on different population groups, particularly regarding CBM. These studies often overlook issues of fairness in the distribution of policy impacts.

These research gaps emphasize the necessity for a comprehensive analysis of the causal effects of NPI policies on CBM and their differential impact on various population groups in the Shenzhen–Hong Kong border region. This study aims to address these gaps by providing valuable insights into the dynamics of border complexity during public health crises and the equitable implementation of border policies. By focusing on the unique Shenzhen–Hong Kong context, this research will contribute to a better understanding of CBM during pandemics and inform more effective and fair border management strategies in similar cross-border regions.

3. Research Data and Method

3.1. Research Area and Data

This study focuses on the CBM between Shenzhen and Hong Kong during the first wave of COVID-19 pandemic. Shenzhen and Hong Kong are neighboring cities situated in the Guangdong–Hong Kong–Macau Greater Bay Area in southern China. Despite their geographical proximity, these two cities have distinctive characteristics. While Shenzhen is part of mainland China, Hong Kong operates as a Special Administrative Region with its separate political and legal systems. Thus, the population flows between two cities is a typical cross-border movements. In recent years, Shenzhen and Hong Kong have cultivated

a strong economic and cultural relationship, complementing each other's strengths and advantages. Hong Kong stands as a prominent gateway for foreign investments and trade, boasting highly developed financial, legal, and service sectors. On the other hand, Shenzhen has emerged as a flourishing center for high-tech innovation and manufacturing. The connectivity between two cities is facilitated through various transportation modes, including cross-border high-speed railway, subway, highway, seaway and various bus services, further supported by numerous border crossings like Luohu Port, Futian Port, and Shenzhen Bay Port, totaling 15 port crossings.

According to the Cross-boundary Travel Survey 2021 conducted by the Hong Kong Planning Department [64], the majority of travelers between Hong Kong and mainland China were Hong Kong residents (63.3% of the total), followed by Hong Kong residents living in the mainland (25.4%), and visitors from the mainland (10.4%). Male travelers accounted for 56.2% of the trips, while females accounted for 43.8%. The age group between 25 and 54 years old represented the majority (68.2%) of cross-border trips. Among the destinations, Shenzhen was the most popular, accounting for 44.7% of total trips. Work, business, visiting relatives and friends, and leisure activities were identified as the primary purposes of cross-boundary travel.

In this paper, we explore the daily dynamics of CBM between Shenzhen and Hong Kong, using anonymized mobile phone tracking data gathered from 1 December 2019, to 31 May 2020. This dataset was derived from 17 million anonymous mobile phone devices in Shenzhen via China Unicom, one of the top three communication corporations in China. Specifically, this dataset comprehensively tracks a wide array of trips, monitoring user locations during activities like phone calls, app usage, internet browsing, and automatic detection of movement, with updates every 30 min. This allows us to effectively gather data on CBM, providing a detailed view of the movement patterns between these two cities. It is important to note that our data comes exclusively from mainland China Unicom operations. As a result, our dataset mainly captures the cross-border activities of mainland residents and any Hong Kong residents who specifically use mainland China Unicom services. However, many Hong Kong residents using Hong Kong-based carriers or other international operators' SIM cards cannot be captured in our dataset. Consequently, our findings primarily reflect the CBM patterns of mainland China Unicom users and their changes during the pandemic period. CBM is defined by the directional movements, either from Shenzhen to Hong Kong or from Hong Kong to Shenzhen, using stay and move information. The aggregation of movements in a specific direction by volume allows for the estimation of the number of CBM flows. It is important to note that our mobile phone data may underrepresent certain demographic groups, particularly older travelers. Analysis of our dataset shows that travelers aged 60+ represent only 3.06% of total cross-border movements, which is lower than proportions reported in traditional cross-boundary travel surveys (approximately 9% according to the Cross-boundary Travel Survey 2017 [20]). This underrepresentation is primarily due to lower smartphone adoption rates among older populations. A detailed breakdown of the demographic distribution in our dataset is provided in Table A1 in Appendix A.

As shown in Figure 1, we observe that there are similarities in the trends for both directions of mobility. For instance, before the outbreak of COVID-19, the average daily cross-border population flow from Hong Kong to Shenzhen was about 5069 person-times. The dataset also provides basic demographic details like age and gender, showing that men made up 3370 of these movements per day, nearly double the female count of 1760. In terms of age groups, the CBM of 20–29-year-olds was the largest, with 2004 person-times/day, followed by the 30–39 age group with 1622, the 40–49 year-olds with 462, the 50–59 year-olds with 245, and those over 60 years old with 44 person-times/day. However,

this flow decreased significantly after 24 January 2020, when Guangdong Province issued the highest-level emergency response, resulting in an abrupt drop of 4096 movements per day.

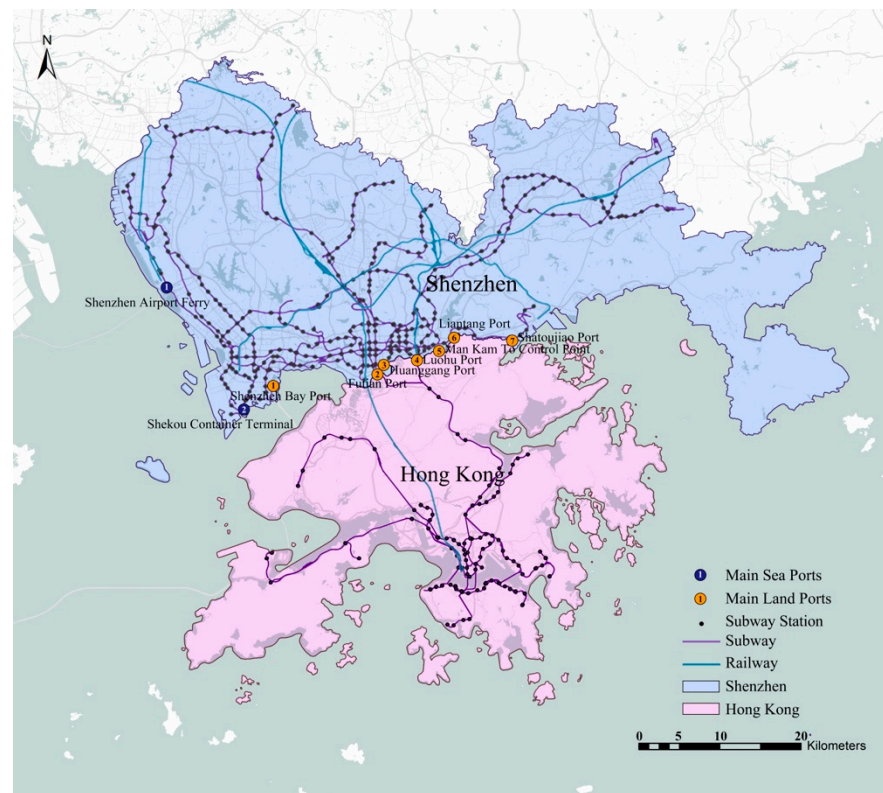


Figure 1. The geographical relationship and main transportation connections between Shenzhen and Hong Kong.

3.2. CBM During the Pandemic

On 19 and 22 January 2020, the first confirmed cases of COVID-19 appeared in Shenzhen and Hong Kong, respectively. From December 2019 to May 2020, there were a total of 1546 confirmed cases of COVID-19 in Shenzhen and Hong Kong combined, with a mortality rate of 0.45%. Among these cases, Shenzhen accounted for 462 cases, while Hong Kong had 1084 cases. In response to the outbreak, both cities implemented several measures to curb the virus' spread. These strategies included restrictions on population movement, increased information disclosure, and public opinion guidance. The aim was to slow down the transmission speed of the virus and prevent further spread within the communities. Considering the timing and content of the policies, this paper classifies the research period into four stages, as follows:

(1) Warning period (15 to 23 January 2020): The initial stage was characterized by significant signals including the release of the first edition of the COVID-19 diagnosis and treatment plan by China's National Health Commission and the acknowledgment by the Hong Kong Food and Health Bureau of the possibility of limited human-to-human transmission of the virus on 15 January, respectively. The situation escalated when Zhong Nanshan, a renowned Chinese respiratory expert, confirmed person-to-person transmission of the virus on 20 January, prompting Shenzhen and Hong Kong to implement stricter measures aimed at curbing the spread of the virus. These measures focused on enhancing information dissemination and guiding public opinion.

(2) Freezing period (24 January to 23 February 2020): During this period, Shenzhen and Hong Kong implemented the most stringent epidemic prevention and control mea-

asures. Guangdong Province activated the highest-level public health emergency response on the evening of the 23 January exactly, effectively impacting measures from 24 January. Subsequently, ten port control stations were shut down, leaving only three operational. On 8 February, Hong Kong began enforcing a mandatory 14-day quarantine for most visitors from the mainland. These strict controls drastically diminished the mobility and interaction between Shenzhen and Hong Kong, curtailing the potential for virus transmission. This period saw the peak of the epidemic in Shenzhen, accounting for 87% of its total confirmed cases from January to May. Initially, Hong Kong's confirmed cases predominantly originated from mainland China, particularly Wuhan, shifting to primarily local transmissions in later stages.

(3) Adjustment period (24 February to 29 April 2020): During this phase, Shenzhen's epidemic prevention and control measures proved to be effective. Thus, Guangdong Province lowered the emergency response level from the highest (first) to the second. However, during this period, there was a significant surge in confirmed cases in Hong Kong. As a result, NPI policies continued to rely on mandatory measures to limit population movement, supplemented by efforts in information dissemination and public opinion management. The cross-border flow of people between Shenzhen and Hong Kong increased slightly compared to the previous period, due to the mainland's supply of food and daily necessities to Hong Kong.

(4) Recovering period (30 April to 31 May 2020): On 30 April, Hong Kong began to reopen public services, reflecting effective management of the COVID-19 outbreak by both Shenzhen and Hong Kong. Additionally, specific groups of cross-border travelers, including schoolchildren, businesspeople, and professionals, were granted exemptions from quarantine requirements.

As shown in Figure 2, the daily cross-border flow varied markedly across these stages. The average daily flow declined from a pre-pandemic baseline of about 5069 person-times to 4736 during the warning period, dropped sharply to about 970 during the freezing period, recovered modestly to around 1000 during the adjustment period, and rose to about 2178 during the recovering period.

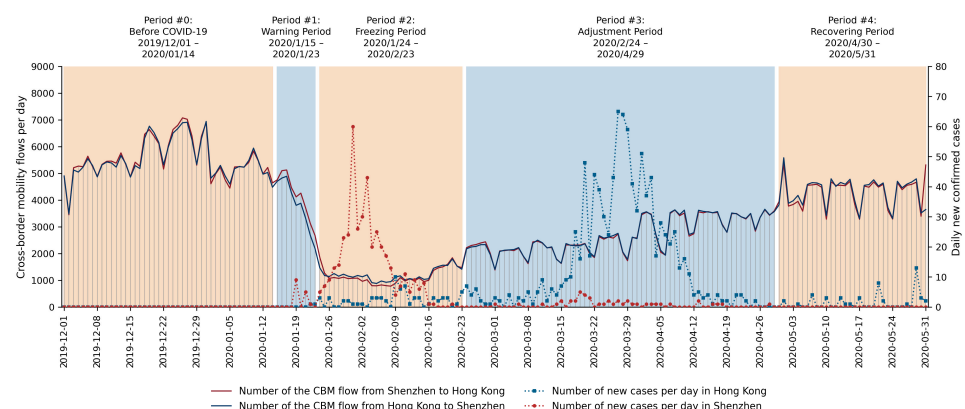


Figure 2. Population flow between Hongkong and Shenzhen and the new cases.

3.3. Method: An Interrupted Time-Series (ITS) Design and Model

This article aims to investigate the causal effects of NPI policies on CBM between Hong Kong and Shenzhen during the first wave of COVID-19 pandemic; especially, we focus on the differences in policies' influence among different groups. We employ an Interrupted Time Series (ITS) research design, renowned for its efficacy in causal inference through the analysis of extended behavioral trend data [65]. ITS precisely evaluates an intervention's effect by extending the pre-intervention trend as a counterfactual benchmark and then comparing it with the actual post-intervention trend. This methodology has been effectively

applied in prior studies to discern the causal impacts of NPI policies on residential travel patterns and intra-city mobility during the pandemic period [16,66]. Through ITS analysis, this study aims to identify both the immediate and long-term effects of NPIs on CBM, providing nuanced insights into their impact.

Table 1 describes the variables used in our ITS model analysis. The dependent variable is the daily CBM between Shenzhen and Hong Kong, capturing the flow of individuals across the border. For independent variables, we consider age and gender to explore how different demographic groups are affected by NPI policies. Control variables include the daily new confirmed COVID-19 cases in both Shenzhen and Hong Kong, the Chinese Spring Festival holidays, and the days of the week. We use the daily new case counts as a proxy for public risk perception during the epidemic, since case numbers were the primary signal shaping risk awareness and behavioral caution in this period.

Table 1. Description of variables.

Variables	Description	Mean	St. Dev.
Dependent variable			
CBM	CBM flows from Hong Kong to Shen Zhen	334.26	355.84
Independent variables			
Day	Daily code for each day in the period of study counting from 1 (1, 2, 3. . ., 183)	92	52.84
Period	Period #1 1: After the intervention at the time point of the warning period; 0: Before.	0.05	0.22
	Period #2 1: After the intervention at the time point of the freezing period; 0: Before.	0.17	0.38
	Period #3 1: After the intervention at the time point of the adjustment period; 0: Before.	0.36	0.48
	Period #4 1: After the intervention at the time point of the recovering period; 0: Before.	0.17	0.38
Time	Time #1 Daily code for each day after the intervention of the warning period counting from 1 (1, 2, 3. . .)	0.20	1.04
	Time #2 Daily code for each day after the intervention of the freezing period counting from 1 (1, 2, 3. . .)	2.54	6.73
	Time #3 Daily code for each day after the intervention of the adjustment period counting from 1 (1, 2, 3. . .)	11.72	19.36
	Time #4 Daily code for each day after the intervention of the recovering period count from 1 (1, 2, 3. . .)	2.71	7.04
Gender (CBM)	1: Male; 0: Female.	4563.42	2084.50
Age (CBM)	20–29 age 20–29 year olds as a reference group	2110.96	1046.47
	30–39 age 1: People aged 30–39; 0: other age groups.	2793.11	1300.74
	40–49 age 1: People aged 40–49; 0: other age groups.	2089.09	987.40
	50–59 age 1: People aged 50–59; 0: other age groups.	1110.74	544.92
	age 60+ 1: People aged 60 and older; 0: other age groups.	492.90	226.74
Control variables			
Case	HK_case New COVID-19 cases in Hong Kong	5.92	12.54
	SZ_case New COVID-19 cases in Shenzhen	2.48	7.37
Holiday	Spring Festival holiday dummies (1: from 24 January to 2 February 2020; 0: other days.)	0.07	0.25
Day of Week	Weekly dummies, includes Monday to Saturday	0.14	0.35

Specifically, we utilized a multilevel mixed-effects model for estimating treatment effects, comprising a two-level structure: time-varying variables at Level-1 and demographic characteristics, such as gender and age, at Level-2. The Level 1 model is as follows:

Level-1: Time-varying model

$$CBM_{it} = \beta_{0i} + \beta_{1i}Day_{it} + \beta_{2i}Period_t + \beta_{3i}(Period_{it} * Time_{it}) + \beta_{4i}Case_{it} + \beta_{5i}Holiday_{it} + \sum_{k=1}^6 \beta_{(k+5)}(Day\ of\ Week_{ij})_k + \varepsilon_{it} \quad (1)$$

where subscript i denotes various population groups distinguished by age and gender, while subscript t indicates time, ranging from 1 to 183 days. The dependent variable, CBM_{it} , represents CBM from Hong Kong to ShenZhen across different population groups of 183 days. Furthermore, Day_{it} is the daily counter, starting at 1 for the first day and ending at 183 for the last day of the study period; $Period_{it}$ is a set of dummy variables indicating different mobility intervention periods; and $Time_{it}$ consists of indicators that are set to 0 before any interventions and sequentially increase (1, 2, 3, ...) following the initiation of an intervention. Control variables include $Case_{it}$, which tracks daily new COVID-19 cases in Hong Kong (HK_Case) and Shenzhen (SZ_Case) over the study period. To account for holidays and weekly variations in CBM, the model incorporates Spring Festival holiday dummies (Holiday) and weekly dummies (Day of Week). It is noteworthy that, in response to the COVID-19 pandemic, the Spring Festival holiday in 2020 was extended from its regular seven days to ten days, spanning from 24 January to 2 February 2020. Importantly, all control variables in the model have been centralized.

In the model, β_0 signifies the baseline level of CBM at day 0, assuming all other influencing factors are held constant, and β_1 represents the average rate of change over time, capturing the trend of CBM in the absence of interventions. Moreover, β_2 captures the abrupt effects of policy interventions, reflecting any sudden shifts in CBM levels following the implementation of policies, whereas β_3 illustrates the change in the rate of CBM over time due to the interventions, essentially showing how the day-to-day trend in CBM adjusts after policy measures take effect. This coefficient is crucial for understanding the long-term causal effects of each intervention on the daily change rate of CBM. Lastly, ε_{it} denotes the error term.

Additionally, we hypothesized that the causal effects of NPI policies might vary across different age and gender groups. Consequently, the coefficients in Equation 1 are influenced by age and gender, with their functional relationships specified in the Level-2 model as follows:

Level-2: Time-invariant model

When considering gender difference

$$\beta_{0i} = \rho_{00} + \rho_{01}Gender_i + \rho_{02}C_Age_i + \rho_{03}Gender_i * C_Age_i + \delta_{0i} \quad (2)$$

$$\beta_{pi} = \rho_{p0} + \rho_{p1}Gender_i + \delta_{pi}, \quad (p = 1 \sim 5) \quad (3)$$

When considering age difference

$$\beta_{0i} = \varsigma_{00} + \varsigma_{01}Age_i + \varsigma_{02}C_Gender_i + \varsigma_{03}Age_i * C_Gender_i + \delta_{0i} \quad (4)$$

$$\beta_{qi} = \varsigma_{q0} + \varsigma_{q1}Age_i + \delta_{qi}, \quad (q = 1 \sim 5) \quad (5)$$

In the given model, we use a dummy variable $Gender_i$, where 1 represents male and 0 represents female. Additionally, C_Gender_i denotes the centered $Gender_i$. The vector Age_i comprises dummy variables for five distinct age groups: 20–29, 30–39, 40–49, 50–59 and above 60, with 20–29 as the reference group. Furthermore, C_Age_i signifies the centered values of Age_i .

Furthermore, ρ_{00} represents the mean of β_{0i} parameters for female, indicating the average CBM for females in each age group, and ρ_{01} illustrates the difference in average CBM between females and males; ρ_{02} captures the variance in female CBM across different

age groups, and ρ_{03} reveals the disparity between the variations in CBM among different male age groups compared to those among different female age groups.

Similarly, ζ_{00} represents the mean of β_{oi} parameters for the 20–29 age group, indicating the average CBM for 20–29 age group, regardless of gender; ζ_{01} indicates the differential in average CBM between the 20–29 age group and other age groups. Additionally, ζ_{02} is the difference in the means of CBM between males and females in 20–29 age group, while ζ_{03} is defined as the variance between the gender differences in other age groups and the gender differences in the 20–29 age group. Moreover, ρ_{p0} is the mean value of β_{pi} for females, and ζ_{q0} is the mean value of β_{qi} for the 20–29 age group, respectively. Lastly, δ_i is introduced as a random effect to account for unobserved individual-specific variations, ensuring that the model can accommodate idiosyncrasies not captured by the observed variables.

4. Results

4.1. Estimated Effects of NPI Policies on General CBM

Table 2 showcases the estimated outcomes for CBM from Hong Kong to Shenzhen, as derived from the ITS model. The results provide insights into the causal effects of NPIs on CBM from Hong Kong to Shenzhen. Given that movement trends between Hong Kong and Shenzhen and vice versa exhibit similar patterns, we focus our discussion on the CBM from Hong Kong to Shenzhen for clarity. Before the pandemic, the daily total CBM from Hong Kong to Shenzhen was about 5069 ($=506.92 \times 10$, $p < 0.01$). The results reveal that several NPI policies, including the announcement of human-to-human transmission, the highest level of public health emergency response, and the second level of response, significantly affected CBM either abruptly or gradually, impacting both the level and trend of CBM.

At the beginning of the warning stage on 15 January, early efforts to disseminate information and provide guidance about COVID-19 did not immediately impact cross-border movements. Nonetheless, the policies enacted during this stage resulted in a consistent decline in CBM, with a decrease rate of 32.30 person-times per day ($p < 0.01$). This trend suggests that the gradual changes in CBM were significantly influenced by official announcements regarding the risk associated with COVID-19. This finding is consistent with previous studies which demonstrate that people tend to change their mobility behaviors prior to the implementation of the stricter mandatory policies by local authorities [16,67].

During the freezing period, which started on 24 January following the issuance of the highest-level emergency response by Guangdong Province, there was an abrupt and gradual decrease in CBM from Hong Kong to Shenzhen. Specifically, CBM from Hong Kong to Shenzhen experienced a significant drop of 4096 person-times per day (i.e., 409.5710, $p < 0.01$). This decline amounted to a significant 75.47% reduction from the expected flow on 24 January, based on the trend before the pandemic (i.e., $-409.57/[506.92 + 0.65 \times 55] = 75.47\%$, where 55 represents the number of days counted from the initial day). The immediate and substantial drop during the freezing stage, led by the highest-level emergency response together with the accompanying port closures and quarantine measures, illustrates the effectiveness of such stringent policy packages in abruptly reducing mobility levels.

During the adjustment period starting on 24 February, when Guangdong Province downgraded its emergency response from the first level to the second, an immediate recovery in CBM from Hong Kong to Shenzhen was observed. Figure 3 illustrates significant abrupt reductions in CBM (3880 person-times/day, $p < 0.01$) compared with the counterfactual scenario (i.e., if there were no pandemic). Specifically, CBM saw an instantaneous decrease of 68.93% (calculated as $387.96/[506.92 + 0.65 \times 86]$, where 86 represents the days counted from the initial date). However, this stage's smaller reduction signals a recovery relative to the previous period. It indicates that, despite the policy downgrade, restrictions continued to significantly influence CBM.

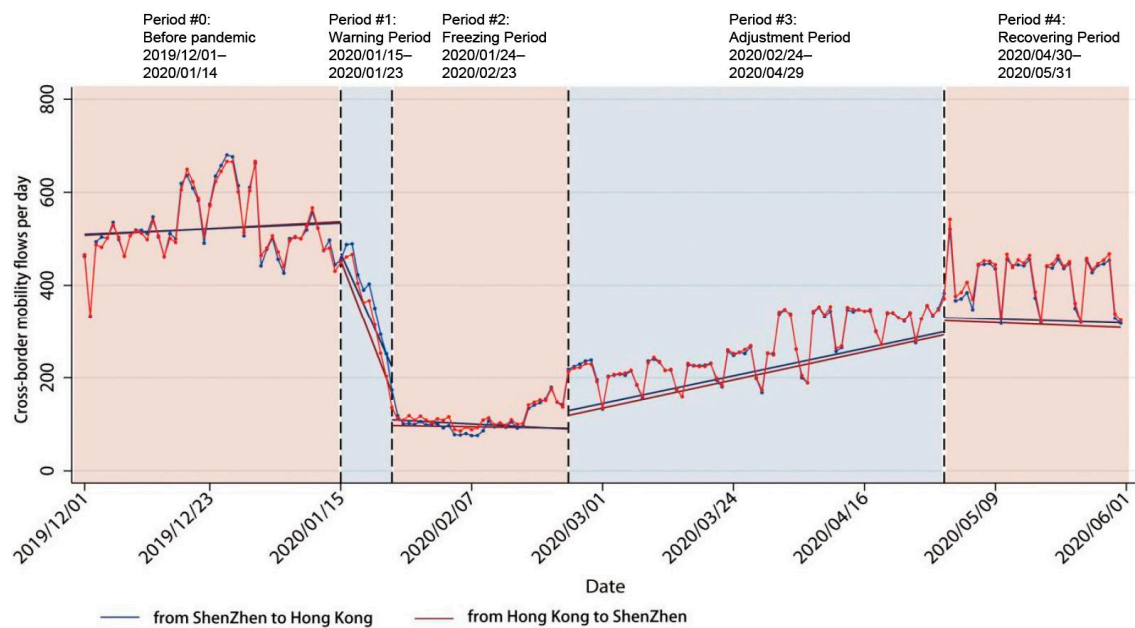


Figure 3. Estimated causal effects (abrupt and gradual effects) of the NPI policies on CBM (Notes: The straight lines denote the model-estimated daily CBM of different directions, with red for Hong Kong to Shenzhen and blue for Shenzhen to Hong Kong. The scattered connecting lines in the background represent the actual daily CBM in different directions.).

Table 2. Estimated results of core variables in the full model.

CBM		From Hong Kong to Shenzhen		
Variables		Coef.	St. Err.	p Value
Pre-pandemic level and trend				
Day (the trend over time)		0.65	1.18	0.58
Constant (the level before the pandemic)		506.92 ***	31.96	0.00
The abrupt effects on CBM flows during four Periods				
Period #1: Warning Period		−53.87	70.67	0.45
Period #2: Freezing Period		−409.57 ***	81.85	0.00
Period #3: Adjustment Period		−387.96 ***	80.59	0.00
Period #4: Recovering Period		−184.00	156.92	0.24
The gradual effects on CBM flows during four Periods				
Period #1 × Time #1: Warning Period		−32.30 **	13.36	0.02
Period #2 × Time #2: Freezing Period		−0.84	3.41	0.81
Period #3 × Time #3: Adjustment Period		1.97	1.35	0.15
Period #4 × Time #4: Recovering Period		−1.13	2.31	0.63
Control Variables				
Holiday		−13.76	41.52	0.74
HK_Cases		−0.29	0.72	0.69
SZ_Cases		−1.20	1.76	0.49
Monday		48.71 *	28.32	0.09
Tuesday		54.42 *	28.36	0.06
Wednesday		62.03 **	28.30	0.03
Thursday		62.18 **	28.34	0.03
Friday		81.80 ***	28.37	0.00
Saturday		29.08	28.27	0.30
Number of obs.	1830	Chi-square		690.81
Prob > chi2	0.000	Akaike crit. (AIC)		21,293.63

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. CBM Gender Difference on the Causal Effects of NPI Policies on CBM

Table 3 highlights the gender-based disparities in the effects of NPI policies on CBM from Hong Kong to Shenzhen in the ITS model. Prior to the pandemic, there was a significant difference in daily CBM: women's movements were approximately 1760 (calculated as 352×5 , considering 5 age groups), whereas men's were nearly double at 3370 ($[352 + 322] \times 5$), underscoring a marked gender disparity during the COVID-19 pandemic.

Table 3. Estimated results of core variables in the ITS model (Gender).

CBM		From Hong Kong to Shenzhen		
Variables		Coef.	St. Err.	p Value
Pre-pandemic level and trend				
Constant (the pre-pandemic level of CBM for female, as reference)		351.69 ***	17.8	0.00
Gender (the pre-pandemic level of CBM for male compared to female)		321.66 ***	25.16	0.00
Day (the trend over time for female)		−0.34	0.67	0.62
Day × Gender (the trend over time for male, compared to female)		1.98 **	0.95	0.04
The abrupt effects on CBM flows during four periods between female and male				
Period #1: Warning Period	Female (as reference, the level changes in the Period #1)	−27.25	40.33	0.50
	Male (compared to female)	−53.23	56.91	0.35
Period #2: Freezing Period	Female (as reference, the level changes in the Period #2)	−238.44 ***	46.77	0.00
	Male (compared to female)	−342.26 ***	66.08	0.00
Period #3: Adjustment Period	Female (as reference, the level changes in the Period #3)	−214.21 ***	46.07	0.00
	Male (compared to female)	−347.51 ***	65.14	0.00
Period #4: Recovering Period	Female (as reference, the level changes in the Period #4)	−39.27	89.70	0.66
	Male (compared to female)	−289.47 **	126.82	0.02
The gradual effects on CBM flows during four periods between female and male				
Period #1 × Time #1: Warning Period	Female (as reference, the slope changes in the Period #1)	−18.15 **	7.63	0.02
	Male (compared to female)	−28.29 ***	10.76	0.01
Period #2 × Time #2: Freezing Period	Female (as reference, the slope changes in the Period #2)	−0.56	1.95	0.78
	Male (compared to female)	−0.61	2.75	0.82
Period #3 × Time #3: Adjustment Period	Female (as reference, the slope changes in the Period #3)	2.03 ***	0.77	0.01
	Male (compared to female)	−0.10	1.09	0.92
Period #4 × Time #4: Recovering Period	Female (as reference, the slope changes in the Period #4)	0.30	1.32	0.82
	Male (compared to female)	−2.85	1.87	0.13
Number of obs.	1830	Chi-square	17,732.79	
Prob > chi2	0.000	Akaike crit. (AIC)	20,915.31	

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$.

Table 3 and Figure 4 demonstrate noticeable gender differences in the trend changes of CBM during the warning period. Specifically, the decline in female CBM was 5.40% (determined by $18.15/[351.69 - 0.34 \times 46]$, with 46 being the days from the start date), in contrast to a 6.20% reduction in male CBM (calculated as $[18.15 + 28.29]/[351.69 + 321.66 + [-0.34 + 1.98] \times 46]$). These findings suggest that women had a slower reaction to the NPIs of the warning period and exhibited lower adaptability than men during this period.

On 24 January, during the freezing period following Guangdong Province's issuance of the highest-level emergency response, there was a notable instantaneous decline in CBM from Hong Kong to Shenzhen for both genders. Specifically, female CBM dropped by approximately 71.61% (calculated as $238.44/[351.69 - 0.34 \times 55]$, with 55 being the days from the start of the period), while male CBM saw a decrease of about 76.05% (i.e., $[238.44 + 342.26]/[351.69 + 321.66 + [-0.34 + 1.98] \times 55]$). These findings suggest that under more stringent policy restrictions, women displayed a smaller reduction in CBM compared to men, a pattern consistent with the findings of Heiler et al. [68] in Austria. This

may be attributed to the fact that women exhibit lower mobility elasticity due to caregiving duties and labor market disadvantages [69]. One possible explanation is that women may have less elastic travel demands, for instance, owing to caregiving duties or labor-market constraints [69].

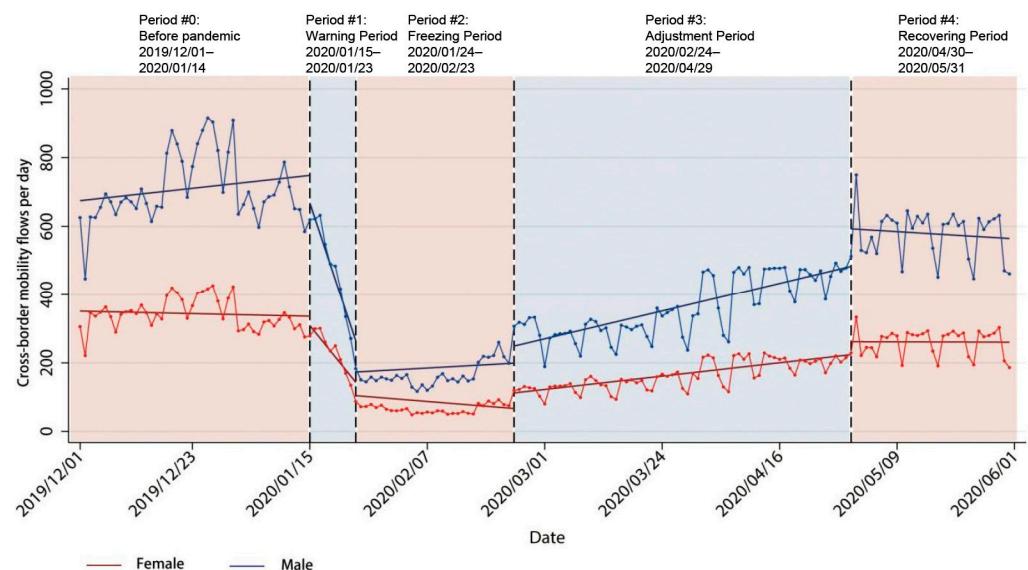


Figure 4. Estimated causal effects (abrupt and gradual effects) of the NPI policies on CBM between male and female (Notes: The straight lines denote the model-estimated daily CBM of different gender, with red for female and blue for male. The scattered connecting lines in the background represent the actual daily CBM for different genders.).

During the adjustment period starting 24 February, with Guangdong Province reducing its emergency response from level 1 to level 2, significant gender differences were observed in the changes in CBM. Compared to the counterfactual scenario (pre-epidemic period), women experienced an instantaneous decrease in mobility of about 66.43% (i.e., $214.21/[351.69 - 0.34 \times 86]$, where 86 represents the number of days counted from the initial day), while men's mobility decreased by approximately 68.97% (calculated as $[214.21 + 347.51]/[351.69 + 321.66 + [-0.34 + 1.98] \times 86]$). This suggests that women are more responsive to gradually relaxed mobility policies than men, possibly due to their need for essential travel to be reinstated as soon as possible. Subsequently, during the recovering period, the CBM trend remained relatively stable.

In summary, there are differences in the CBM demands and characteristics of men and women, and their travel elasticity and adjustability under NPI policies are also different. Men show greater flexibility in adjusting their travel behaviors, often reducing their mobility more quickly under less stringent restrictions. In contrast, women display less travel elasticity, with some continuing cross-border movements even after the confirmation of human-to-human transmission, until the enactment of mandatory restrictions at the freezing period. Furthermore, during the recovery phase, women's mobility rebounds rapidly following policy relaxation, emphasizing the importance of this segment of travel demand, while men experience a gradual long-term recovery.

4.3. Age Difference in the Causal Effects of NPI Policies on CBM

Table 4 presents the age-related differences in the causal effects of NPI policies on CBM from Hong Kong to Shenzhen in the ITS model. These findings reveal significant variations in CBM across different age groups from Hong Kong to Shenzhen. Before the pandemic, the largest CBM was observed among individuals aged 20–29, with a daily average of 2004 person-times (calculated as 1002×2 , accounting for both female and male groups). This was followed

by the 30–39 age group, with 1622 person-times/day (i.e., $[1002 - 191] \times 2$). Following this, the 40–49 age group saw 462 person-times/day, the 50–59 group had 245 person-times, and the group aged over 60 recorded the lowest at 44 person-times/day.

Table 4. Estimated results of core variables in the ITS model (Age).

CBM		From Hong Kong to Shenzhen		
Variables		Coef.	St. Err.	p Value
Pre-pandemic level and trend				
Constant (the pre-pandemic level of CBM for 20–29 age group, as reference)		1001.58 ***	19.21	0.00
30–39 age (20–29 vs. 30–39)		−191.04 ***	27.16	0.00
40–49 age (20–29 vs. 40–49)		−539.75 ***	27.16	0.00
50–59 age (20–29 vs. 50–59)		−756.47 ***	27.16	0.00
60+ age (20–29 vs. 60+)		−958.06 ***	27.16	0.00
Day (the trend over time for 20–29 age group, as reference)		3.01 ***	0.73	0.00
Day × 30–39 age (20–29 vs. 30–39)		−2.26 **	1.03	0.03
Day × 40–49 age (20–29 vs. 40–49)		−3.08 ***	1.03	0.00
Day × 50–59 age (20–29 vs. 50–59)		−3.41 ***	1.03	0.00
Day × 60+ age (20–29 vs. 60+)		−3.03 ***	1.03	0.00
The abrupt effects on CBM flows during four periods among different age groups				
Period #1: Warning Period	20–29 age (the level changes in the Period #1, as reference)	−122.45 ***	43.47	0.01
	30–39 age (20–29 vs. 30–39)	19.68	61.42	0.75
	40–49 age (20–29 vs. 40–49)	95.75	61.42	0.12
	50–59 age (20–29 vs. 50–59)	112.31 *	61.42	0.07
	60+ age (20–29 vs. 60+)	115.16 *	61.42	0.06
Period #2: Freezing Period	20–29 age (the level changes in the Period #2, as reference)	−932.94 ***	50.44	0.00
	30–39 age (20–29 vs. 30–39)	312.05 ***	71.32	0.00
	40–49 age (20–29 vs. 40–49)	599.90 ***	71.32	0.00
	50–59 age (20–29 vs. 50–59)	789.88 ***	71.32	0.00
	60+ age (20–29 vs. 60+)	915.04 ***	71.32	0.00
Period #3: Adjustment Period	20–29 age (the level changes in the Period #3, as reference)	−878.10 ***	49.71	0.00
	30–39 age (20–29 vs. 30–39)	292.33 ***	70.30	0.00
	40–49 age (20–29 vs. 40–49)	562.90 ***	70.30	0.00
	50–59 age (20–29 vs. 50–59)	744.08 ***	70.30	0.00
	60+ age (20–29 vs. 60+)	851.39 ***	70.30	0.00
Period #4: Recovering Period	20–29 age (the level changes in the Period #4, as reference)	−501.26 ***	96.79	0.00
	30–39 age (20–29 vs. 30–39)	240.51 *	136.87	0.08
	40–49 age (20–29 vs. 40–49)	380.21 ***	136.87	0.01
	50–59 age (20–29 vs. 50–59)	482.77 ***	136.87	0.00
	60+ age (20–29 vs. 60+)	482.81 ***	136.87	0.00
The gradual effects on CBM flows during four periods among different age groups				
Period #1 × Time #1: Warning Period	20–29 age (the slope changes in the Period #1, as reference)	−74.13 ***	8.22	0.00
	30–39 age (20–29 vs. 30–39)	25.24 **	11.61	0.03
	40–49 age (20–29 vs. 40–49)	48.18 ***	11.61	0.00
	50–59 age (20–29 vs. 50–59)	62.54 ***	11.61	0.00
	60+ age (20–29 vs. 60+)	73.21 ***	11.61	0.00
Period #2 × Time #2: Freezing Period	20–29 age (the slope changes in the Period #2, as reference)	−1.59	2.10	0.45
	30–39 age (20–29 vs. 30–39)	0.28	2.97	0.93
	40–49 age (20–29 vs. 40–49)	1.11	2.97	0.71
	50–59 age (20–29 vs. 50–59)	1.13	2.97	0.70
	60+ age (20–29 vs. 60+)	1.23	2.97	0.68
Period #3 × Time #3: Adjustment Period	20–29 age (the slope changes in the Period #3, as reference)	2.58 ***	0.83	0.00
	30–39 age (20–29 vs. 30–39)	0.84	1.18	0.48
	40–49 age (20–29 vs. 40–49)	−0.42	1.18	0.72
	50–59 age (20–29 vs. 50–59)	−1.03	1.18	0.38
	60+ age (20–29 vs. 60+)	−2.41 **	1.18	0.04
Period #4 × Time #4: Recovering Period	20–29 age (the slope changes in the Period #4, as reference)	−5.51 ***	1.43	0.00
	30–39 age (20–29 vs. 30–39)	4.13 **	2.01	0.04
	40–49 age (20–29 vs. 40–49)	6.06 ***	2.01	0.00
	50–59 age (20–29 vs. 50–59)	5.92 ***	2.01	0.00
	60+ age (20–29 vs. 60+)	5.80 ***	2.01	0.00
Number of obs.	1830	Chi-square	23,547.75	
Prob > chi2	0.000	Akaike crit. (AIC)	20,879.47	

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, the adaptability of older populations to changes in policy is notably lower, as they do not exhibit the immediate and substantial responses seen in younger age groups. As detailed in Figure 5, the warning period did not trigger an immediate significant impact, yet it resulted in a continuous decrease in CBM. Compared to the counterfactual scenario without the pandemic, the 20–29 age group experienced the most significant change in trend, with a 6.50% decrease (i.e., $-74.13/[1001.58 + 3.01 \times 46]$, where 46 represents the number of days counted from the initial day). In contrast, the age group of 60 and above responded the slowest and had the smallest decrease, which amounted to 2.16% per day (i.e., $[-74.13 + 73.21]/[1001.58 - 958.06 + [3.01 - 3.03] \times 46]$).

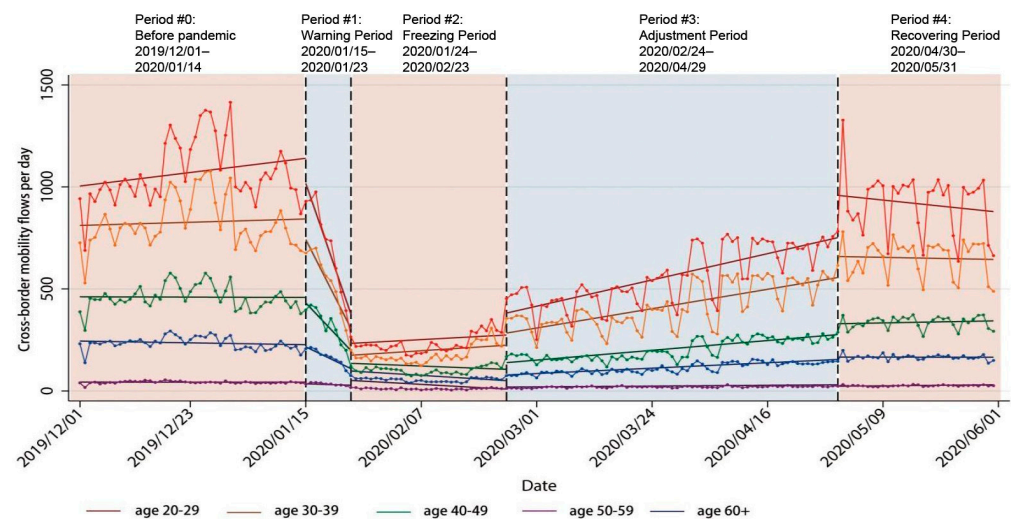


Figure 5. Estimated causal effects (abrupt and gradual effects) of the NPI policies on CBM among different age groups (Notes: The straight lines denote the model-estimated daily CBM of different ages, with red for age 20–29, orange for age 30–39, green for age 40–49, purple for age 50–59 and blue for age 60+. The scattered connecting lines in the background represent the actual daily CBM of different age groups.).

During the freezing period, the immediate reduction effects of the NPIs on CBM varied among different age groups. Among them, the 20–29 age group faced the most substantial reduction, with a decrease of 932.94 person-times per day, translating to a 79.93% decline (calculated as $-932.94/[1001.58 + 3.01 \times 55]$, with 55 being the days from the start). Conversely, the older population (60+ years) saw the lowest reduction, with a drop of 18 person-times, which constitutes 42.20% (calculated as $[-932.94 + 915.04]/[1001.58 - 958.06 + [3.01 - 3.03] \times 55]$) of their CBM compared to pre-pandemic level. Notably, the decrease in mobility among those aged 60+ was significantly less pronounced than in other age groups, indicating a relatively weaker immediate impact of the first-level response on the mobility of older people. This suggests that some older individuals maintain essential cross-border activities, such as seeking medical care, and thus might continue to cross the border between Shenzhen and Hong Kong despite the risks posed by human-to-human transmission and the implementation of strict response policies.

During the adjustment period, an immediate recovery in CBM was observed, with variations across age groups compared to the freezing period. The older age groups, specifically those aged 50–59 and 60+, showed more substantial recovery compared to younger counterparts. For example, in comparison to a counterfactual scenario (assuming no pandemic), the CBM of the 50–59 age group decreased instantaneously by 63.60% (i.e., $[-878.10 + 744.08]/[1001.58 - 756.47 + (-3.41 + 3.01) \times 86]$, with 86 being the days from the start), and the 60+ age group saw a 63.90% decrease (calculated as $[-878.10 + 851.39]/[1001.58 - 958.06 + (-3.03 + 3.01) \times 86]$). In contrast, the 20–29 age group experienced the most significant

reduction of 69.67% (calculated as $-878.10/[1001.58 + 3.01 \times 86]$), indicating a slower recovery rate. It is essential to emphasize that, during this period, a smaller reduction implies a faster recovery. Therefore, the observation that older age groups had smaller reductions in CBM suggests they rebounded more swiftly, possibly due to a more pressing need for cross-border activities such as accessing medical care or other essential services.

During the recovering period, we can observe significant and immediate effects of NPI policies on CBM across various age groups, as detailed in Table 4. To elaborate, when compared to a counterfactual scenario (assuming no pandemic), individuals aged 30–60 experienced a relatively minor decline in CBM, with reductions ranging from 10.03% to 28.20%. Conversely, the CBM for those aged 60 and above saw the most significant decrease, with a 45.58% drop from the expected flow on 30 April, according to pre-pandemic patterns. This indicates that during the recovering phase, contrary to earlier periods, the older population demonstrated the slowest rebound in mobility, whereas the 30–60 age group showed quicker recovery. This difference could be attributed to the recovery policies issued on 30 April, primarily targeting the working population, such as cross-border truck drivers, rather than retired older individuals. Additionally, older adults may have been more hesitant to resume CBM due to health concerns related to the risk of infection [70]. We also noted a distinctive trend for the 20–29 age group during the recovering period, where the slope change is negative. This reflects that, as the most mobile group, they rebounded sharply once restrictions were eased, and after this pent-up demand was largely released early in the period, their activity level first declined and then stabilized.

5. Conclusions

This study takes the Shenzhen–Hong Kong region as a case study and summarizes the impact of NPI policies on cross-border mobility (CBM) in the early spread of COVID-19 from December 2019 to May 2020. The study divides this period into five periods (before the pandemic, the warning period, the freezing period, the adjustment period, and the recovering period). Subsequently, based on the interrupted time series (ITS) quasi-experimental analysis using the longitudinal anonymous mobile phone location big data, this study explores the causal effects and differences in the important policies issued during the study period, especially focusing on the agility and recovery of traditional vulnerable groups (women and older people) in responding to NPI policies of different stages.

The findings indicate that the NPI stages had significant effects on CBM between Hong Kong and Shenzhen. The strictest control measures, led by the highest-level emergency response, produced an abrupt and substantial contraction in cross-border flow, while the subsequent downgrading of restrictions brought only a partial recovery, indicating their persistent restrictive effects, a pattern consistent with the findings of Zhang and Ning [55]. Both the immediate and the gradual effects of these interventions thus played significant roles in shaping CBM.

The analysis also reveals significant gender differences. Before mobility restrictions, men's daily CBM was nearly twice as high as women's. Both when initial warnings were issued and under the strictest lockdown, women reduced their cross-border mobility more slowly than men, suggesting that their cross-border travel was relatively less flexible. These findings align with the existing literature on gendered mobilities, which attributes women's lower mobility elasticity to caregiving duties and labor market disadvantages [69], and notes their heavier childcare burden during crises [71].

Regarding age heterogeneity, older people showed weaker policy adaptability, with no significant immediate reduction when initial warnings were issued, a pattern that persisted even during the strict lockdown of the freezing period, suggesting a relatively rigid cross-border need among some older adults, possibly for healthcare in Hong Kong. During the later

relaxation, the older travelers captured in our data were the slowest to regain cross-border flow, pointing to them being a potentially vulnerable group. This may be attributed to lower technological aptitude, risk tolerance, and health resilience among older people [72], while strict cross-border controls may also have impeded their access to medical services and family visits, potentially exacerbating issues such as loneliness and heightened anxiety [73,74].

In conclusion, on the one hand, Shenzhen and Hong Kong have demonstrated effective alignment of requirements and regulations during emergencies, facilitating secure and smooth cross-border mobility. However, on the other hand, most NPI policies were applied homogeneously and produced differential impacts across demographic groups such as age and gender. These differential impacts suggest that more differentiated and group-sensitive cross-border management could better accommodate the varying needs of specific populations during public health crises [75]. For women, essential channels such as those for childcare and schooling could be maintained during periods of strict control and prioritized when restrictions are eased. Older adults, in turn, would benefit from dedicated channels for essential cross-border healthcare during control periods, along with assistance for digital registration and clearance procedures, while their medical-related travel could be prioritized in reopening exemptions. Younger adults, whose travel is more elastic, could instead serve as a primary margin for adjustment, with their mobility restricted earlier when controls tighten and monitored for rapid rebound when restrictions are relaxed to avoid congestion at reopening. Together, these differentiated measures would help align cross-border management with the heterogeneous needs of different population groups.

This study has several limitations that also point to directions for future research. First, like other quasi-experimental designs based on observational data, ITS cannot fully separate the policy interventions from every co-occurring time-varying factor during the pandemic period, although we control for case counts, the Spring Festival holiday, and day-of-week effects to mitigate this. Second, our data come exclusively from mainland China Unicom operations and cannot capture the cross-border activities of Hong Kong residents using Hong Kong-based carriers, which limits representativeness. Third, our model does not explicitly include classic determinants of cross-border mobility such as exchange rates, transportation infrastructure, and commuting costs, as these factors remained relatively stable over the short study period. Nevertheless, our real-time daily records provide unique insights into the immediate impact of policy changes during the pandemic. Future research could collaborate with Hong Kong mobile operators for more comprehensive datasets, incorporate additional dimensions such as income and education level, and examine cross-border mobility over longer time horizons to account for these structural factors.

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Abbreviations

The following abbreviations are used in this manuscript:

CBM	Cross-border mobility
ITS	Interrupted time series
NPIs	Non-pharmaceutical interventions
HSCB	Hong Kong–Shenzhen cross-boundary

Appendix A

Appendix A.1

Table A1 presents the demographic distribution of cross-border mobility by age group and gender based on our China Unicom mobile phone data before the pandemic.

Table A1. Average daily CBM from China Unicom mobile phone data before the COVID-19 pandemic.

Age Group	Male	Female	Total
20–29	2847 (40.11%)	1422 (41.28%)	4269 (40.50%)
30–39	2288 (32.24%)	1019 (29.59%)	3307 (31.38%)
40–49	1247 (17.57%)	596 (17.31%)	1843 (17.49%)
50–59	522 (7.36%)	277 (8.06%)	799 (7.58%)
60+	193 (2.72%)	130 (3.76%)	323 (3.06%)
Total	7098 (100%)	3443 (100%)	10,541 (100%)

Appendix A.2

Table A2 shows the full model estimation results with CBM from Shenzhen to Hong Kong as the dependent variable, which corresponds to the results in Table 2 in the paper. It can be found that the coefficients and significance levels are basically consistent, indicating the robustness of the results. Based on this, this paper focuses on the CBM from Hong Kong to Shenzhen.

Table A2. Estimated results of core variables in the full model (Dependent variable: CBM from Shenzhen to Hong Kong).

CBM	From Shenzhen to Hong Kong		
Variables	Coef.	St. Err.	p Value
Pre-pandemic level and trend			
Day (the trend over time)	0.53	1.17	0.65
Constant	509.21 ***	31.76	0.00
The abrupt effects on CBM flows during four periods			
Period #1: Warning Period	−40.80	70.23	0.56
Period #2: Freezing Period	−399.67 ***	81.35	0.00
Period #3: Adjustment Period	−380.00 ***	80.10	0.00
Period #4: Recovering Period	−179.69	155.96	0.25
The gradual effects on CBM flows during four periods			
Period #1 × Time #1: Warning Period	−27.76 **	13.28	0.04
Period #2 × Time #2: Freezing Period	−1.17	3.39	0.73
Period #3 × Time #3: Adjustment Period	2.04	1.35	0.13
Period #4 × Time #4: Recovering Period	−0.90	2.30	0.70

Table A2. Cont.

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Control Variables				
Holiday		−17.33	41.26	0.67
HK_Cases		−0.33	0.71	0.64
SZ_Cases		−1.65	1.75	0.35
Monday		52.13 *	28.15	0.06
Tuesday		58.16 **	28.18	0.04
Wednesday		66.82 **	28.13	0.02
Thursday		66.59 **	28.16	0.02
Friday		86.72 ***	28.20	0.00
Saturday		30.37	28.09	0.28
Number of obs.	1830	Chi-square	105.16	
Prob > chi2	0.000	Akaike crit. (AIC)	24,339.12	

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.3

Table A3 shows the estimation results of the ITS model for gender differences with CBM from Shenzhen to Hong Kong as the dependent variable, which corresponds to the results in Table 3 in the paper. It can be found that the coefficients and significance levels are basically consistent, indicating the robustness of the results.

Table A3. Estimated results of core variables in the ITS model for gender differences (Dependent variable: CBM from Shenzhen to Hong Kong).

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Pre-pandemic level and trend				
Day (the trend over time of female)		−0.32	0.68	0.63
Constant (Female, as reference)		354.06 ***	17.85	0.00
Gender (Male compared to female)		324.71 ***	25.24	0.00
Day × Gender (the trend over time of male, compared to female)		1.72 *	0.96	0.07
The abrupt effects on CBM flows during four periods between female and male				
Period #1: Warning Period	Female (as reference, the level changes in the Period #1)	−22.23	40.44	0.58
	Male (compared to female)	−37.14	57.08	0.52
Period #2: Freezing Period	Female (as reference, the level changes in the Period #2)	−233.69 ***	46.90	0.00
	Male (compared to female)	−331.96 ***	66.27	0.00
Period #3: Adjustment Period	Female (as reference, the level changes in the Period #3)	−216.12 ***	46.21	0.00
	Male (compared to female)	−327.74 ***	65.33	0.00
Period #4: Recovering Period	Female (as reference, the level changes in the Period #4)	−50.33	89.97	0.58
	Male (compared to female)	−258.71 **	127.19	0.04
The gradual effects on CBM flows during four periods between female and male				
Period #1 × Time #1: Warning Period	Female (as reference, the slope changes in the Period #1)	−14.41 *	7.65	0.06
	Male (compared to female)	−26.69 **	10.79	0.01
Period #2 × Time #2: Freezing Period	Female (as reference, the slope changes in the Period #2)	−0.96	1.95	0.62
	Male (compared to female)	−0.41	2.76	0.88
Period #3 × Time #3: Adjustment Period	Female (as reference, the slope changes in the Period #3)	2.00 **	0.78	0.01
	Male (compared to female)	0.08	1.10	0.94
Period #4 × Time #4: Recovering Period	Female (as reference, the slope changes in the Period #4)	0.34	1.33	0.80
	Male (compared to female)	−2.48	1.87	0.19

Table A3. Cont.

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Control Variables				
Age (Female)	Age1 (age 30–39)	−149.28 ***	13.76	0.00
	Age2 (age 40–49)	−50.16 ***	19.46	0.01
	Age3 (age 50–59)	−284.31 ***	13.76	0.00
	Age4 (age 60+)	−267.41 ***	19.46	0.00
Age × Gender (Male)	Age1 (age 30–39)	−360.84 ***	13.76	0.00
	Age2 (age 40–49)	−380.16 ***	19.46	0.00
	Age3 (age 50–59)	−435.05 ***	13.76	0.00
	Age4 (age 60+)	−469.28 ***	19.46	0.00
Holiday (Female)		−11.97	23.77	0.62
Holiday × Gender (Male)		−10.74	33.57	0.75
HK_Cases (Female)		−0.10	0.41	0.81
HK_Cases × Gender (Male)		−0.47	0.58	0.42
SZ_Cases (Female)		−1.37	1.01	0.17
SZ_Cases × Gender (Male)		−0.56	1.42	0.69
Monday		52.13 ***	11.49	0.00
Tuesday		58.16 ***	11.50	0.00
Wednesday		66.82 ***	11.48	0.00
Thursday		66.59 ***	11.49	0.00
Friday		86.72 ***	11.51	0.00
Saturday		30.37 ***	11.46	0.01
Number of obs.	1830	Chi-square	20,617.91	
Prob > chi2	0.000	Akaike crit. (AIC)	20,952.60	

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.4

Table A4 shows the estimation results of the ITS model for age differences with CBM from Shenzhen to Hong Kong as the dependent variable, which corresponds to the results in Table 4 in the paper. It can be found that the coefficients and significance levels are basically consistent, indicating the robustness of the results.

Table A4. Estimated results of core variables in the ITS model for age differences (Dependent variable: CBM from Shenzhen to Hong Kong).

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Pre-pandemic level and trend				
Age0 (Age 20–29 as reference)		1008.38 ***	19.25	0.00
Age1 (30–39, as reference, compared to age 20–29)		−194.73 ***	27.22	0.00
Age2 (40–49, compared to age 20–29)		−544.82 ***	27.22	0.00
Age3 (50–59, compared to age 20–29)		−757.48 ***	27.22	0.00
Age4 (60+, compared to age 20–29)		−962.80 ***	27.22	0.00
Day (the trend over time of age 20–29, as reference)		2.47 ***	0.73	0.00
Day × Age1 (the trend over time of age 30–39)		−1.78 *	1.03	0.08
Day × Age2 (the trend over time of age 40–49)		−2.49 **	1.03	0.02
Day × Age3 (the trend over time of age 50–59)		−2.92 ***	1.03	0.01
Day × Age4 (the trend over time of age 60+)		−2.51 **	1.03	0.02
The abrupt effects on CBM flows during four periods among different age groups				
Period #1: Warning Period	Age0 (age 20–29 as reference, the level changes in the Period #1)	−83.93 *	43.56	0.05
	Age1 (age 30–39 compared to age 20–29)	4.70	61.55	0.94
	Age2 (age 40–49 compared to age 20–29)	67.20	61.55	0.28
	Age3 (age 50–59 compared to age 20–29)	70.83	61.55	0.25
	Age4 (age 60+ compared to age 20–29)	72.94	61.55	0.24

Table A4. Cont.

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Period #2: Freezing Period	Age0 (age 20–29 as reference, the level changes in the Period #2)	−888.60 ***	50.56	0.00
	Age1 (age 30–39 compared to age 20–29)	268.70 ***	71.47	0.00
	Age2 (age 40–49 compared to age 20–29)	554.11 ***	71.47	0.00
	Age3 (age 50–59 compared to age 20–29)	749.18 ***	71.47	0.00
	Age4 (age 60+ compared to age 20–29)	872.64 ***	71.47	0.00
Period #3: Adjustment Period	Age0 (age 20–29 as reference, the level changes in the Period #3)	−833.26 ***	49.82	0.00
	Age1 (age 30–39 compared to age 20–29)	249.31 ***	70.45	0.00
	Age2 (age 40–49 compared to age 20–29)	513.72 ***	70.45	0.00
	Age3 (age 50–59 compared to age 20–29)	697.35 ***	70.45	0.00
	Age4 (age 60+ compared to age 20–29)	805.97 ***	70.45	0.00
Period #4: Recovering Period	Age0 (age 20–29 as reference, the level changes in the Period #4)	−444.19 ***	97.01	0.00
	Age1 (age 30–39 compared to age 20–29)	171.18	137.17	0.21
	Age2 (age 40–49 compared to age 20–29)	302.45 **	137.17	0.03
	Age3 (age 50–59 compared to age 20–29)	422.55 ***	137.17	0.00
	Age4 (age 60+ compared to age 20–29)	426.33 ***	137.17	0.00
The gradual effects on CBM flows during four periods among different age groups				
Period #1 × Time #1: Warning Period	Age0 (age 20–29 as reference, the slope changes in the Period #1)	−61.68 ***	8.24	0.00
	Age1 (age 30–39 compared to age 20–29)	19.39 *	11.64	0.10
	Age2 (age 40–49 compared to age 20–29)	36.66 ***	11.64	0.00
	Age3 (age 50–59 compared to age 20–29)	51.94 ***	11.64	0.00
	Age4 (age 60+ compared to age 20–29)	61.61 ***	11.64	0.00
Period #2 × Time #2: Freezing Period	Age0 (age 20–29 as reference, the slope changes in the Period #2)	−2.29	2.10	0.28
	Age1 (age 30–39 compared to age 20–29)	0.69	2.97	0.82
	Age2 (age 40–49 compared to age 20–29)	1.55	2.97	0.60
	Age3 (age 50–59 compared to age 20–29)	1.54	2.97	0.61
	Age4 (age 60+ compared to age 20–29)	1.83	2.97	0.54
Period #3 × Time #3: Adjustment Period	Age0 (age 20–29 as reference, the slope changes in the Period #3)	2.99 ***	0.84	0.00
	Age1 (age 30–39 compared to age 20–29)	0.44	1.18	0.71
	Age2 (age 40–49 compared to age 20–29)	−0.98	1.18	0.41
	Age3 (age 50–59 compared to age 20–29)	−1.42	1.18	0.23
	Age4 (age 60+ compared to age 20–29)	−2.81 **	1.18	0.02
Period #4 × Time #4: Recovering Period	Age0 (age 20–29 as reference, the slope changes in the Period #4)	−4.94 ***	1.43	0.00
	Age1 (age 30–39 compared to age 20–29)	3.91 *	2.02	0.05
	Age2 (age 40–49 compared to age 20–29)	5.57 ***	2.02	0.01
	Age3 (age 50–59 compared to age 20–29)	5.49 ***	2.02	0.01
	Age4 (age 60+ compared to age 20–29)	5.25 ***	2.02	0.01
Control Variables				
Gender	Age0 (age 20–29, the difference between male and female)	477.61 ***	9.39	0.00
	Age1 (age 30–39 compared to age 20–29)	−50.16 ***	13.27	0.00
	Age2 (age 40–49 compared to age 20–29)	−267.41 ***	13.27	0.00
	Age3 (age 50–59 compared to age 20–29)	−380.16 ***	13.27	0.00
	Age4 (age 60+ compared to age 20–29)	−469.28 ***	13.27	0.00

Table A4. Cont.

CBM		From Shenzhen to Hong Kong		
Variables		Coef.	St. Err.	p Value
Holiday	Age0 (age 20–29, the difference between holidays and non-holidays)	−14.64	25.61	0.57
	Age1 (age 30–39 compared to age 20–29)	−38.05	36.20	0.29
	Age2 (age 40–49 compared to age 20–29)	3.00	36.20	0.93
	Age3 (age 50–59 compared to age 20–29)	7.90	36.20	0.83
	Age4 (age 60+ compared to age 20–29)	13.71	36.20	0.71
HK_Cases	Age0 (age 20–29)	−0.47	0.44	0.29
	Age1 (age 30–39 compared to age 20–29)	−0.11	0.62	0.86
	Age2 (age 40–49 compared to age 20–29)	0.09	0.62	0.89
	Age3 (age 50–59 compared to age 20–29)	0.27	0.62	0.67
	Age4 (age 60+ compared to age 20–29)	0.43	0.62	0.49
SZ_Cases	Age0 (age 20–29)	−2.94 ***	1.08	0.01
	Age1 (age 30–39 compared to age 20–29)	0.19	1.53	0.90
	Age2 (age 40–49 compared to age 20–29)	1.90	1.53	0.22
	Age3 (age 50–59 compared to age 20–29)	2.02	1.53	0.19
	Age4 (age 60+ compared to age 20–29)	2.33	1.53	0.13
Monday		52.13 ***	7.83	0.00
Tuesday		58.16 ***	7.84	0.00
Wednesday		66.82 ***	7.83	0.00
Thursday		66.59 ***	7.84	0.00
Friday		86.72 ***	7.85	0.00
Saturday		30.37 ***	7.82	0.00
Number of obs.	1830	Chi-square	21,731.62	
Prob > chi2	0.000	Akaike crit. (AIC)	20,970.64	

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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