

Article

Estimating Distance Equivalence for Sustainable Mobility Management: Evidence from China's "Stay-in-Place" Policy

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Abstract

Travel policies during crises strongly reshape mobility patterns, raising the challenge of protecting public health while minimizing socio-economic disruption—an essential concern for sustainable development. Most evaluations quantify changes in travel volume, which hampers cross-city comparison and policy monitoring. This study proposes a distance-based sustainability metric—distance equivalence (DE)—that translates policy-induced mobility frictions into interpretable “added distance” within a gravity framework, enabling consistent measurement and monitoring of policy impacts. Using inter-city flows for 358 Chinese cities during the Stay-in-Place for Lunar New Year (SIP) guidance, we map DE, test spatial dependence (Moran's I; LISA), and apply fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify city-level configurations associated with high DE. DE exhibits significant spatial clustering, concentrating east of the Hu line, where dense urban networks amplify advisory checks. Three recurrent configurations—combining case counts, health-care capacity (hospital beds), and average inter-city distance—are linked to high DE. As a sustainability assessment tool, DE supports adaptive management, region-differentiated strategies, and ex-ante risk assessment for governments, public-health authorities, and transport agencies. The framework generalizes to short-term mobility interventions under crisis conditions, advancing the quantification of policy impacts on sustainable mobility and urban resilience.

Keywords: distance equivalence; sustainable mobility; crisis management; policy evaluation; urban resilience



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1. Introduction

The focus on mobility during pandemics is important for the sustainable development of regional economies and transportation [1,2] and for disaster prevention [3]. In response, many countries and regions have adopted non-pharmaceutical interventions (NPIs) such as unprecedented global travel bans and stay-at-home measures, which have hindered spatial movement—especially inter-city mobility [4]. Numerous studies have shown that NPIs are effective and rapid in the early prevention and control of outbreaks [5–7]. However, most evaluations quantify changes in mobility volumes; comparatively fewer analyze policy

effects through the lens of distance, which is widely used to indicate the magnitude of resistance in geographic, urban, mobility, and related fields [8–10].

To address this conceptual and measurement gap, we recast policy impacts as spatial frictions. We define distance equivalence (DE) as the additional spatial distance that would, in a gravity framework, generate the same reduction in inter-city flows observed under a policy intervention. This provides an interpretable, comparable metric that links policy evaluation with spatial-interaction theory.

Against this backdrop of NPI research, the 2020 Wuhan lockdown has been extensively examined for its mobility effects [5,6,11], whereas the Stay-in-Place for Lunar New Year (SIP) policy announced on 25 January 2021 has received comparatively less scholarly attention. SIP was advisory rather than legally enforced: local authorities encouraged enterprises and public institutions to offer flexible leave so employees would celebrate locally; as a result, over 100 million people reportedly stayed in place nationwide [12]. Occurring at the height of Chunyun, SIP provides a distinct setting where mobility responses likely differ from coercive interventions. We therefore examine SIP’s impact through a distance equivalence lens to quantify its policy-induced resistance to inter-city travel.

This study contributes by (i) operationalizing policy-induced mobility resistance as a distance-equivalent metric; (ii) integrating gravity-based measurement with fsQCA to bridge “how much resistance” with “under what configurations”; and (iii) offering a portable tool for adaptive countermeasure planning. The remainder proceeds as follows: Section 2 reviews related work; Section 3 presents data and methods; Section 4 reports results; Section 5 discusses implications and limitations; Section 6 concludes. Positioned within sustainability science, our DE metric informs adaptive, least-disruptive interventions that maintain essential mobility, support economic continuity, and reduce unnecessary travel curbs—key aims of sustainable transport and resilient cities.

2. Literature Review

Multiple studies have indicated that NPIs, such as travel bans, stay-at-home orders, and activity restrictions, have altered inter-urban and intra-urban mobility, leading to significant short-term declines and heterogeneous recovery patterns across different regions [13,14]. Pre-existing regional socio-economic development factors have contributed to the disparate impacts of NPIs and the subsequent recovery of mobility [4,15]. In the context of China, spatial heterogeneity is often interpreted through the influence of the “Hu Line”, a demographic demarcation that shapes fundamental patterns of social interaction and policy responses [16,17], potentially leading to varied outcomes from the pandemic’s impact. Furthermore, beyond strict measures like lockdowns, it has been shown that advisory or “soft” restrictions, as well as voluntary behavioral changes (e.g., risk aversion, norm compliance), can also generate substantial adjustments in the absence of legal enforcement [18,19]. Although many studies have precisely quantified the effects of NPIs on mobility through the analysis of flow data, such as device trajectories and traffic records [20,21], the majority of these assessments have concentrated on changes in volume rather than the spatial aspects of distance.

Distance is a foundational concept in spatial interaction modeling [10,22]. Classical distance-decay and gravity models posit that spatial separation acts as an impedance to movement, wherein the frequency of interaction decreases as distance increases [23]. This principle transcends the purely physical realm; analogous “distances” within economic, cultural, or institutional spaces can similarly impede mobility and connectivity [9,24]. In the fields of epidemiology and network science, the concept of effective distance has emerged to capture the resistance within mobility networks, rather than mere geometric distance [25]. This approach recalibrates the strength of connections based on factors like

traffic flow or travel time, and research has demonstrated that it significantly enhances the predictive accuracy of the timing and geographic scope of disease transmission [25]. In essence, these models treat distance as a form of resistance to show how connectivity impacts the movement of people and the spread of disease. However, policy actions like lockdowns are rarely converted into an equivalent “distance” within these frameworks. This gap makes it difficult to consistently compare the spatial impacts of such policies across different cities or times [14].

Research on border effects demonstrates that even after controlling for physical distance and demographic factors, human mobility experiences a sharp decline at administrative boundaries [26]. The concept of “border distance equivalence” operationalizes this decline—often termed a “border penalty”—by converting it into an equivalent additional distance within gravity models [14,27]. In other words, the inhibitory effect of crossing a provincial or national border on mobility can be quantitatively assessed as being equivalent to traveling hundreds of additional kilometers [28,29]. During crises, NPIs often function as temporary borders or internal checkpoints, increasing the cost of travel without entirely halting movement [29,30]. For example, travel restrictions during the COVID-19 pandemic in China effectively established persistent inter-provincial border friction within the domestic mobility network [14]. By extending the logic of border effects to policy interventions, researchers can quantify the impact of policies as an additive distance in interaction models. A recent analysis applied a modified gravity model to inter-city mobility data to estimate the distance equivalence of China’s pandemic-related travel controls, finding a significant, though often temporary, increase in the effective distance between locked-down cities [14]. This method of expressing the mobility impedance of NPIs on a distance scale provides an intuitive and comparable metric for policy-induced friction. In line with emerging usage, we term this metric “distance equivalence”. The focus of our research is on temporally-bound, policy-induced resistance—that is, the short-term barriers created by emergency interventions rather than long-term, structural separation.

3. Materials and Methods

3.1. Measurement of the Distance Equivalence

To measure the distance equivalence of SIP policy, the relationship between distance and mobility needs to be clarified. In many studies on the relationship between passenger mobility and distance, the gravity model is the most commonly used modeling approach. Gravity models take several forms; using GDP (Gross domestic product) as the mass term between places is standard practice [31,32]. The equation is as follows:

$$F_{ij} = B \frac{(GDP_i)^\alpha (GDP_j)^\lambda}{(Dist_{ij})^\xi} U_{ij} \quad (1)$$

where F_{ij} is the gravitational value between two regions, which in this study is the passenger flow from city i to city j ; GDP_j is the GDP value of city j ; and $Dist_{ij}$ is the distance between city i and city j . Here, we use the common spherical Euclidean distance between two cities; U_{ij} is a log-normal distributed error term; and B , α , λ and ξ are parameters to be estimated. Taking the logarithm of the above model yields the following model:

$$F_{ij} = \beta + \alpha \ln GDP_i + \lambda \ln GDP_j - \xi \ln Dist_{ij} + \varepsilon_{ij} \quad (2)$$

A further transformation can be obtained as follows:

$$\ln Dist_{ij} = \frac{\beta + \alpha \ln GDP_i + \lambda \ln GDP_j - F_{ij} + \varepsilon_{ij}}{\xi} \quad (3)$$

This clarifies the general relationship between distance and passenger flow. Following the approach of Smith and Xie [27] regarding distance equivalence at national boundaries, we compare a policy year with the SIP policy (2021) to a policy year without the SIP policy (2020) and calculate the difference between the two years' distances, controlling for the effect of the two-year GDP factor, and the extra distance is the distance equivalence for the SIP policy. Accordingly, the following equation is obtained:

$$\text{LnDist}_{ij1} - \text{LnDist}_{ij0} = \frac{\alpha(\text{LnGDP}_{i1} - \text{LnGDP}_{i0}) + \lambda(\text{LnGDP}_{j1} - \text{LnGDP}_{j0}) - (F_{ij1} - F_{ij0})}{\xi} \quad (4)$$

The subscripts 1 and 0 in the above equation represent SIP policy year and no-SIP policy year, respectively; we reorganize the equations to obtain the following equation:

$$\text{LnDist}_{equi} = \frac{\alpha\Delta\text{LnGDP}_i + \lambda\Delta\text{LnGDP}_j - \Delta F_{ij}}{\xi} \quad (5)$$

where LnDist_{equi} is the distance equivalence of the SIP policy. The parameters B , α , λ and ξ are estimated via Equation (2) using data from the year without the SIP policy (2020) to determine the parameters in the normal case. The Baidu migration index is based on Baidu map positioning technology, and through big data calculations, it can present the value of passenger migration between two cities; thus, it is widely used to examine the Chunyun transportation, the pandemic and other scenarios in the study of passenger flow [4,33,34].

In this study, the Python 3.9 crawling technique is used to obtain O-D (Origin–destination) migration data for 2020 and 2021 the early phase of Chunyun (i.e., before Spring Festival) in 358 cities in China. The Chunyun period follows the National Development and Reform Commission (NDRC) announcement. This study chooses to examine the early phase of Chunyun not only because it is the time when people return to their hometowns, which can reflect the impact of the SIP policy on the wave of returns, but also because the iconic period of the 2020 outbreak occurred during the lockdown of Wuhan (23 January), which was enforced on the day before New Year's Eve 2020; thus, the early 2020 Chunyun period was less affected by the outbreak and can serve as a baseline without the SIP policy.

The choice of 2020 as the baseline year is strategic, as it serves as the most appropriate counterfactual scenario to assess the effects of the SIP policy. Unlike 2019, which represents a year without any pandemic-related mobility restrictions, 2020 reflects a period where mobility restrictions began to take shape (e.g., Wuhan lockdown), but before the nationwide SIP policy was implemented in 2021. Using 2020 as a baseline enables us to isolate the effects of SIP-induced mobility resistance, while still accounting for the broader crisis conditions impacting mobility.

In summary, the periods selected for this study are 10 January–24 January 2020, and 28 January–11 February 2021, and the values of the intercity passenger flows between the two periods are summarized as the total value of the two years' returning-home passenger flows. GDP_i is the GDP value of city i . Since the pre-Spring Festival period comprises the end of the previous year and the beginning of the new year, the GDP of the city in the previous year has a significant effect on mobility during Chunyun; here, GDP_{i1} is the annual GDP of the city in 2020, and GDP_{i0} is the GDP in 2019. By inputting the data from Chunyun in 2020 into Model (2), we obtain the estimation results of the gravity model shown in Table 1.

From this, we obtain the following estimation equation model of the distance equivalence:

$$\text{LnDist}_{equi} = \frac{0.081 * \Delta\text{LnGDP}_i + 0.517 * \Delta\text{LnGDP}_j - \Delta\text{LnF}_{ij}}{1.748} \quad (6)$$

Distance equivalence between pairs of O-D cities can be obtained from the corresponding data. Taking the average of the distance equivalence from the place of origin to the other cities yields the average distance equivalence of the SIP policy from that city to the other cities.

Table 1. Results of Gravity Model Estimation.

	Coefficient	T Value	VIF
constant	6.882	83.648	
$\ln GDP_i$	0.081	14.915	1.162
$\ln GDP_j$	0.517	85.274	1.055
$Dist_{ij}$	−1.748	−209.586	1.164
DW value		0.773	
R^2		0.698	

3.2. FsQCA Method

Recent work applies fuzzy-set Qualitative Comparative Analysis (fsQCA) to account for spatial heterogeneity in policy outcomes, highlighting conjunctural causation, equifinality, and asymmetry across cities [35,36]. To explain spatial heterogeneity in policy outcomes, we use fuzzy-set Qualitative Comparative Analysis (fsQCA) to interpret our gravity-based distance equivalence (DE) metric. While the DE metric quantifies policy-induced resistance, fsQCA identifies the specific configurations of public-health, socioeconomic, and spatial conditions that lead to high or low DE values across different cities. This configurational lens is appropriate because (i) high DE is theoretically expected to arise when multiple conditions act together, rather than through additive main effects; (ii) different city types can reach similar outcomes via different pathways, and the routes to high vs. low DE need not mirror each other; (iii) fsQCA yields transparent, minimal “recipes” that are interpretable for policy; and (iv) fsQCA complements gravity: gravity measures DE, fsQCA explains under what combinations it is elevated.

Following standard practice, we (i) calibrate conditions and the outcome into fuzzy-set memberships in (0,1); (ii) conduct necessity tests; (iii) construct a truth table and perform sufficiency analysis with a consistency threshold chosen at the observed break in raw-consistency ordering; (iv) report intermediate solutions, distinguishing core and peripheral conditions; and (v) present full diagnostics, including consistency, PRI, and raw/unique coverage, together with checks for contradictory configurations. Consistent with best practice, we also examine calibration-threshold sensitivity and summarize typical cases for each configuration to aid interpretation. As emphasized in methodological reviews, fsQCA primarily supports theory-building rather than strong causal identification given potential endogeneity and unobserved heterogeneity in cross-sectional designs [37].

3.3. Framework for Analysis

Factors that have an impact on regional mobility can constitute antecedent conditions for the distance equivalence of an SIP policy. The first is pandemics and health-related factors. Pandemics are thought to have an impact on mobility. Related studies have demonstrated that the number of confirmed cases during a pandemic has a key influence on mobility [4,38]. This study uses the number of confirmed COVID-19 cases in each city as one of the antecedent factors (this variable is expressed as COVID-19). Sanitary conditions are also thought to affect mobility [39–41]. This study uses the number of hospital beds as an indicator of health conditions (denoted as hosbed). Furthermore, Urban economic development status is an important factor influencing mobility during pandemics [42]. Herein, we use GDP per capita as an antecedent variable (denoted as PGDP), which provides support conditions for people to move. In addition, we use foreign direct investment as an

antecedent variable (denoted as DFI), which captures the degree of outward orientation of the city's economy and is an important factor influencing mobility [43,44]. Population underpins urban mobility [45]; we use population density (popden) to represent the population base (denoted as popden). Dialects are recognized as important factors influencing population movement during pandemics, with people preferring to move to culturally similar areas [4]. With reference to the relevant literature [46], we use dialect diversity as the antecedent variable (denoted as dialect). Finally, distance and transportation are indicators that are closely related to mobility, with distance being an impediment to mobility [42,47]. We use the average distance from the city to other cities as an indicator (denoted as AVE_dis). Better transportation facilities tend to compress spatial distances [48] and enhance mobility. We use road network density as an indicator in this study (abbreviated as roadden). FsQCA analyzes the effect of the antecedent variable configuration on the outcome variable. The analytical model is constructed on the basis of existing theories and the abovementioned analysis, as shown in Figure 1.

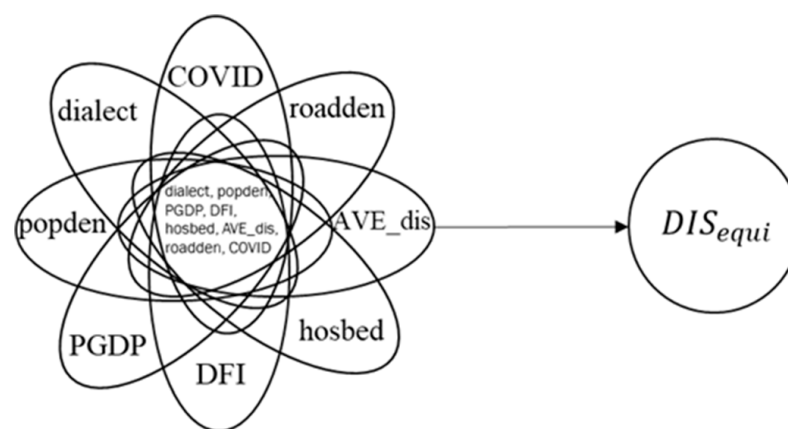


Figure 1. Framework for Analyzing the SIP Policy Distance Equivalence Configuration Effect.

3.4. Data and Calibration

Most of the data on socioeconomic antecedent variables, such as urban population density, GDP per capita, national trade and investment, number of hospital beds, and density of the road network, come from government statistical yearbooks such as the National Statistical Yearbook of China and the Statistical Yearbook of Urban Construction of China. The number of confirmed COVID-19 cases is integrated for each of the corresponding periods; these numbers are compiled from information published by the National Health Commission of the PRC http://www.nhc.gov.cn/yjb/pzhgli/new_list.shtml (accessed on 29 July 2021). The date of the dialect diversity index of the cities used is drawn from the research of Xu, Liu and Xiao [46]. The average distance between cities (AVE_dis) is obtained by averaging the spherical Euclidean distance between government locations. All variables are logarithmized, and descriptive statistics are shown on the right side of Table 2.

Table 2. Summary of City Distribution and Core Socioeconomic Indicators.

City Class	Number of Cities	Proportion (%)	Avg Pop (Millions)	Avg Pop Density (People/km ²)	Avg GDP (Billion CNY)
Mega/Very Large	102	34.5	7.75	624	542.4
Large	174	58.8	2.91	355	190.8
Medium	14	4.7	0.76	139	47.7
Small	6	2	0.33	70	37.9

To better characterize the sample, we include a summary table (Table 2) that groups cities by the official size classes—mega/very large (≥ 5 million), large (1–5 million), medium (0.5–1 million), and small (< 0.5 million)—and reports, for each class, the number and share of cities together with class-level averages of population size, population density, and GDP. For transparency, Supplementary Table S1 reports city-level descriptive statistics in natural-log form ($\ln$ GDP, $\ln$ population size, $\ln$ population density) for all sample cities with complete data, consistent with the log-linear gravity specification.

As part of the preparation for the fsQCA analysis, precalibration of the conditions and outcome variables under consideration is needed. This precalibration converts the considered condition and outcome variables (initially on their own scales) into fuzzy affiliation scores that range from 0 to 1. The calibration performed herein follows the direct method described by Ragin [49]. Typically, 0.95 is used for full membership, while 0.05 is used for full-nonmembership. The threshold of 0.5 indicates the crossover point about the set affiliation. These values do not represent probabilities but rather convert quantitative scales to degrees of affiliation within categories [50]. The left side of Table 3 indicates the calibration points for the analyzed variables.

Table 3. Calibration Points and Descriptive Statistics.

	Calibration Points			Descriptive Statistics			
	Full-Nonmembership	Crossover Point	Full Membership	Mean Value	Standard Deviation	Minimum Value	Maximum Value
<i>Lndialect</i>	−5.700	−1.200	−0.339	−1.972	1.721	−7.130	−0.250
<i>Lnpopden</i>	3.546	5.845	6.940	5.634	1.147	0.430	7.860
<i>LnPGDP</i>	10.118	10.815	11.810	10.868	0.527	9.450	12.160
<i>LnDFI</i>	6.120	10.160	13.180	9.890	2.196	2.710	14.360
<i>Lnhosbed</i>	0.859	1.470	2.160	1.492	0.366	0.580	2.570
<i>Lnroadden</i>	2.990	4.645	5.300	4.525	0.806	1.730	10.910
<i>LnCOVID</i>	1.100	3.300	6.729	3.356	1.599	0.000	10.830
<i>LnAVEdis</i>	7.210	7.480	8.012	7.494	0.291	5.710	8.350
<i>lnDIS_{equi}</i>	0.628	0.910	1.322	0.936	0.209	0.477	2.020

The selection of 0.95 and 0.05 was based on both domain consensus and the data distribution characteristics of the study. Our analysis of the data distribution showed that, after standardization, very few cases exceeded 0.95 or fell below 0.05. Therefore, these thresholds are appropriate for our data, capturing the main variations while adhering to standard practice in the field. To ensure robustness, we also tested alternative thresholds (e.g., 0.90/0.10), and the core configurations and conclusions remained stable, demonstrating that our findings are not sensitive to the choice of these thresholds.

4. Results

4.1. Descriptive Statistics

The increase in the distance equivalence between each O-D city due to the SIP policy is calculated via Equation (6). The mean value of the distance equivalence from each originating city to the other cities is calculated to obtain the policy distance equivalence for travel in each city. The results are visualized in Figure 2. The distance equivalence of the SIP policy shows a pattern of low values in the west and north regions and relatively high values in the east and south regions. DE is generally higher east of the Hu line and lower to the west, consistent with China's socioeconomic spatial structure [16]. In addition, first-tier cities such as Beijing, Shanghai, Guangzhou and Shenzhen and second-tier cities such as Jinan, Qingdao, Chongqing, et al. have higher values of distance equivalence than their lower-tier counterparts. These cities have a higher level of modernization and urbanization,

strong implementation of SIP policies, and a larger workforce, which results in a more pronounced distance equivalence.

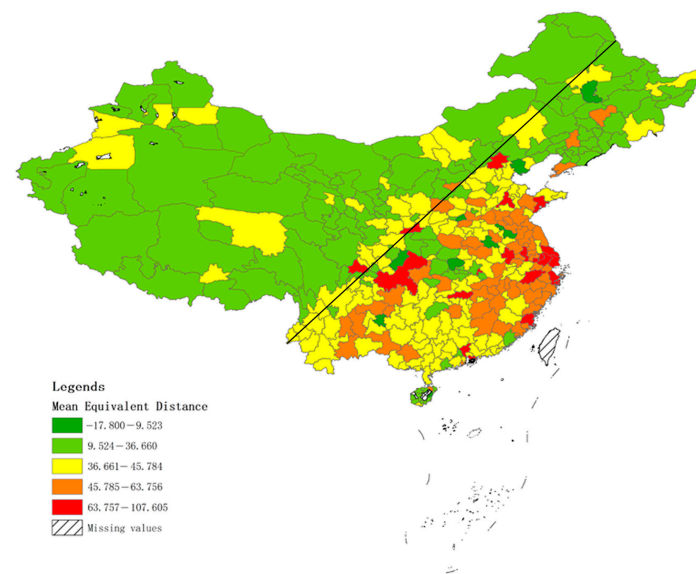


Figure 2. Spatial Distribution of the Distance Equivalence of the SIP Policy. Note: Basemap and administrative boundaries: NGCC, National Fundamental Geographic Information Database, 2020 (WGS84). Hu line drawn by authors.

4.2. Spatial Correlation Analysis

To further verify the spatial distribution pattern of the distance equivalence, spatial autocorrelation and agglomeration are calculated via Moran's index and the local Moran's index. Using the distance spatial weights, we calculate Moran's I value for the distance equivalence. A global Moran's I = 0.326 and Z value = 28.1176 are obtained, which are significant at the p value < 0.01 level; thus, the cities' distance equivalence show an overall correlated distribution. As seen from the results of the localized Moran's I index (Figure 3), the distance equivalence show a clustering of high values in southeastern, central and southwestern cities and a clustering of low values in northwestern and northeastern cities. Overall, the distance effect produced by the SIP policy is more pronounced in southeastern cities and is characterized by clustering.

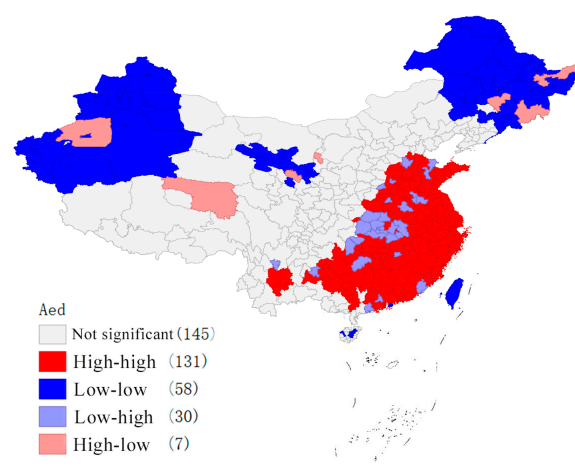


Figure 3. Univariate Moran's I LISA Cluster Maps for the distance equivalence of SIP Policy. Note: Basemap and administrative boundaries: NGCC, National Fundamental Geographic Information Database, 2020 (WGS84).

4.3. Configuration Analysis

This paper first analyzes the necessity conditions by fsQCA for each condition separately. The consistency level of necessity analysis has a value range of [0, 1]; usually, the consistency level is higher than the critical value of 0.900, which indicates that the condition may be a necessary condition for generating the results and needs to be further tested. The highest level of consistency among all the conditions is 0.740 (see Table 4), which is less than the critical value of 0.900, indicating that none of the eight conditions are necessary to constitute the distance equivalence of the SIP policy.

Table 4. Necessity analysis for high DE (Y) and not-high DE (~Y).

Condition	Consistency (Y)	Coverage (Y)	Consistency (~Y)	Coverage (~Y)
dialect	0.671	0.572	0.686	0.712
~dialect	0.662	0.633	0.587	0.685
popden	0.866	0.702	0.626	0.618
~popden	0.529	0.538	0.698	0.864
PGDP	0.77	0.71	0.575	0.647
~PGDP	0.617	0.544	0.743	0.74
hosbed	0.712	0.641	0.608	0.732
~hosbed	0.702	0.633	0.673	0.739
roaddden	0.842	0.658	0.67	0.638
~roaddden	0.534	0.571	0.641	0.632
COVID	0.772	0.748	0.565	0.667
~COVID	0.656	0.553	0.787	0.808
AVEdis	0.613	0.633	0.609	0.767
~AVEdis	0.775	0.619	0.708	0.691
DFIb	0.884	0.704	0.657	0.638
~DFIb	0.545	0.566	0.695	0.879

Threshold for necessity: Consistency ≥ 0.90 ; none of the conditions meets this threshold.

Configuration analysis is used to reveal the multiple conditions that make up the pathways by which the results are produced. Referring to a related study [51], the frequency of cases is set to 1. The consistency threshold is set on the basis of whether there is a significant break in the raw consistency ordering; it is set to 0.932 herein because there is a break in the descent after this value. Following the presentation of the results proposed by Ragin and Fiss [52], Table 5 is obtained, which shows 3 paths explaining the high policy distance, with each path representing one possible conditional configuration. The solution consistency of the high distance equivalence for cities is 0.943, indicating that 94.3% of the cities that satisfy these 3 types of conditional configurations exhibit high distance equivalence. Solution coverage describes the extent to which the outcome of interest can be explained by configurations and is comparable to the R-squared reported by regression-based methods [53]. Herein, the solution coverage is 0.409, indicating that the 3 condition configurations explain 40.9% of the cases with high distance equivalence. On the basis of the condition configuration analysis, the differential fitness relationships of different conditions influencing the distance equivalence can be further identified. The 3 condition configurations and the corresponding paths for the presence of SIP policy distances are shown in the table below.

Configuration 1 has the number of confirmed outbreaks, average distance, number of hospital beds and international investment as core conditions, with population density as a secondary condition. The consistency of configuration 1 is 0.937, and models with a consistency above 0.80 are useful to serve theoretical advances [54]. The raw coverage is 0.351 and can be used to identify 20 case cities, such as Suzhou, Ningbo, Shenyang and Nanjing. These cities are not located in the center of China's map; rather, they are

mostly coastal cities and have a greater average spatial distance from other cities. Thus, when a SIP policy is implemented and traffic is regulated in such areas, the resulting distance equivalence is greater. In addition, coastal cities have a high degree of economic outward orientation and vulnerability to pandemics; however, because of the severity of pandemics, they tend to implement relatively stringent SIP policies, which leads to greater distance equivalence. Furthermore, these cities have a greater number of hospital beds and healthcare packages. Under SIP policies, people generally prefer to stay in places with better healthcare rather than move to other cities, thus increasing the distance equivalence. Finally, these cities are more densely populated and have a greater basic number of people whose travel is restricted as a result of SIP policies, which also results in greater policy distance.

Table 5. Configuration Results of the High distance equivalence of the SIP Policy.

	①	②	③
dialect		●	●
popden	●	⊗	⊗
PGDP		●	
DFI	●		●
hosbed	●	●	●
roadden		⊗	⊗
COVID	●	●	●
AVEdis	●	●	●
Raw coverage	0.351	0.233	0.229
Unique coverage	0.158	0.023	0.018
Consistency	0.937	0.960	0.962
Typical cases	Suzhou, Ningbo, Shenyang, Nanjing, Dalian, Zhuhai, Shenzhen, Wuxi, Hangzhou, Zhongshan, Changzhou, Dongguan, Jiaxing, Guangzhou, Shaoxing, Yantai, Weihai, Fuzhou, Xiamen, Jinhua	Urumqi, Jinlin, Harbin, Kunming, Daqing	Mudanjiang, Harbin, Kunming, Daqing
PRI consistency	0.786	0.720	0.689
Solution coverage	0.409		
Solution consistency	0.943		

Note: ● indicates that the core condition is present, ⊗ indicates that the core condition is missing, ● indicates that the auxiliary condition is present, ⊗ indicates that the auxiliary condition is missing, and the spot being blank represents a fuzzy state; i.e., the presence or absence of the condition has no effect on the result.

Configuration 2 reveals the configurations leading to high distance equivalence, with pandemic, health, average distance and GDP per capita as the core conditions, dialect diversity as the secondary condition, and population density and road network density missing as conditions. The consistency of this configuration is 0.960, the raw coverage is 0.233, and five cities, namely, Urumqi, Jilin, Harbin, Kunming and Daqing, can be identified by this configuration. These cities are similar to configuration 1 cities in that none of them are located in the center of China's map; rather, they are farther away from other cities on average, while at the same time, they are more affected by the pandemic and have better medical support. The difference is that these cities are not large eastern coastal cities but rather located more centrally in the northeast, southwest, and northwest along some of the borders. Although the GDP per capita values of these cities is not low, their population densities and road network coverage percentages are lower, and the dialect diversity is greater. A higher GDP per capita makes people more likely to stay local rather than move to other regions. Dialectal diversity reflects greater regional cultural distance and results in greater distance equivalence. The low population density and predominantly local population structure of these cities caused people to prefer to stay local during the COVID-19 pandemic. The low density of the city's road network made traveling to other cities more costly and increased the distance equivalence during this period.

Configuration 3 reveals the configuration of high distance equivalence with pandemic, health, average distance and economic outward orientation as core conditions, dialect diversity as an auxiliary condition, and population density and road network density missing as conditions. The consistency of this configuration is 0.962, the raw coverage is 0.229, and the four cities of Mudanjiang, Harbin, Kunming, and Daqing can be identified by this configuration. These configuration cities are similar to configuration 2 cities, and the cases overlap in many instances. The difference between the two configurations is that GDP per capita is not the core condition in configuration 3, whereas economic outward orientation is the core condition. Almost all of these cities are border cities with better foreign trade development; thus, outward orientation plays an important role in increasing the distance equivalence of SIP policies.

4.4. Robustness Check

To assess the robustness of the gravity model underpinning the distance equivalence calculation, we conducted two complementary checks.

First, we re-estimated Equation (2) using a Poisson Pseudo Maximum Likelihood (PPML) specification. PPML is widely recommended in the trade and migration literature for its ability to handle heteroskedasticity and zero flows. Table A1 (Appendix A) compares the baseline log-linear OLS and PPML estimates. The coefficients for distance and destination GDP remain consistent in sign and close in magnitude across the two models, while PPML produces slightly smaller elasticities. This aligns with previous findings that OLS tends to overstate elasticities under heteroskedasticity. Moreover, the spatial clustering patterns identified through Moran's I and LISA remain essentially unchanged under the alternative specification.

Second, we extended the baseline model by incorporating additional explanatory variables—population density and road network density at both origin and destination cities—to capture demographic and transport influences on mobility. Results (Appendix Table A2) show that the explanatory power of the model improved slightly (R^2 rose from 0.698 to 0.72). More importantly, the coefficients for GDP and distance remained stable in sign, magnitude, and significance, confirming that the core gravity relationships are robust. Variance Inflation Factor (VIF) diagnostics indicated no serious multi-collinearity (all VIF values < 5). Interestingly, destination population density and road density exhibit significant positive effects, consistent with the view that larger and more accessible cities are more attractive for in-migration.

Third, Table 5 reports standard set-theoretic diagnostics—consistency, raw/unique coverage, and PRI (Proportional Reduction in Inconsistency)—for each high-DE configuration. All retained paths have consistency ≥ 0.90 and PRI ≥ 0.65 , indicating limited overlap with the negation of the outcome and no contradictory configurations among the reported solutions. We also conducted a calibration-threshold sensitivity check by varying the direct-method anchors from 0.95/0.05 to 0.90/0.10 and using a median-based crossover; the core conditions and solution structure remain unchanged, and solution-level consistency/coverage vary only marginally (about ± 0.01 – 0.02). Necessity tests show that no single condition is necessary for high DE (all necessity consistency < 0.90), consistent with a configurational explanation.

Overall, both sets of robustness checks demonstrate that the distance equivalence measure is not an artifact of the baseline model specification. The results are stable across estimators and robust to the inclusion of additional socioeconomic and transport variables, reinforcing the validity of DE as a consistent reflection of policy-induced resistance across cities.

5. Discussion

City-level distance equivalence (DE) exhibits a clear spatial pattern. Global Moran's $I = 0.326$ ($Z = 28.118$, $p < 0.01$) confirms positive spatial autocorrelation, and LISA pinpoints high-high clusters along the eastern/central–southern urban corridors and low-low clusters in parts of the northwest/northeast. These results match the gravity-based estimates and the DE maps. A key regularity is that higher DE concentrates east of the Hu line, where dense city networks and larger economic mass make cross-boundary checks more binding—so the same advisory guidance (SIP) is amplified into stronger mobility frictions. In short, baseline interaction structure shapes how a uniform policy translates into resistance, which justifies reading results by the Hu line and major corridor systems.

Although the SIP policy was implemented in a top-down manner across the country, there was spatial variation in the distance equivalences it produced; thus, this study uses configuration analysis to explore the reasons for the complexity of its spatial divergence. Given our cross-sectional design, we interpret the fsQCA solutions as set-theoretic associations (conjunctural sufficiency and equifinality) rather than single-factor causal effects. Across high-DE configurations, confirmed cases, average inter-city separation, and hospital bed capacity emerge as core conditions. One pathway combines higher case burden $\otimes$ larger average separation $\otimes$ greater hospital beds, consistent with stronger cross-boundary resistance and greater willingness to remain local. A second pathway pairs higher case burden $\otimes$ larger separation $\otimes$ higher GDP per capita with supportive cultural context (e.g., dialect diversity). A third pathway features outward economic orientation (FDI) with health capacity and spatial separation. Diagnostics indicate high consistency/coverage with $PRI > 0.75$ and no contradictory configurations; anchor robustness ($0.95/0.05 \rightarrow 0.90/0.10$) does not overturn solutions (see Appendix A).

The robustness checks further strengthen these interpretations: both the alternative estimator (PPML) and extended specifications with demographic and transport variables confirm that the distance-equivalence patterns are not model-dependent but reflect stable policy-induced resistance. This consistency provides a firmer basis for linking the quantitative results to differentiated countermeasure design.

5.1. Theoretical Implications

We reconceptualize policy-induced mobility resistance as distance equivalence (DE)—an interpretable added distance rather than a mere change in flows. Formally, distance equivalence is the additional separation that, within a gravity framework, makes the predicted flow without the policy match the observed flow under the policy. By tying this added separation to the estimated distance elasticity, the metric yields a comparable, kilometer-equivalent scale across cities and periods, directly linking policy evaluation to spatial-interaction theory.

We also bound the concept theoretically. DE targets temporary, policy-generated frictions under crisis or emergency conditions (e.g., advisory guidance, screening, time-bounded checks). It is not intended to capture long-run structural distances (geographic, cultural, economic, institutional) or network-diffusion path lengths. Our scope conditions are explicit: short-lived interventions with clear temporal/spatial bounds and documented policy salience/enforcement.

Compared with border distance equivalence [27], which quantifies an enduring geopolitical border penalty in gravity models, DE addresses time-bounded, policy-generated boundaries by mapping observed policy-induced flow changes into added distance. Relative to effective distance in epidemic studies [25], DE measures static flow resistance for an origin–destination snapshot in distance units suited to policy evaluation. Unlike CAGE (multi-dimensional structural separations used as covariates) [9], DE is outcome-proximate

and policy-endogenous, derived directly from flow changes. Finally, whereas the gravity distance-decay parameter describes how flows decline with distance [23], DE translates a specific policy shock into an effect size in distance units.

We treat the Hu line as a key geographic–demographic boundary that shapes the baseline interaction structure underlying gravity relationships. This provides a principled rationale to stratify the interpretation of DE (east vs. west of the Hu line) and to specify contextual moderators in the fsQCA discussion, aligning the theoretical construct with observed spatial heterogeneity in the results.

Conceptually, DE targets temporary, policy-generated frictions and is not confined to the Chinese institutional setting. Where crisis-time interventions define clear temporal and spatial bounds, DE offers a gravity-consistent metric to compare policy-induced resistance across countries.

5.2. Managerial Implications

Although our empirical case centers on COVID-19's SIP guidance, the distance-equivalence (DE) metric is intended for short-term, crisis-time mobility interventions more broadly—for example, pollution red-alert driving curbs, mega-event security perimeters, disaster-related road controls, or energy-rationing transport limits—provided policy salience/enforcement are documented, mobility data are comparable, and temporal/spatial scope is clearly defined. In this sense, SIP illustrates a general framework that translates policy-induced, time-bounded frictions into an interpretable, gravity-consistent distance scale. Besides, the operational logic generalizes to other national contexts.

DE enables an adaptive management loop: tighten measures when DE shows a sustained rise relative to the pre-event baseline (in parallel with epidemiological indicators) and relax them as DE returns toward baseline. Where DE is high prioritize earlier and tighter inter-city screening at rail/bus/highway hubs, short and clearly communicated staggered return schedules, and coordinated actions across adjacent jurisdictions. Where DE is low emphasize targeted risk communication, continuity of essential services and lifeline routes, and short, calibrated interventions around identified risks to avoid unnecessary disruption. Operationalizing DE as a trigger indicator helps authorities minimize social and economic costs, protect lifeline services, and tailor measures across regions—thereby aligning crisis response with sustainable mobility and urban resilience goals.

For stakeholders, local governments can monitor city- and pair-level DE to support differentiated management across regions; public-health authorities can track DE alongside incidence and hospitalization to calibrate NPI intensity and pre-position testing/surge capacity in persistent high-DE clusters; transport agencies can integrate DE into mobility dashboards to retime and right-size services, manage holiday peaks, and protect freight and essential travel on links where policy friction is greatest.

Finally, pairing DE with fsQCA helps anticipate where and when resistance is likely to be high: the configurations identified in our results—combining case burden, inter-city separation, and health capacity—can guide targeted messaging, resource placement, and region-specific controls in future crises.

5.3. Limitations and Future Research

This study has limitations. First, passenger flows come from passively collected big-data sources, which may contain measurement error. Second, the fsQCA design limits the number of antecedent conditions; despite our efforts to include relevant social, economic, and geographic variables, some factors affecting DE may be omitted. Third, our analysis uses data from China only; external validity to other national contexts requires further testing. Future studies could compare cultural regions (e.g., East Asia vs. Western countries)

to examine the transferability of DE under different policy regimes. Fourth, fsQCA does not address endogeneity; reverse causality and unobserved heterogeneity may remain. Future work should consider temporal QCA and multi-method causal designs (panel/DID, IV, natural experiments) to probe mechanisms.

6. Conclusions

To study the resistance added to travel by SIP policy implementation, an exploratory approach to SIP policy distance equivalence is proposed. SIP policy distance equivalence is measured for 358 cities in China for the 2020 SIP policy implementation period. The greater policy distance equivalence is distributed mainly on the right side of the Hu line. The overall distribution of urban distance equivalence is correlated, with high values of distance equivalence clustered in southeastern, central, and southwestern cities and low values located in the northwestern and northeastern parts of the country.

This study analyzes the configuration conditions for high SIP policy distance equivalence. Overall, three configuration paths constitute the high SIP policy distance equivalence. Configuration 1 is a combination of conditions dominated by pandemics, health, average distance, and economic outward orientation, with the number of confirmed COVID-19 cases, average distance, number of hospital beds, and amount of international investment as the core conditions and population density as a secondary condition. Configuration 2 is a combination of high policy distances, with the number of confirmed COVID-19 cases, health, average distance, and GDP per capita as the core conditions, dialect diversity as the auxiliary condition, and population density and road network density missing as conditions. Configuration 3 is a combination of high policy distances, with pandemics, health, average distance, and economic outward orientation as the core conditions, dialect diversity as a secondary condition, and population density and road network density missing as conditions. By translating policy frictions into comparable distance units, DE provides a scalable tool for sustainable transport management in future crises.

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Abbreviations

The following abbreviations are used in this manuscript:

NPI	Non-pharmaceutical interventions
SIP	Stay in place for Lunar New Year
DE	Distance equivalence
Distequi	Distance equivalences between paired cities
O–D	Origin–destination
GDP	Gross domestic product

PGDP	GDP per capita
DFI	Foreign direct investment (city-level outward orientation)
hosbed	Number of hospital beds
AVE_dis	Average distance from the city to other cities
popden	Population density
roadden	Road network density

Appendix A

Table A1. Comparison of gravity model estimates between log-linear OLS and PPML specifications (2020 data).

Variable	OLS (log-linear)	PPML
ln (Distance)	−1.747 *** (0.008)	−1.633 *** (0.001)
ln (Destination GDP)	0.517 *** (0.006)	0.395 *** (0.001)
ln (Origin GDP)	0.081 *** (0.005)	−0.268 *** (0.001)
Constant	6.882 *** (0.082)	10.940 *** (0.013)
Observations (N)	59,470	59,483
R ² /Pseudo R ²	0.487	~1.0 (Cox–Snell)

Notes: Standard errors in parentheses. *** denote significance at the 1% level. OLS excludes zero flows due to log transformation, while PPML includes all observations and accounts for heteroskedasticity.

Table A2. Robustness check: OLS gravity estimates with additional variables (2020 data).

Variable	Baseline Model (GDP & Distance)	Extended Model (GDP, Distance + Pop. Density & Road Density)
ln (Origin GDP)	0.081 *** (14.92)	0.075 *** (13.10)
ln (Destination GDP)	0.517 *** (85.27)	0.452 *** (50.30)
ln (Distance)	−1.748 *** (−209.59)	−1.701 *** (−198.60)
ln (Origin population density)	–	0.021 (0.55)
ln (Destination population density)	–	0.103 *** (3.02)
ln (Origin road density)	–	0.049 * (1.78)
ln (Destination road density)	–	0.084 *** (3.15)
R ²	0.698	0.72
VIF range	1.06–1.16	–3.5

Notes: Dependent variable: ln (Migration value). All variables in natural logarithms. t-values in parentheses. *** $p < 0.01$, * $p < 0.10$.

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