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Large-scale mountains that affect civilized linguistic exchanges over space offer potentially profound cultural difference landscape implications. This article uses China's national trunk mountain system as a natural experiment to explore the connection between spatial adjacency of mountains and cultural difference landscapes. Our spatial design documents that the presence of mountains widens the linguistic difference between two cities located on the opposite mountain sides, particularly when they are adjacent to administrative borders. The effect dwindles as spatial contiguity margins between city pairs increases. The results shed light on the importance of conceptualizing geographic contextual constraints to the configuration of cultural difference landscapes. *Key Words: cultural difference, geocomputation, geographic contextual, spatial econometrics.*

影响各地文明的语言交换的大规模山岳, 为深刻的文化差异地景提供了潜在的意涵。本文运用中国全国山系作为自然实验, 探讨山岳的空间邻近性与文化差异地景之间的连结。我们的空间设计, 记录了山岳的存在, 的确加深了坐落于山岳两翼的两座城市间的语言差异, 特别是当两座城市邻近行政边界之时。该效应随着两座城市间的空间持续边缘增加而减少。本研究结果, 对于概念化地理脉络限制之于文化差异地景构成的重要性提供了洞见。 *关键词： 文化差异, 地理计算, 地理脉络, 空间计量经济。*

Las montañas de escala mayor que afectan los intercambios lingüísticos civilizados a través del espacio potencialmente generan implicaciones para el paisaje reflejadas en profundas diferencias culturales. Este artículo usa el sistema montañoso principal de China a manera de experimento natural para explorar la conexión entre la contigüidad espacial de las montañas y la diferenciación cultural de los paisajes. Nuestro diseño espacial permite establecer que la presencia de las montañas amplía la diferencia lingüística entre dos ciudades localizadas en los lados opuestos de las montañas, particularmente cuando ellas son adyacentes a los límites administrativos. El efecto se disminuye en la medida en que se incrementan los márgenes de contigüidad entre pares de ciudades. Los resultados arrojan luz sobre la importancia de conceptualizar los obstáculos geográficos contextuales con la configuración de paisajes con diferencia cultural. *Palabras clave: diferencia cultural, geocomputación, contexto geográfico, econometría espacial.*

Once upon a time, there were only mountains (e.g., Himalayas, Rockies, Andes, Alps, Pyrenees, and Scandinavia mountains) but no civilized societies on the Earth. Over time, civilized societies developed through trade and linguistic exchanges across cities and regions. Historically, mountains are prominent geographic barriers that have been involved with configurations of cultural difference landscapes over space.

In *Patterns of Culture*, Benedict (1934) transformed the literature by using anthropological methodology to draw attention to the spatial configurations of cultures. Benedict argued that each culture had its own configuration and involved linguistic exchanges. This anthropological methodology has been widely applied to understanding the geography of civilized development, although there have been critical debates about the reconceptualization and reinvention of patterns of culture (see, e.g., Tuan 1974; Duncan 1980; Cosgrove 1992; Gregson 1992; Price and Lewis 1993; Jackson 1996).

Interest in cultural difference landscapes has a long history. Recently, there has been an appeal to use the geography of linguistics or dialects as the evolutionary outcome of cultural identities in civil society (Lazear

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1999; Grogger 2011). In light of Darwin's seminal work *Origin of Species*, these dialect data are proxy for "genome" and have recorded configurations of cultural differences in the geographic context (Cavalli-Sforza 2000; Huang et al. 2016). The growing body of literature on empirical evaluations has so far paid little attention to the roles of mountains in the spatial manifestation of cultural ties or cultural differences—identified by linguistic dissimilarity across cities.

This article presents a novel step in this direction. As one of the largest mountainous countries in the world, China and its diversified dialect environments provide a suitable case for our investigation. For the configuration of cultural difference landscapes, we ask whether a mountain would influence the linguistic difference between city pairs located on the opposite sides. Measuring the linguistic difference between two administrative regions is potentially challenging, as each Chinese region is likely to have a spectrum of dialects. Following the recent literature, we measure the linguistic difference between dialects by using a city pair's *linguistic distance*—a reduced-form expression about cultural difference landscapes (Spolaore and Wacziarg 2009; Tabellini 2010; Falck et al. 2012; Wu, Wang, and Dai 2016).

Methodologically, our analyses proceed in two stages. In the first stage, we estimate the effect of mountains on the linguistic distances between city pairs. As mountains involved in the study are the outcome of prehistorical geological processes, they are less likely to induce endogeneity concerns in the regression analysis. It is possible, however, that the linguistic distance between city pairs is not only affected by the existence of mountains but also influenced by other geographic features such as rivers, lakes, and canyons. This is particularly the case when two cities are separated by a long geographical distance with more unobservable geographical factors in between, making it difficult to infer the role of mountains. We resolve this issue by focusing on city pairs located close by. The level of closeness is measured in term of various orders of spatial contiguity margins; for example, whether two cities directly share an administrative border (first order). In reality, we restrict our focus to those city pairs within third-order spatial contiguity margins. Focusing on city pairs within close spatial contiguity margins requires less modeling effort to account for variation induced by the differences in other characteristics. To further control for potential unobservable factors, our model specifications include origin city fixed effect and destination city fixed effect. A number of controls, such as geographical and socioeconomic factors, are also added to the regression models to assess the sensitivity of the estimates. We control for whether there are substantial impacts arising from political border changes since the late Qing Dynasty. Additionally, we assess the sensitivity of the observed effects to changes in different spatial contiguity margins. Overall, we find evidence supporting the claim that mountains have significant effects on shaping the cultural difference landscapes.

In the second stage, we complement the regression approach with a spatial synthetic control method. This method allows us to go beyond offering the average generalized effects and provide new insights into the detailed localized effects of cultural difference landscapes on the basis of individual treatment cases. We define city pairs that are spatially adjacent with each other and that are on the opposite side of mountains as individual treatment cases. To circumvent the drawbacks of the linear regression model in statistical inference, the synthetic control method was pioneered by Abadie and his coauthors (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010, 2015) under the panel data context. It is designed to construct a synthetic control for a treated case by taking a weighted average of selected control units. In our article, a key methodological innovation has been to improve on this methodology by matching each city pair with a synthetic counterfactual under the cross-sectional spatial data context. Wong (2015) pointed out that under confoundedness, linear regression is a special case of synthetic control method. By bringing the identification power of the synthetic control method into the spatial setting, we look at a specific city pair treatment case (Tianjin and Chengde), which is obstructed by the Yan Mountain. Our analysis quantifies the localized cultural difference effects of the Yan Mountain through constructing a synthetic city pair for comparison. The city pair is constructed by taking the weighted average over a selection of city pairs without the mountain blockage. The weights are specified in such a way that characteristics of the treatment case and synthetic city pair are as similar as possible. To our knowledge, our proposed estimator is new to the previous work in this literature and can be fruitfully applied in other geographical contexts.

The remainder of this article is organized as follows. The next section outlines the theoretical framework. We then describe the data coding and sources and the methodology. After that, we discuss the results supporting the claim that mountains have significant effects on shaping the cultural difference patterns before concluding.

Theoretical Framework

In the study of human and cultural geography, a variety of theoretical frameworks exist. The evolution of theories in the literature exhibits a trajectory from describing civilized development to theorizing social and geographic contextual constraints to consider the conceptualization of cultural difference landscapes over space. Cultural difference is a sophisticated concept to measure quantitatively. Empirically, proxies for cultural differences are often calculated by using linguistic dissimilarity between cities and regions (Falck et al. 2012). The empirical evaluation of cultural differences has not received much attention in a large developing country context, and quantitative research on this has been rare. This section frames our conceptual view of how mountains might affect linguistic dissimilarity. The theoretical framework motivates the empirical models and provides a lens to interpret geographical implications. This study views the presence of mountainous topographies and their inherent barriers as an evolutionary response to influencing the formation of cultural difference landscapes. The whole process is constrained by the context of a country's political economy. For example, federal countries such as Russia and India and the province of Quebec in Canada that have accommodated linguistic dissimilarity with institutional governance create unique nationwide cultural difference landscapes. Linguistic dissimilarity occurs across locations through trade and economic development and thus forms a nexus of spatial interactions against the backdrop of a wider range of contextual constraints including mountains. Differing from nation to nation, linguistic dissimilarity might follow predominantly or historical administrative borders. Linguistic dissimilarity across locations, seen as a by-product outcome of this underlying process, thus sheds light on cultural difference landscapes. Our existing knowledge about the spatial manifestation of linguistic dissimilarity is rather limited, however. By showing that Eastern Europe and former Soviet countries have a relatively high level of cultural fractionalization, Fearon (2003) provided convincing evidence of significant differences in linguistic dissimilarity over space, on which we can base our measurement.

China has a unique and diversified linguistic system in the global society. On the one hand, Han culture has a long tradition influencing ethnic and religious divisions throughout most parts of China in history. Since Mao's era, China has imposed a unified Chinese character writing system (*han zi*) and a unified spoken language system (*pu tong hua*) that can influence cultural exchanges between different ethnic and religious groups. On the other hand, China is characterized by the coexistence of different languages (for an overview, see, e.g., Ramsey 1987; Norman 1988). There are significant variations in local dialects that play an important role in cultural difference landscapes between cities. For example, Cantonese, Shanghainese, and Fukienese have unique pronunciations of Chinese characters (*han zi*). These dialects are widely spoken by people in the coastal regions but cannot be understood by people in the northern and western regions. Although the formation of linguistic dissimilarity is affected by physical geography constraints, recent studies of linguistic dissimilarity have focused mainly on economic consequences (Guiso, Sapienza, and Zingales 2009; Tabellini 2010; Falck et al. 2012; Herrmann-Pillath, Libman, and Yu 2014). For example, in European countries, Guiso, Sapienza, and Zingales (2009) find that trade and investment flows across countries are affected by cultural similarities. Tabellini (2010) suggested the important role of the interaction of culture and institutions in influencing economic output across European regions. Falck et al. (2012) found the significant effect of cultural ties on economic exchange using dialect data in Germany. In China, Herrmann-Pillath, Libman, and Yu (2014) suggested that political and cultural boundaries are important factors of fragmentation of gross domestic product growth in Chinese cities. These effects are inherently dependent on the prevailing physical geography constraints such as mountains, particularly topographical favoritism of some places over others and political constraints on administrative boundaries. Direct evidence to support the conceptual foundations of how mountains affect configurations of cultural difference landscapes across political and dialect borders remains scarce, however. This perspective requires that we understand the geographical legacy of mountains in the social–spatial context.

Worldwide, populations are obstructed by large mountains. The belief that large mountains, by affecting ridging, terracing, biodiversity, and farming (Figure 1), can facilitate cultural difference landscapes has led to important cultural implications of mountains. The trunk mountain system of China is pronounced in terms of shaping the livelihoods and cultural identities at places close to large-scale

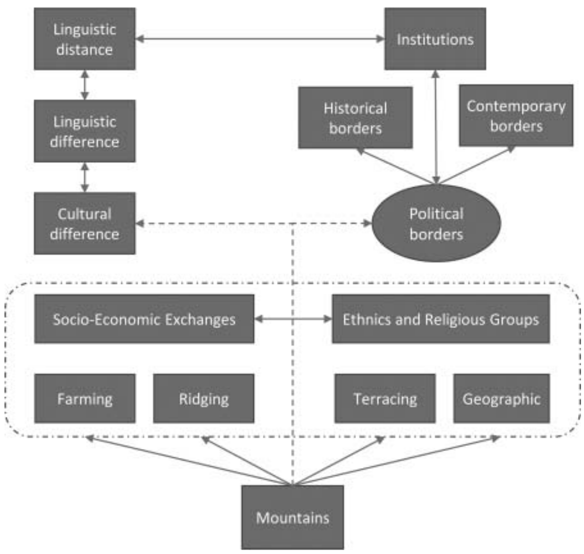

Figure 1. A conceptual framework.

mountains. For example, different physical geography on different sides of a mountain could lead to complementary economic patterns and stimulate cultural and economic exchanges. A typical example is the trade between nomads and peasants on different sides of the Yin Mountain even in the present-day Inner Mongolia region and Ningxia region. Another channel might work via the steep terrain and geographic inaccessibility associated with mountains. A case in point is that mountains might help lock the historical formation of self-sufficient local economies and cultural identities within the Sichuan Basin region and deter human exchanges between the Sichuan Basin region and other regions. Evolutionarily, this aspect of geographic inaccessibility induced by mountains contributes to dialect difference landscapes over space.

The empirical investigation of the connection between cultural difference landscapes and mountains could also be rooted in the institutional analysis of changes in political administrative borders. China offers a typical scenario for contributing to the existing literature in two ways. First, different from many Western countries such as the United Kingdom and United States, political administrative borders in China have experienced gradual transitions since the late Qing Dynasty in the 1800s. The changes in the political administrative border process can be summarized as follows. Before the First Opium War in the 1840s, China was a closed economy with no international trade with other countries. The significant feature of political administrative borders was the dominant role of military defense and physical geographic constraints. The twenty-two provincial borders in the Qing Dynasty established the foundation for provincial borders and prefecture city borders in contemporary China. Second, after years of civil wars, the administrative situation of China in the early 1900s in terms of resilience of political fragmentation was by far more prominent than that of the Qing Dynasty. In this context, political administrative borders might not overlap with ethnic, religious, and linguistic divisions. There have also been some institutional variations in political administrative borders since the establishment of the People's Republic of China in 1949, although patterns of dialects have remained relatively stable.

Data

Geography of Mountain Data

The data set for our investigation is geographically coded based on several sources. The geographical data of China's national trunk mountain system are obtained from the National Administration of Surveying, Mapping and Geoinformation of China (Editorial Board of Physical Geography of China, Chinese Academy Sciences 1980; Editorial Board of National Atlas of China 1999). Mountains are spatially explicit and observed by their dividing ranges, which can be accurately mapped at a fine resolution scale. The richness of spatial details of our mountain data allows us to precisely visualize the mountains by using geographic information system (GIS) techniques (Figure 2). These mountains are mapped at spatial scales that can provide reliable depiction of mountain dividing ranges, on which we can base our estimation.

Geography of Linguistic Data

The second data source is the geography of linguistics. Linguistics, characterized by phonological and grammatical variations, is not distributed randomly over space within a country. As suggested by Darwin's evolution theory, linguistics have been created in a process of human evolution over hundreds of years and, therefore, reflect cultural difference landscapes from history. Empirical research progress has been accompanied by the literature documenting the appropriateness of using the linguistics dissimilarity to capture specifics of cultural difference landscapes (Lazear 1999; Fearon 2003; Spolaore and Wacziarg 2009). Figure 3 shows the distribution of linguistic zones across Chinese cities

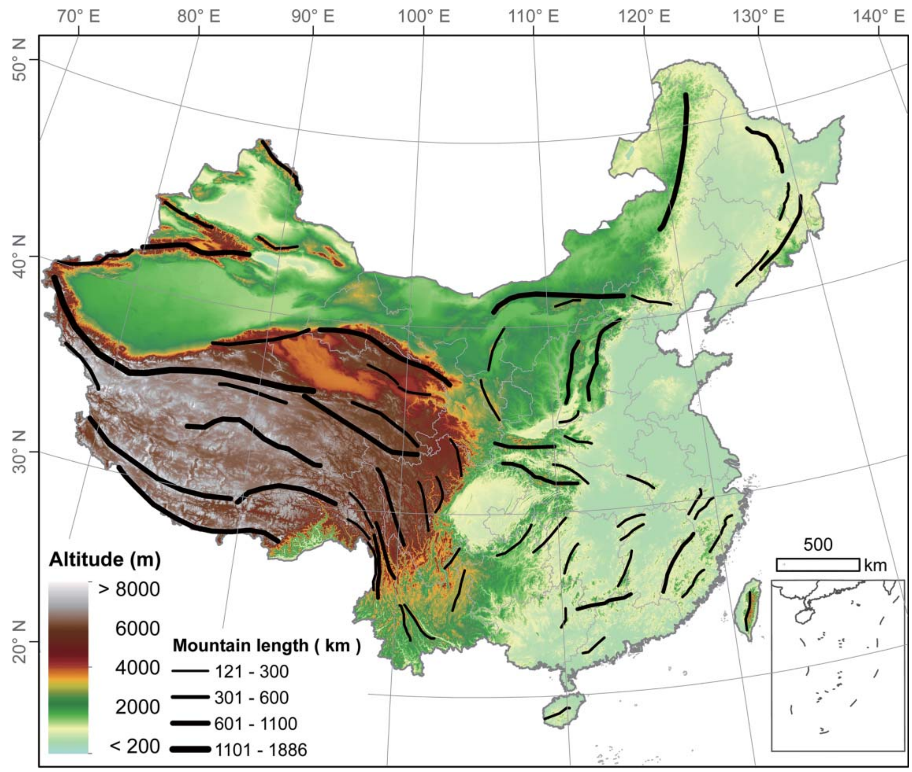

Figure 2. The geography of trunk mountains in China. *Note:* This graph indicates China's trunk mountain distributional pattern, on which we base our analysis. (Color figure available online.)

and regions. These linguistic zone data were obtained from the 2012 Atlas of Chinese Dialects (ACD) and were geographically coded using a GIS platform. A linguistic zone is identified by its distinctive dialect characteristics such as vocabulary, tone or voice, and grammar. In terms of spatial coverage, our data have the Han dialect information for mainland China but exclude some minority ethnic group–concentrated areas such as Tibet and some parts of Qinghai province and Inner Mongolia due to the lack of fine-scale dialect information (Figure 3). Our geography of linguistic data applied quantifies a much more detailed spatial distribution pattern of linguistic zones than most existing studies in China. As suggested by recent studies (Falck et al. 2012; Melitz and Toubal 2014; Wu, Wang, and Dai 2016), linguistic data can be regarded as a reliable proxy indicator for identifying cultural diversity when more accurate data information are unavailable at finer geographical scales.

Our measurement of cultural difference landscapes relies on the linguistic distance index that has been intensively accepted in the linguistic literature based on Greenberg's (1956) implicit function: $LD_{AB} = \sum_{i=1}^{I}\sum_{j=1}^{J}(s_{A_i} \times s_{B_j} \times \delta_{ij})$, where LD_{AB} indicates the linguistic distance between city A and city B; i indicates the language of city A; j indicates the language of city B; s_{A_i} is the proportion of population in city A who speak the language i; s_{B_i} is the proportion of population in city B who speak the language j; and δ_{ij} is the linguistic dissimilarity between language i and language j; i, j are the total number of languages spoken in city A and B, respectively. The population data are obtained from the 2000 population census. We follow Fearon's (2003) formula to quantify the empirical implementation. In essence, the value of δ_{ij} is between 0 and 1 when there are some shared linguistic characteristics between i's and j's dialects. The value of δ_{ij} is 1 when the two dialects are completely different from each other and the value of δ_{ij} is 0 when the two dialects are identical.

Spatial Contiguity Margin, Treatment Status, and Regression Data

We take care of processing spatial contiguity margin selections. Cities are often observed on polygon entities with administrative boundaries. To avoid the modifiable areal unit problem (Openshaw 1984; Kwan 2012), the spatial contiguity relationship between cities and mountains will be concerned with areal

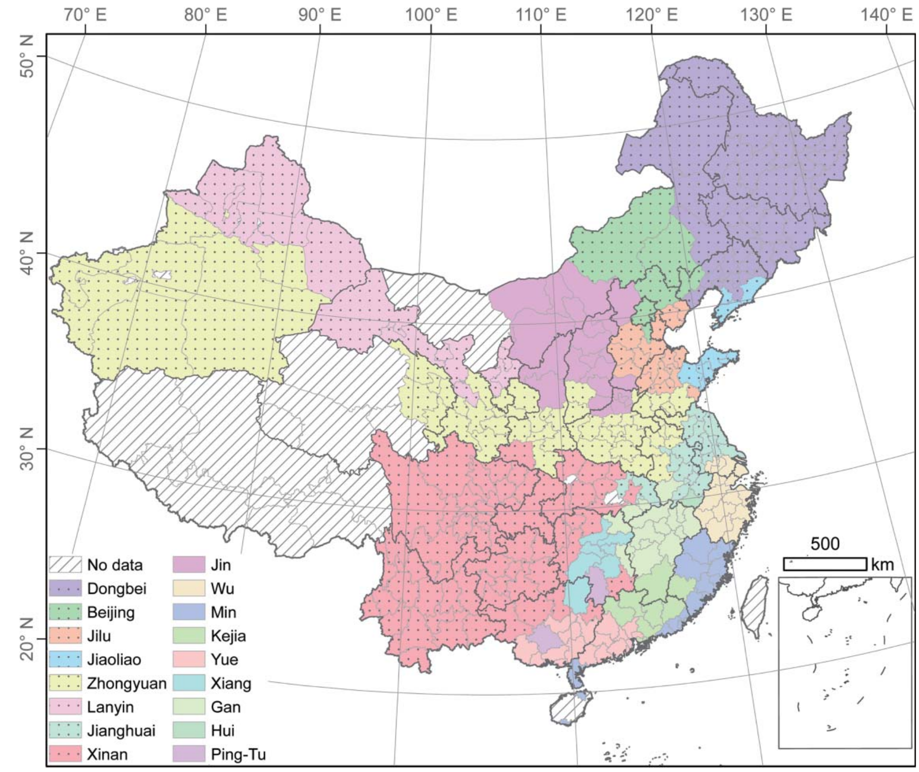

Figure 3. The geography of linguistic distributions in China. *Note:* The color key indicates the spatial coverage of major dialect zones. (Color figure available online.)

entities that are defined as neighbors, for chosen definitions of neighbors. In light of this precision issue, we did not apply the conventional method for identifying the geographical proximity to mountains based on the straight-line distance from a city center location to the mountain dividing range. When the sizes of cities show great difference, distance-based criteria cannot capture the real spatial relations between cities. For our preferred contiguity-based neighbor measurement, we use heuristics for identifying polygons that are sharing boundaries as neighbors and assign the set of entities into members or nonmembers of the neighbor set. Figure 4 illustrates our identification procedure. Take Beijing as an example: Gray lines in Figure 4 represent the city pairs with no mountain barriers between them, whereas the colored lines represent the city pairs located on the opposite side of a given mountain. To be specific, the red lines connect city pairs that are within the first-order spatial contiguity margin because these cities (e.g., Chengde) directly share an administrative boundary with Beijing. The blue lines connect city pairs that are within the second-order spatial contiguity margin where cities (e.g., Chifeng, Chaoyang, Xinzhou) are the neighbors of first-order spatial contiguities of Beijing. The green lines connect city pairs that are within the third-order spatial contiguity margin, where cities (e.g., Tongliao, Fuxin, Jinzhou) are the neighbors of second-order spatial contiguities of Beijing. The distance to the target city (e.g., Beijing) is not fixed but depends on the size and shape of the two cities. Figure 5 shows the density distribution of distance to Beijing within third-order spatial contiguity margins. Taking third contiguity order as an example, the distance to Beijing varies from 200 km to 800 km because the physical sizes of contiguity cities vary substantially. In this situation, contiguity-based neighbors are more appropriate to capture the spatial relationship between cities (Schabenberger and Gotway 2004; Anselin, Syabri, and Kho 2006; LeSage 2009). Our regression analysis relies on a cross-sectional data set and our observation is a city pair instead of a single city. Throughout the study, our regression samples are restricted into city pairs within the third-order contiguity margin. To identify whether a city pair is defined as the treatment group, we make use of a two-stage identification procedure. We first identify city pairs that are located on the opposite side of mountains based on their spatial relationships with mountain dividing ranges. The mountain dividing ranges are then used to stratify pair-wise cities into different spatial

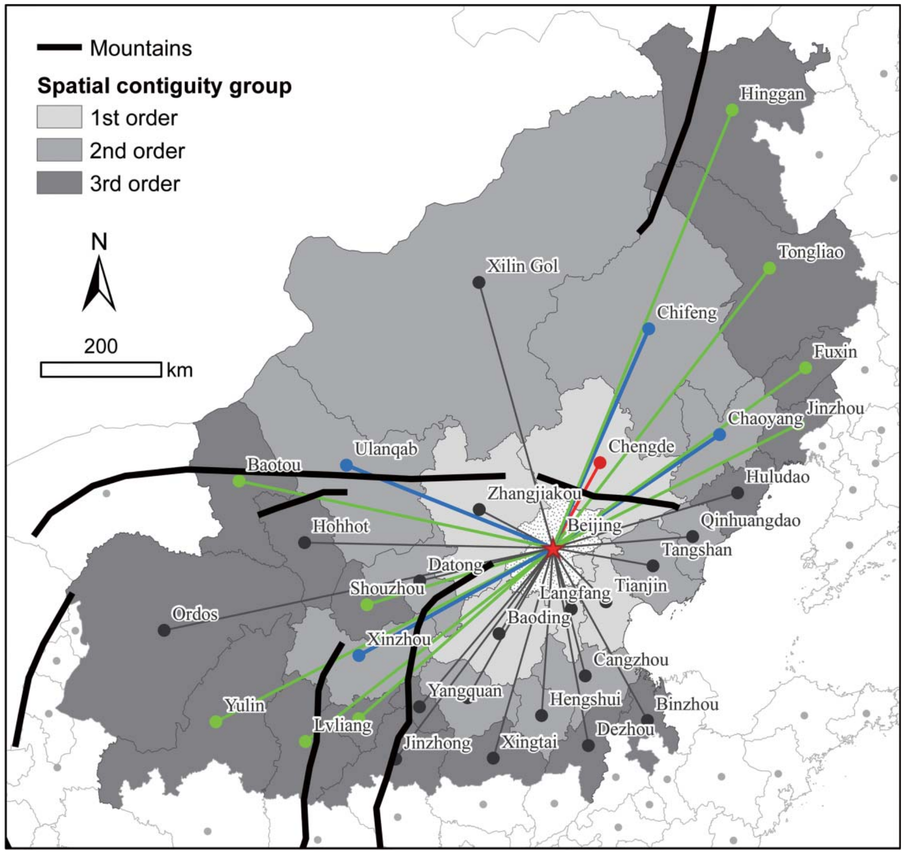

Figure 4. Identification of spatial continuity groups using Beijing as an example. *Note:* The red arrow indicates the city pair(s) that are blocked by mountains and are within the first-order spatial contiguity margin. The blue arrows indicate the city pair(s) that are blocked by mountains and are within the second-order spatial contiguity margin. The green arrows denote the city pair(s) that are blocked by mountains and are within the third-order spatial contiguity margin. Gray arrows indicate city pairs that are not blocked by mountains. (Color figure available online.)

contiguity margins relative to mountains. If a city pair is blocked by at least a trunk mountain, it will be regarded as a potential treatment group. Our estimation controls for political administrative border and demographic and physical geography characteristics that might relate to the configurations of cultural difference landscapes between city pairs (see Table 1).

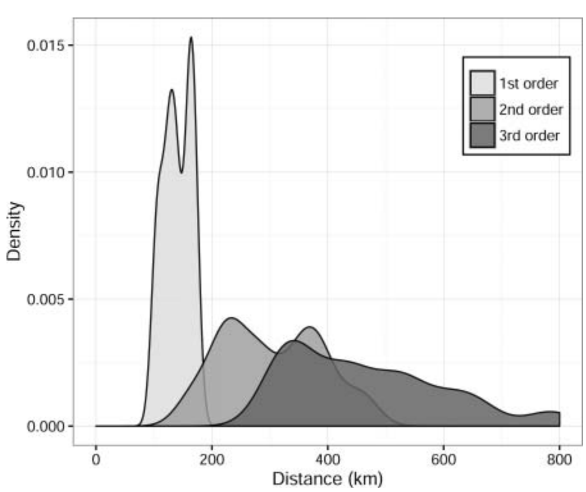

Figure 5. The density distribution of distance to Beijing within third-order spatial contiguity margins. *Note:* This graph illustrates that spatial contiguity–based city neighbors are appropriate to capture the spatial relationship between cities.

Model

Baseline Model Specification

We fit the following econometric model to estimate the impacts of mountains on cultural differences between city pair (mn):

$$Y_{mn} = \alpha_1 \ M_{mn} + \sum\nolimits_{j=2}^{3} \gamma_j 1[j\text{th-order contiguity}]_{mn}$$
$$+ \sum\nolimits_{k=2}^{3} \alpha_k M_{mn} 1[k\text{th-order contiguity}]_{mn}$$
$$+ \ \mathbf{x}_{mn}^{T} \beta + F_n + F_m + \in_{mn}, \ \ (mn) \in S,$$

S is the set of unique city pair indexes that are used for regression $Y_{mn} =$ log$[LD_{mn}]$, the natural logarithm of

Table 1. Descriptive statistics

Variable name	Definition	M	*SD*
Linguistic distance	Linguistic distance that measures the similarity of dialects used in two cities. The index ranges from 0 (identical) to 1 (completely different)	0.518	0.311
Mountain	1 = at least one mountain lies on the straight line between a city pair's centroids; 0 = no mountain lies on the straight line between a city pair	0.349	0.477
Spatial contiguity groups	1 = the city pair shares an administrative boundary; 0 = the city pair does not share an administrative boundary	0.158	0.365
First-order spatial contiguity			
Second-order spatial contiguity	1 = the city pair shares an administrative boundary with a third city; 0 = the city pair does not share an administrative boundary with a third city. Second-order does not include first-order contiguity	0.337	0.473
Third-order spatial contiguity	1 = the city pair shares boundaries with another city pair that shares a boundary; 0 = otherwise. Third-order does not include first-order and second-order contiguity	0.504	0.500
Geographic controls	The straight line geographical distance between two cities' centroids (unit: km)	341.49	184.16
Geographical distance			
D_ltpp	Difference in light and temperature potential productivity (in logs)	0.697	0.860
D_height	Difference in height level between city pairs (in logs)	0.837	0.804
Socioeconomic controls	Difference in wages between city pairs (in logs)	0.207	0.164
D_wage			
D_industry	Difference in employment share of nonagricultural sectors between city pairs (in logs)	13.923	11.667
D_light	Difference in night light intensity level between city pairs (in logs)	0.907	0.767
Administrative border controls	1 = two cities in the same province; 0 = two cities in the different provinces	0.332	0.471
Province dummy			
Administrative border change	1 = at least one of the cities has experienced administrative border change since Qing dynasty: 0 = both cities have not experienced border change since Qing dynasty	0.951	0.215

Note: Information about wages and employment shares is collected from the Chinese city statistic yearbooks (2012). Physical geography data in the year 2012 are from National Science & Technology Infrastructure of China, Data Sharing Infrastructure of Earth System Science (www.geodata.cn). The night light intensity-level data are from the Defense Meteorological Satellite Program–Operational Linescan System satellite nighttime light image data in the year of 2012 (version 4; see http://ngdc.noaa.gov/eog/dmsp.html). It has been averaged within the city boundary.

the linguistic distance between city m and n; M_{mn} is a binary variable that takes 1 if city m and n are located at the opposite sides of a mountain; and 1 [kth-order contiguity]$_{mn}$ is a binary variable that equals 1 if city m and n belongs to the kth-order spatial adjacent group and 0 otherwise. The first-order spatial contiguity group serves as benchmark. We include not only adjacent group dummies in the regression to control the effect of distance or border sharing on linguistic distance but also interaction terms with the mountain dummy variable. The construction offers a spatial difference-in-differences style estimation and reveals the potential contiguity variation in the estimated effects. $\mathbf{x}_{mn}$ is a vector of control variables relating to city m and n, including the difference of geographical and socioeconomic variables between m and n. We also control for whether a city pair has experienced political border changes since the late Qing Dynasty. F_m and F_n are the fixed effects of city m and n, respectively. They capture city-invariant effects on linguistic dissimilarity. ε_{mn} is idiosyncratic error associated with city pair (mn). $\alpha_1, \alpha_2, \alpha_3, \gamma_2, \gamma_3, \beta, F_m, F_n$s are regression coefficients to be estimated. We are mainly interested in α_1, $(\alpha_1 + \alpha_2)$, $(\alpha_1 + \alpha_3)$, and the differential impacts of mountains on linguistic distance over a range of spatial contiguity margins.

Spatial Synthetic Control Model

The baseline regression provides the starting point to investigate the relationship between mountain and linguistic distance. It is able to provide direct estimates for the generalized effects but is less capable of offering insights into the localized mountain effects on individual treatment cases. For example, what is the effect induced by a specific mountain? What is the effect of a mountain on one particular city pair? Questions of this kind require careful and transparent construction of a control group for the city pair exposed to the mountain blockage.

To analyze the localized mountain effect, we developed a spatial synthetic control method, which is adapted from synthetic control methods for panel data studies (Abadie, Diamond, and Hainmueller 2010, 2015). This method enables us to further check the robustness of the results derived from the baseline regression and understand how a particular mountain influences the linguistic distance between two cities.

Borrowing Rubin's (2005) studies, for a given city pair (mn), let Y_{mn} be a binary function of mountains' presence,

$$Y_{mn} = \begin{cases} Y_{mn}(0) & \text{if } M_{mn} = 0, \\ Y_{mn}(1) & \text{if } M_{mn} = 1. \end{cases}$$

We call $Y_{mn}(0)$ and $Y_{mn}(1)$ potential linguistic distances between city pair (mn), the difference that could be realized if there was or was not a mountain between (mn). Y_{mn} without brackets is referred to as observed linguistic distance, the value of which is either $Y_{mn}(0)$ or $Y_{mn}(1)$. The causal effect of a mountain on linguistic distance between city m and n, denoted by α_{mn}, is therefore defined as follows:

$$\alpha_{mn} = Y_{mn}\ (1) - Y_{mn}(0).$$

α_{mn} informs the mountain effect on a specific city pair (mn) that we are interested in. Estimating α_{mn} is essentially a missing value problem, as one of the potential outcomes is unobservable. For example, if city pair (mn) is obstructed by a mountain, then $Y_{mn} = Y_{mn}\ (1)$. $Y_{mn}(0)$ would not be measured had the mountain not been there.

To estimate the missing $Y_{mn}(0)$, we construct a synthetic control by taking a weighted average of all the available linguistic distances between city pairs unobstructed by mountains,

$$\hat{Y}_{mn}(0) = \sum\nolimits_{kl \in S_0} w_{kl}\ \ Y_{kl} = \sum\nolimits_{kl \in S_0} w_{kl}\ Y_{kl}(0),$$

where S_0 is a set of city pairs without mountain blockage, w_{kl}s are weights that satisfy (1) $\sum_{kl \in S_0} w_{kl}$(sum to 1) and (2) $w_{kl} \geq 0$ (nonnegativity). Optimal weights are determined such that the characteristics of the city pair (mn) are as close to the synthetic control characteristics as possible (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010, 2015; Wong 2015).

With mild abuse of terminology, let $\mathbf{x}_{mn}$ be the standardized control variables betwen city pair (mn), and let $\sum_{kl \in S_0} w_{kl}\mathbf{x}_{kl}$ be the standardized control variables of the synthetic control. We define the discrepancy between two values in quadratic form as

$$\left\| \mathbf{x}_{mn} - \sum\nolimits_{kl \in S_0} w_{kl}\mathbf{x}_{kl} \right\| :$$

$$= \sqrt{\left[\mathbf{x}_{mn} - \sum\nolimits_{kl \in S_0} w_{kl}\mathbf{x}_{kl}\right]^T \left[\mathbf{x}_{mn} - \sum\nolimits_{kl \in S_0} w_{kl}\mathbf{x}_{kl}\right]}.$$

Weights are selected such that the difference is minimized so that city pair (mn) and the synthetic control are as similar as possible,

$$(\hat{w}_{kl})_{kl \in S_0} = \underset{w_{kl} \geq 0, \Sigma_{kl} w_{kl} = 1}{\operatorname{argmin}} \left\| \mathbf{x}_{mn} - \sum\nolimits_{kl \in S_0} w_{kl}\mathbf{x}_{kl} \right\|.$$

The calculation of this equation is a classic quadratic programming problem and can be solved using the *quadprog* function in MATLAB.

We plug the optimal weights into ([sync]) to obtain an estimate of $Y_{mn}(0)$:

$$\hat{Y}_{mn}(0)\ = \sum\nolimits_{kl \in S_0} \hat{w}_{kl}\ Y_{kl}.$$

Next, we estimate the effect of the mountain on city pair (mn) as

$$\hat{\alpha}_{mn} = Y_{mn}\ (1) - \hat{Y}_{mn}(0)\ = Y_{mn}\ - \sum\nolimits_{kl \in S_0} \hat{w}_{kl}\ Y_{kl}.$$

It is worthwhile to note that the objective of the synthetic control method is to construct a suitable comparison unit for a treatment unit such that two units are similar in terms of control variable values. In deriving the optimal weights, the inclusion of control variables $\mathbf{x}$ plays a similar role to the inclusion of control in the regression analysis. It is likely that the inclusion of different control variables would lead to different weights and estimates. Hence, robustness checks are required to assess the sensitivity of the key estimates to changes in the set of control variables.

Table 2. Regression estimates

	1	2	3	4
Mountain effect (first-order contiguity)	0.133***	0.143***	0.104**	0.105**
	(2.82)	(3.07)	(2.19)	(2.20)
Mountain effect (second-order contiguity)	0.0728***	0.071**	0.056**	0.056**
	(2.61)	(2.56)	(1.99)	(1.98)
Mountain effect (third-order contiguity)	0.0155	0.0088	0.00007	0.00011
	(0.72)	(0.40)	(0.00)	(0.00)
Δ Mountain effect (first–third)	0.118**	0.134***	0.104**	0.104**
	(2.39)	(2.75)	(2.10)	(2.1)
Δ Mountain effect (second–third)	0.057*	0.062**	0.056*	0.056*
	(1.85)	(2.01)	(1.79)	(1.78)
Geographic controls	No	Yes	Yes	Yes
Socioeconomic controls	No	No	Yes	Yes
Administrative boundary change	No	No	No	Yes
Origin–destination fixed effect	Yes	Yes	Yes	Yes
N	5,221	4,955	4,807	4,807

Note: This table reports the estimation results for models with fixed effects for both origin city and destination city. Dependent variable is log(Linguistic distance). t statistics are reported in parentheses.
$*p < 0.05$.
$**p < 0.01$.
$***p < 0.001$.

Results

Baseline Results

Table 2 presents the estimated coefficients for the regression between mountains and linguistic distances. Row 1 reports the coefficients associated with the impacts of mountains on cultural difference landscapes of city pairs at the first-order spatial contiguity margin with the obstruction of mountains relative to city pairs at the same spatial contiguity margin but without the obstruction of mountains. Following the same logic, the second and third rows report the coefficients associated with the impacts of mountains on cultural difference landscapes of city pairs at the second-order and third-order spatial contiguity margins, respectively, with the obstruction of mountains relative to city pairs at the same corresponding spatial contiguity margins but without the obstruction of mountains. The fourth and fifth rows allow the interaction of M_{mn} and $1[k\text{th-order contiguity}]_{mn}$, suggesting the differential impacts of mountains on cultural difference landscapes of city pairs at the immediate spatial contiguity margin relative to those further away. The first data column reports the results by including origin city fixed effects and destination fixed effects but with no other controls. The second column augments the specification by including differences in physical geography characteristics such as altitudes and agricultural productivity of temperature and light as predetermined natural environment factors that could relate to the formation of cultural difference landscapes. The third data column controls for differences in socioeconomic characteristics such as wages, night light intensity scores, and employment share of nonagricultural sectors between city pairs. The last column further controls for whether there have been historical administrative border changes since the late Qing Dynasty. All model specifications have included origin city and destination city fixed effects. We estimate these model specifications on a restricted set of city pair observations, excluding a subset of city pairs beyond the third-order spatial contiguity margin range.

The estimates suggest that the presence of mountains increases cultural difference landscapes between city pairs in the immediate spatial contiguity margin of mountains. The first row indicates that the presence of mountains within the immediate (first-order) spatial contiguity margin is associated with a 1.05 to 1.33 percent increase in the linguistic distance index. The point estimates in the second and third rows are generally of a smaller magnitude and become less significant, suggesting that the effects of mountains on cultural difference landscapes tend to fade with distance. Hence, in the fourth and fifth rows we compare the impacts between city pairs within the first-order spatial contiguity margin with those at higher order spatial contiguity margins. Specifically, the fourth row indicates that the differential impact of mountains at the immediate (first-order) spatial contiguity margin relative to those at the third-order spatial contiguity margin is statistically significant. Such effects become less significant when comparing the differences between city pairs at the second-order spatial contiguity margin and those at the third-order spatial contiguity margin (fifth row). Overall, the results appear to be robust across model specifications, suggesting that the effects are highly concentrated at close spatial contiguity margins.

Additional Results: A Synthetic Control Case Study

The preceding section presented empirical evidence suggesting that mountain obstructions have led to enhanced linguistic-based cultural differences among city pairs on the opposite side of the mountains relative to adjacent city pairs on the same side of the mountains. These effects appear to be generalized consequences. This section provides a discussion and additional estimation results to further investigate the localized effects through a specific case study. The main focus here looks at the localized effect of a particular mountain on linguistic distance between individual treatment city pair cases located on the opposite sides.

The Yan (*Yan shan*) mountains are an east-to-west mountain range lying at the north of the North China Plain (*Hua bei ping yuan*). Periodically, the Yan Mountains have been recognized as a dividing line between the main Han cultural landscape and the north nomadic cultural landscape. Due to its unique location, the Yan Mountains had served as part of the northern border of the historical Chinese empires and had been located in parallel with numerous large-scale defensive structures. For example, the Great Wall, which was originally designed as a defensive protection from northern nomads, is located alongside the Yan Mountains to intervene in the social interactions of residents living on the opposite sides of the Yan Mountains. Consequently, it is expected to enforce cultural difference landscapes over space. Our synthetic control case study focuses on a specific city pair, Tianjin–Chengde (Figure 6). Tianjin is located at the south of the Yan

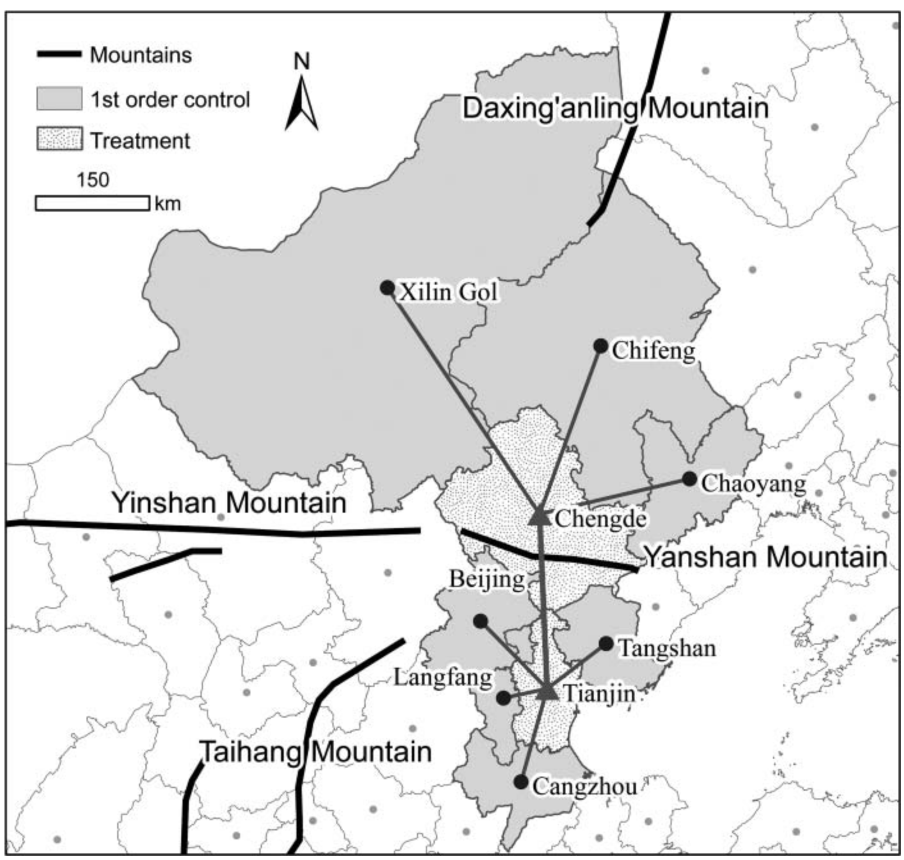

Figure 6. Synthetic control case study. *Note:* The arrow line indicates the treated city pair (Tianjin–Chengde) that is blocked by the Yan Mountains and is within the first-order spatial contiguity margin. The gray arrows indicate the control cities that are within the first-order spatial contiguity margin relating to either Tianjin or Chengde and that are not blocked by the Yan Mountains.

Table 3. Synthetic control estimates

City pair	LD (1)	Treatment status (2)	ΔLD (3)	%Δ LD (4)	Δ Covariates (5)
Treatment city pair					
Tianjin–Chengde	0.408	Yes	—	—	—
Synthetic control city pairs					
Tianjin–Chengde synthetic control (1)	0.343	No	0.065	16	3.967
Tianjin–Chengde synthetic control (2)	0.327	No	0.081	24	4.899
Tianjin–Chengde synthetic control (3)	0.387	No	0.021	6	5.263

Mountains, whereas Chengde is located on the north side. Tianjin and Chengde are geographically close to each other and directly share an administrative border (first-order spatial contiguity).

To estimate the effect of the Yan Mountains on the linguistic distance between Tianjin and Chengde, it is essential to construct a reliable counterfactual control group. We construct the counterfactual control group using the weighted average of all the city pairs without mountain blockage, following the spatial synthetic control method elaborated earlier. As the size of the control group pool is relatively large (3,051 observations[1]), it is computationally challenging to obtain the optimal weights. To resolve this issue, we consider the following strategy to reduce the computational burden. First of all, 0 weight is assigned to city pairs with different spatial contiguity orders than Tianjin–Chengde (first order). Therefore, city pairs with second or third spatial contiguity orders are excluded. Second, 0 weight is assigned to city pairs not involving Tianjin or Chengde. This implies that only pairs that start from Tianjin or Chengde will be considered, and the approach echoes the origin and destination city fixed effects in the regression. After imposing these restrictions, eight city pairs (Figure 6) are identified as observations to construct the synthetic control.

Table 3 reports the localized mountain effects estimated by the synthetic control. The upper panel of Table 3 reports the original linguistic distance outcome of the treatment city pair case (Tianjin–Chengde) calculated using the dialect census data as the benchmark for comparison. The lower panel of Table 3 shows the estimated linguistic distances for the synthetic control using weights derived from different control variables.

The first Tianjin–Chengde synthetic control takes into account of all the control variables for deriving the optimal weights. The second Tianjin–Chengde synthetic control considers the geographic distance only to obtain optimal weights; hence, city pairs with geographical distance similar to that of Tianjin–Chengde would receive higher weights. The third Tianjin–Chengde synthetic control does not consider any additional control variables and eight city pairs are equally weighted to construct the synthetic control. The first data column reports the estimated linguistic distance values. The second column reports the treatment status. The localized mountain effects on cultural differences are reported in the subsequent two columns, by using the absolute difference (third column) and the difference by percentage (fourth column) between estimated linguistic distance values and the original linguistic distance outcome of the treatment city pair case (Tianjin–Chengde), respectively. The last column reports a summarized statistic term as a proxy indicator for the covariates' matching accuracy. It is calculated by using the square root of the sum of squared difference between the standardized treatment unit covariate and synthetic control unit covariate. After all covariates are added to the model, we can get the highest covariates' matching accuracy. This is expected, as each synthetic case study is essentially providing a tailored matched covariates estimate for treated cases. We find that the enhancement in cultural differences resulting from the differences in linguistic distance is estimated to be 0.065 (16 percent). Notably, even with the changes in the matched covariates of those estimates, the effect on cultural differences remains substantial, ranging from 6 percent to 24 percent.

Taken together, the results suggest that the inclusion of counterfactual control groups and synthetic control estimates could respond to the localized effects of a specific mountain on cultural difference landscapes through an individual treatment case study. To the extent that this type of synthetic control case study exercise can be generalized, these results clarify the important role mountains play in the formation of geographical legacies of cultural difference landscapes. Are there any other mountains that would exert these impacts on cultural difference landscapes? Of course, yes. As a baseline, though, these additional results from Table 3 provide two implications. On the one hand, it is expected that the localized mountain effects vary across individual treatment cases. On the other hand, localized mountain effects could be largely consistent with the average generalized mountain effects from Table 2, suggesting the robustness of the results through choosing reliable counterfactual control groups.

Conclusion

Mountains have been and will remain an important component of geographic contextual constraints in shaping cultural difference landscapes. This study presents a unique microgeographical data set for exploring the effects of mountains on configurations of cultural difference landscapes at the scale of city pairs in a large developing country context. This is accomplished by developing a spatial approach that isolates exogenous variation in cultural difference landscapes between adjacent city pairs at close spatial contiguity margins relative to mountains. We propose a spatial synthetic control estimator that can accommodate the complexities of matching each city pair with a synthetic counterfactual, bringing the identification power of an empirical econometric design into a cross-sectional spatial data context.

Our results suggest that the impact of mountains is substantial. After controlling for a range of sociodemographic contextual characteristics, our point estimates remain robust to explain the impact of mountains on configurations of cultural difference landscapes. In addition, our results go beyond the generalized effects and provide clear evidence on the localized effects of the Yan Mountains on cultural difference landscapes at individual treatment cases through the spatial synthetic control approach. These findings have useful implications for applying microgeographical data in urban analysis. The heterogeneous cultural difference landscapes of city pairs are the true picture of human geography. With this intangible cultural connection, the physical geography barrier presented by mountains provides a new instrument for exploiting the exogenous variation to social, cultural, and economic phenomena in urban contexts.

This study has been a first step toward understanding geographical legacies of cultural difference landscapes in developing countries. We agree with the classic exposition that genes, languages, and social activity exchanges encourage patterns of cultures to emerge in the geographic context (Tuan 1974; Crang 1998; Anderson and Gale 1999; Valentine 2001). We have also seen the usefulness of spatial continuity margins for deriving spatial closeness relationships between city pairs and for shedding light on the fundamental law of geography (Tobler 1970). The localized cultural difference consequence of mountains largely arises from the complex nature of geographic contexts, and the innovative application of the appropriate spatial approach could help better deal with the generalized modeling problem. More research, however, is needed to assess the availability of historical transport routes between city pairs and the interaction of mountains and public policy shocks such as Mao's Rustication policy to shape human migration between cities. Future work is encouraged to pursue this productive area of research.

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Note

1. The number of all city pairs without mountain blockage.

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