The Geographical Legacies of Mountains: Impacts on Cultural Difference Landscapes

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Abstract: 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 by administrative borders. The effect dwindles as spatial contiguity margins between city pairs increases. The results shed lights on the importance of conceptualising geographic contextual constraints to the configuration of cultural difference landscapes.

Keywords: *Cultural difference*, *Geographic contextual*, *Spatial econometrics*, *Geocomputation*

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Introduction

Once upon a time, there were only mountains (such as Himalaya, Rocky, Andes, Alpen, 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 a prominent geography barrier that have been evolved with configurations of cultural difference landscapes over space.

In *Patterns of Culture*, Benedict (1934) transformed the literature by using the anthropological methodology to draw attention on 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, though there have been critical debates about the reconceptualisation and reinvention of patterns of culture (see, e.g. Tuan 1974; Duncan 1980; Cosgrove 1992; Gregson 1992; Price and Lewis 1993; Jackson 1996).

Interest on the configurations of cultural difference landscapes has a long history. Recently, there is an appeal to use the geography of linguistics or dialects as the evolutionary outcome of cultural identities in the civil society (Lazear 1999; Grogger 2011). In light of Charles Darwin's seminal work on Origins 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 differences—identified by linguistic dissimilarity across cities.

This article presents a novel step towards this direction. As one of the largest mountainous countries in the world, China's diversified dialect environments provide a typical case for our investigation. For the configuration of cultural difference landscapes, we ask if 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 a 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 mountain on linguistic distances between city pairs. As mountains involved in the study are the outcome of prehistory geological processes, they are less likely to induce endogeneity concerns in the regression analysis. However, it is possible that the linguistic distance between city pairs are not only affected by the existence of mountains, but also influenced by other geographic features such as rivers, lakes, canyons. This is particularly the case when two cities are separated by long geographical distance with more unobservable geographical factors in between, making it difficult to infer the role of mountain. 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, e.g. whether two cities directly share an administrative border (first order). In reality, we restrict our focus to those city pairs within 3rd 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 socio-economic 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 the 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 localised 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 linear regression model in statistical inference, the synthetic control method was pioneered by Alberto Abadie and his co-authors (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 paper, a key methodological innovation has been to improve on this methodology by matching each city pair with a synthetic counter-factual under the cross-sectional spatial data context. Wong (2015) points 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 a way such 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: Section 2 outlines on the theoretical framework; Section 3 describes the data coding and sources; Section 4 presents the methodology; Section 5 discusses the results supporting the claim that mountains have significant effects on shaping the cultural difference patterns. Section 6 concludes.

Theoretical Framework

In the study of human and cultural geography, a variety of theoretical frameworks exist. The evolutionary of theories in the literature exhibits a trajectory from describing civilized development to theorizing social and geographic contextual constraints to consider the conceptualisation of cultural difference landscapes over space. Cultural difference is a sophisticated concept to be quantitatively measured. 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, India, and 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 form a nexus of spatial interactions against the backdrop of a wider range of contextual constraints including mountains. Differing from nation to nation, linguistic dissimilarity may follow pre-dominantly 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. However, our existing knowledge about the spatial manifestation of linguistic dissimilarity is rather limited. By showing that Eastern Europe and formerly Soviet Union countries have a relatively high level of cultural fractionalization, Fearon (2003) provides the 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 in influencing ethnic and religious divisions throughout most parts of China in history. Since the 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 linguistics (for an overview see e.g. Ramsey1987; Norman 1988; Xiao, 2009). There are significant variations in local dialects that play an important role on 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. While the formation of linguistic dissimilarity is affected by physical geography constraints, recent studies into linguistic dissimilarity have mostly focused 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) suggest the important role of the interaction of culture and institutions in influencing economic output across European regions. Falck et al. (2012) find the significant effect of cultural ties on economic exchange using dialect data in Germany. In China, Herrmann-Pillath, Libman, and Yu (2014) suggest that political and cultural boundaries are important factors of fragmentation of GDP growth in Chinese cities. These effects are inherently dependent on the prevailing physical geography constraints such as mountains, particularly topographical favouritism of some places over others and political constraints on administrative boundaries. However, direct evidence to support the conceptual foundations of how mountains affect configurations of cultural difference landscapes across political and dialect borders remains scarce. This perspective entails the necessity to understand about 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 international agencies such as the International Union for Conservation of Nature[1] to recognize the 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 mountains. For example, different physical geography on different sides of a mountain may lead to complementarity 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 may work via the steep terrain and geographic inaccessibility associated with mountains. A case in point is that mountains may 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 may also be rooted in the institutional analysis of changes in political administrative borders. China offers a typical scenario for contributing to the existing

[1] https://www.iucn.org/protected-areas/world-commission-protected-areas/wcpa/what-we-do/cultural-and-spiritual-values

literature in twofold. First, different from many Western countries such as the UK and US, 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 is a closed economy with no international trade with other countries. The significant feature of political administrative borders was the predominant role of military defense and physical geographic constraints. The 22 provincial borders in the Qing Dynasty have established the foundation for provincial borders and prefecture city borders in the contemporary China. Second, after years of civil wars, the administrative situation of China in the early 1900s in terms of resilience of political fragmentation is by far more prominent than that of the Qing Dynasty. Under this context, political administrative borders may not be overlapped with ethnic, religious and linguistic divisions. There have also been some institutional variations in political administrative borders after the establishment of the People's Republic of China in 1949, though patterns of dialects may have remained relatively stable.

Data

Geography of Mountain data. The dataset for our investigation is geographically-coded based on several sources. The geography of China's national trunk mountain system data 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 on a fine resolution scale. The richness of spatial details of our mountain data allows us to precisely visualize the mountains by using the Geographically Information System (GIS) techniques (Figure 2). These mountains are mapped at spatial scales that can provide reliable depicted 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, are not distributed randomly over space within a country. As suggested by Charles Darwin's evolution theory, linguistics have been created in a process of human evolution over hundreds of years and, therefore, reflect cultural difference landscapes left from the 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 and regions. These linguistic zone data have been obtained from the 2012 Atlas of Chinese Dialects (ACD) and have been geographically coded by using the Geographic Information System (GIS) platform. The linguistic zone is identified by its distinctive dialect characteristics such as vocabulary, tone or voice, and grammar. In terms of the spatial coverage, our data have the Han dialect information for the 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 (1956)'s 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 linguistic of city A; j indicates the linguistic of city B; s_{A_i} is the proportion of population in city A who speak the linguistic i; s_{B_i} is the proportion of population in city B who speak the linguistic j; δ_{ij} is the linguistic dissimilarity between linguistic i and linguistic j. The population data is obtained from the 2000 population census. We follow the Fearon (2003)'s formula to quantify in 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 cities' dialects are completely different from each other and the value of δ_{ij} is 0 when the two cities' 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 entities that are defined as neighbours, for chosen definitions of neighbours. In light of this precision issue, we didn't apply the conventional way for identifying the geographical proximity to mountains based on the straightline distance from a city center location to the mountain dividing range. When the size of cities show great difference, distance-based criteria can not 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 neighbours and assign the set of entities into members or non-members of the neighbour set. Figure 4 illustrates our identification procedure. Take Beijing as an example, grey lines of Figure 4 represent the city pairs with no mountain barriers between them, whereas the colored lines of Figure 4 represent the city pairs located in the opposite side of a given mountain. To be specific, the red lines connect city pairs that are within the 1st order spatial contiguity margin because these cities (e.g. Chengde) directly share administrative boundary with Beijing. The blue lines connect city pairs that are within the 2nd order spatial contiguity margin where cities (e.g. Chifeng, Chaoyang, Xinzhou) are the neighbours of 1st order spatial contiguities of Beijing. The green lines connect city pairs that are within the 3rd order spatial contiguity margin, where cities (e.g. Tongliao, Fuxin, Jinzhou, et al) are the neighbours of 2nd 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 two cities. Figure 5 shows the density distribution of distance to Beijing within 3rd order spatial contiguity margins. Takes 3rd contiguity order as an example, the distance to Beijing varies from 200 km to 800 km because that the physical sizes of contiguity cities vary substantially. In this situation, contiguity-based neighbours 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 dataset 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 3rd 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 in 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 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, demographic and physical geography characteristics that may relate to the configurations of cultural difference landscapes between city pairs (see Table 1).

Model

Baseline model specification

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

$$Y_{mn} = \alpha_1 M_{mn} + \sum_{j=2}^{3} \gamma_j \mathbf{1}[jth\ order\ contiguity]_{mn} + \sum_{k=2}^{3} \alpha_k M_{mn} \mathbf{1}[kth\ order\ contiguity]_{mn} + \mathbf{x}_{mn}^{T} \boldsymbol{\beta} + F_n + F_m + \epsilon_{mn}, \qquad (mn) \in S$$ [2]

where $Y_{mn} = \log[LD]_{mn}$, the natural logarithm of the linguistic distance between city m and n; M_{mn} is a binary variable which takes 1 if city m and n are located at the opposite sides of a mountain; $\mathbf{1}[k\text{th order contiguity}]_{mn}$ is a binary variable that equals 1 if city m and n belongs to kth order spatial adjacent group and 0 otherwise; 1[st] order spatial

[2] The order of a city pair does not matter, therefore city pair (❍■) is equivalent to (■❍). ⧫ is a set of all the unique city pair indexes that are used to estimate the regression.

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 interactions terms with the mountain dummy variable. The construction offers a spatial difference-in-differences style estimation and reveal 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 socio-economic 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 effect on linguistic dissimilarity. ϵ_{mn} is idiosyncratic error associated with city pair (mn). $\alpha_1, \alpha_2, \alpha_3, \gamma_2, \gamma_3, \boldsymbol{\beta}, F_m, F_n$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 mountain 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 flexible to offer 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 such kind requires careful and transparent construction of control group for the city pair exposed to the mountain blockage.

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

Borrowing Rudin's terminology (Rubin 2005), 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/wasn't a mountain between (mn). Y_{mn} without brackets is referred to as observed linguistic distance, whose value 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), which 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 $Y_{mn} = Y_{mn}(1)$. $Y_{mn}(0)$ is not 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,

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

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) $w_{kl} \geq 0$ (non-negativity). Optimal weights are determined such that the 'characteristics' of the city pair (mn) is 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

$$\left\|\mathbf{x}_{mn}-\sum_{kl\in S_0} w_{kl}\,\mathbf{x}_{kl}\right\| := \sqrt{\left[\mathbf{x}_{mn}-\sum_{kl\in S_0} w_{kl}\,\mathbf{x}_{kl}\right]^T\left[\mathbf{x}_{mn}-\sum_{kl\in S_0} w_{kl}\,\mathbf{x}_{kl}\right]}$$

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

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

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

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

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

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

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

It is worthwhile to note that the objective of 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 **x** plays the similar role as 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.

Results

Baseline results

Table 2 presents the estimated coefficients for the regression between mountains and linguistic distances. Row (1) report 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, rows (2)-(3) reports 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. Rows (4)-(5) allows the interaction of M_{mn} and $\mathbf{1}[k\text{th order contiguity}]_{mn}$, suggesting the differential impacts of mountains on cultural difference landscapes of city pairs at the immediate spatial contiguity margin relative to those at further distance away. Column (1) reports the results by including origin city fixed effects and destination fixed effects but with no other controls. Column (2) argument the specification by including differences in physical geography characteristics such as altitudes and agricultural productivity of temperature and light as pre-determined natural environment factors that may relate to the formation of cultural difference landscapes. Column (3) controls for the differences in the socio-economic characteristics such as wages, night light intensity scores and employment share of non-agricultural sectors between city pairs. The last column further controls for whether there are 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. Row (1) indicates that the presence of mountains within the immediate (first order) spatial contiguity margin is associated with a 1.05-1.33 percent increase in the linguistic distance index. The point estimates in rows (2)-(3) are generally of a smaller magnitude and become less significant, suggesting the effects of mountains on cultural difference landscapes tend to fade with distance. Hence, in rows (4) and (5) we compare the impacts between city pairs within the first order spatial contiguity margin with those at higher order spatial contiguity margins. Specifically, row (4) indicates 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 (row 5). 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 has 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 in 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) mountain, is a east-to-west direction mountain range lying at the north of North China Plain (Hua bei ping yuan). Periodically, the Yan mountain has been recognised as a dividing line between the main Han culture landscape and the north nomadic culture landscape. Due to its unique location, Yan mountain 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 locating alongside with the Yan mountain to intervene social interactions of residents living at the opposite sides of the Yan mountain. 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 mountain, whereas Chengde is located at the north side. Tianjin and Chengde are geographically close to each other and directly share an administrative border (1^{st} order spatial contiguity).

To estimate the effect of Yan mountain on the linguistic distance between Tianjin and Chengde, it is essential to construct a reliable counter-factual control group. We construct the counter-factual control group using the weighted average of all the city pairs without mountain blockage, following the spatial synthetic control method elaborated in section spatial synthetic control model. As the size of the control group pool is relatively large (3501 observations[3]), 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 as Tianjin-Chengde (first-order). Therefore, city pairs with second or third spatial contiguity orders are excluded. Secondly, 0 weight is assigned to city pairs not involving Tianjin or Chengde. This implies only pairs 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, 8 city pairs (Figure 6) are identified as observations to construct 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 (column 1) for synthetic control using weights derived from different control variables.

[3] The number of all city pairs without mountain blockage.

Tianjin-Chengde synthetic control 1 takes into account of all the control variables for deriving the optimal weights; Tianjin-Chengde synthetic control 2 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; Tianjin-Chengde synthetic control 3 does not consider any additional control variables and 8 city pairs are equally weighted to construct the synthetic control. Column (1) reports the estimated linguistic distance values. Column (2) reports the treatment status. The localized mountain effects on cultural differences are reported in the subsequent two columns, by using the absolute difference (column 3) and the difference by percentage (column 4) between estimated linguistic distance values and the original linguistic distance outcome of the treatment city pair case (Tianjin-Chengde), respectively. The last column (column 5) reports a summarized statistic term as a proxy indicator for the co-variates matching accuracy. It is calculated by using the square root of sum of squared difference between standardized treatment unit co variate and synthetic control unit co variate. After all covariates are added to the model, we can get the highest co-variates 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 counter-factual 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 of mountains to play in the formation of geographical legacies of cultural difference landscapes. Are there any other mountains that would exert the impacts on cultural difference landscapes? Of course yes. But as a baseline, 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, and suggests the robustness of the results through choosing reliable counter-factual 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 micro geographical dataset 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 counter-factual, 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 socio-demographic 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 mountain on cultural difference landscapes at individual treatment cases through the spatial synthetic control approach. These findings have useful implications for applying micro-geographical 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 induced 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 may 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 the 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 is largely arising from the complexity 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 are encouraged to pursue this productive area of research.

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Figure list

Figure1. A conceptual framework.

Figure2. The geography of trunk mountains in China. Note: This graphs indicates China's trunk mountain distributional pattern, on which we can base our analysis.

Figure3. The geography of linguistic distributions in China. Note: The color ramp indicates the spatial coverage of major dialect zones.

Figure4. Identification of spatial continuity groups using Beijing as an example. Note: The red color arrow indicates the city pair(s) that are blocked by mountains and are within the first order spatial contiguity margin. The blue color arrows indicate the city pair(s) that are blocked by mountains and are within the second order spatial contiguity margin. The green color arrows the city pair(s) that are blocked by mountains and are within the third order spatial contiguity margin. Grey color arrows indicate city pairs that are not blocked by mountains.

Figure5. The density distribution of distance to Beijing within third order spatial contiguity margins. Note: This graph illustrates that spatial contiguity-based city neighbours are appropriate to capture the spatial relationship between cities.

Figure6. Synthetic control case study Note: The arrow line indicates the treated city pair (Tianjin-Chengde) that is blocked by the Yan mountain and is within the first order spatial contiguity margin. The grey color 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 mountain.

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