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THREE ESSAYS ON CULTURAL GOODS TRADE AND DYADIC DATA ANALYSIS

by

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Chapter 1

Introduction

In the field of economics, culture and art have been discussed long before the term "Cultural Economics" was coined in the twentieth century. The accumulated research findings are summarized in the "Handbook of the Economics of Art and Culture" (Ginsburgh and Throsby (2006)), which covers the broader topics of economic problems related to art and culture. Economists have addressed economic problems related to cultural topics, for example, "positive or negative externalities associated with arts," "an effect of patronages on arts," "whether a free market achieves supplies of arts at an optimal level or not," and "the government's role as a supporter or operator in a market of art" (Goodwin (2006)).

These economic topics related to culture and art have been discussed from the past right up to the present day. In particular, to deal with the problem of cultural convergence or invasion, the roles of government and international institutions have been discussed by many cultural economists and cultural institutions such as United Nations Educational, Scientific and Cultural Organization (UNESCO). The recent development of distribution technologies and communication tools has led to a reduction in trade costs. As a result, imports from large countries have increased and influx of foreign culture prevails against their own culture. For example, we can eat a hamburger, drink a Coke and enjoy Hollywood movies, and American pop music in almost every country on earth. This type of consumption can be viewed as cultural convergence or as a cultural invasion by economically developed countries.

UNESCO has declared its commitment to protect and promote diversity of cultural expressions (the 2005 Convention for the Protection and Promotion of the Diversity of Cultural Expressions, UNESCO (2013)). Economic researchers often discuss the relationship between trade and cultural diversity. Mas-Colell (1999) raised the question of whether or not should we differentiate cultural goods from other conventional goods. Using trade data, Ferreira and Waldfogel (2013) confirmed whether there is cultural convergence in the music market or not. They focused on cultural protection polices, such as "airplay quota," in some countries (for example, Canada, France, Australia, and New Zealand) and analyzed whether the policy could limit the cultural invasions, such as by the U.S., or not. Disdier et al. (2010) use naming data in France and suggest that the audio-visual service trade could transform domestic tastes and cause foreign culture to supersede domestic culture.

While there are some discussions that cultural goods exports from large countries cause cultural convergence, others suggest that exports from a large country do not have an impact on the domestic culture. If cultural differences (or lack of cultural proximity) between two countries act as trade costs, they reduce the export from culturally distant countries. In this case, consumers tend to choose domestic or culturally familiar foreign goods and the prevalence of exports from large countries could not occur as a result (a home consumption bias). One example is export of "Country" music from U.S. to Asian countries. Country music have smaller market share in Asia compared to that in U.S. This could be considered that, because Asian countries do not share the cultural backgrounds of U.S., the market share of country music in Asia is small. In this case, the difference of cultural backgrounds acts as trade friction cost and inhibits the export from culturally distant countries.

To summarize, discussions of the cultural convergence or invasions are related not only to economic statuses but also proximity of cultural backgrounds each country has. If cultural proximity promote demands for culturally familiar foreign goods, the serious cultural convergence or invasions would not occur and vice versa. Hence, to reveal the role of cultural proximity as a cost in cultural goods trade is an essential work.

A gravity model of trade is suitable to analyze this topic[1]. The model states that there are mainly two important factors of the cultural goods trade corresponding to the aforementioned discussions. One is the effect of economic conditions such as the gross domestic product (GDP) and the other is the effect of trade friction costs that includes cultural factors. On one hand, it is clear that economic size has substantial influence on the trade of cultural goods. Existing studies show that the size of an economy has a significant effect on cultural goods being traded in the same way as conventional goods (Schulze (1999); Holloway (2014)).

On the other hand, the effect of cultural proximity as trade friction costs on consumers is hard to reveal. Many of the existing empirical studies on trade attempt to control cultural factors using linguistic differences, religious proximity, and past colonial relations. However, they represent not only the cultural proximity but also the other trade friction costs such as negotiation costs. Hence, these cultural variables could not be suitable for our research question. For example, a positive estimated coefficient of linguistic proximity could not imply that consumers prefer culturally similar goods, since it represents not only cultural proximity but also the trade negotiation cost of cultural goods. For this reason, we need to consider cultural factors more carefully and introduce cultural variables that represent the proximity itself when discussing the effect of culture on the trade of cultural goods.

Some studies highlight the importance of cultural factors in the trade and introduce novel

[1] The gravity models under a monopolistic competition assumption are summarized in Feenstra (2015).

cultural variables that can capture cultural proximity itself. Guiso et al. (2009) introduce bilateral trust measures taken from a survey conducted by Eurobarometer as a cultural variable. Felbermayr and Toubal (2010) use cultural variables based on the Eurovision Song Contest Score and analyze the trade within Europe. Tadesse and White (2010) use the data of Inglehart et al. (2004) and Hagenaars et al. (2003) to calculate the "Cultural Distance" between the two countries. Giuliano et al. (2014) use a "Genetic Differences" index as a proxy of the cultural differences index.

One common way to create a cultural variable is to use the World Values Survey[2], the most well-known and popular survey related to social sciences (including cultural studies). The survey is conducted globally and provides a rich insight into people's beliefs, values, and information. Noteworthy characteristics of this survey are that the raw results of questionnaires are available and we can extract some feature values that represent people's values by using methods of multivariate analysis such as Principal Component Analysis (PCA). However, we need to be careful when using the aforementioned data, since it is hard to decide whether the value represents the cultural factors that we intend to capture. The term "culture" is an ambiguous concept; culture is made up of linguistic factors, religious concepts, differences in values, nationality, humanity, history, and many other factors. It is necessary to specify what the value captures when we use the World Values Survey data.

The other way to create a cultural variable, we demonstrate in this dissertation, is to use interview-based studies as a source of data. Although this restricts the research subject to one specific cultural good, the cultural variables that are based on such studies can adequately capture cultural factors. For example, our cultural variable based on an ethnomusicological study (Lomax (1959)[3]) can capture cultural factors in the context of music. The ambiguous definition

[2] The World Values Survey is one of the largest, repeated cross-section survey. The data and the documentations are available at: *http://www.worldvaluessurvey.org/wvs.jsp*

[3] Some researches raise critical comments on this study (for examples, Driver and Downey (1970), Nettl (1970)).

of culture occurs when we treat cultural goods as one category. We can define culture in the context of movies, music, paintings, or novels if only we focus on these goods.

In addition, we propose a novel method to extract cultural factors from the data of traded cultural goods. Cultural factors can be thought of as country-specific, as each country has its own culture. When countries trade, we can control the effects of such cultural factors with additive fixed effects if one cultural factor (for example, the exporting country's culture) is independent of the other one (importing country's culture). However, this is not necessarily the case. For example, Japanese culture may be preferred by one country but disliked by another. In this case, Japanese culture is Japan-specific, but the effects depend on the partner country. We consider that the effect of country-specific culture that affects the trade of cultural goods depends on the partner country, and we call this the "cultural relations."

Cultural relations are represented in the empirical model as interactive fixed-effect terms. Following the estimation procedure of Bai (2009), we can identify the values of interactive terms. It should be noted that we should carefully discuss whether the values of interactive terms represent the cultural relations, since our estimation procedure is similar to the PCA. While our estimated value of interactive terms contains information on cultural relations, it also contains information on other relations, for example, spatial correlations. Nevertheless, our approach toward the cultural relationship is noteworthy. This type of approach extends the knowledge of cultural studies in the field of cultural economics, especially in the trade of cultural goods.

To summarize, the main purpose of this dissertation is to reveal the relations between cultural factors and trade of cultural goods. First, we show the impact of cultural proximities (or differences) on the trade of cultural goods, using cultural variables that are based on other cultural studies. We then extract the cultural relations from the data of cultural goods traded, controlling

Recent studies (for examples, Panteli et al. (2017), Gold et al. (2017)) shed new light on Lomax (1959)'s attempts using machine-learning and other computerized technologies of analyzing music data.

the other economic factors that are used in many existing studies of trade. Through this dissertation, we employ the gravity model of trade proposed in Helpman et al. (2008). Our approach toward the cultural factors and trade of cultural goods is novel and sheds some light on the role of cultural factors in cultural economics. This dissertation consists of five chapters. Chapter 1 is the introduction. In Chapter 2, we show the empirical result of the effect of cultural differences on the trade of cultural goods. In Chapter 3, we discuss the analytical bias correction method used in Chapter2, that is incidental to the panel data analysis with two-way fixed effects. We extend the concept of cultural differences to cultural relations and show the estimated result of the cultural relations in Chapter 4 and Chapter 5 concludes the dissertation.

Chapter 2

Do Cultural Differences Affect the Trade of Cultural Goods? – A Study in Trade of Music

2.1 Introduction

In recent years, music has become one of the most valuable items in the trade of cultural goods [1]. A report by UNESCO (2016) shows that the export share of recorded sound media was the second largest in the trade of cultural good from 2004 to 2013. Cameron (2015) points out that owing to the recent technological progress in media recording and broadcasting through the internet, music became a "highly global economic phenomenon." Music producers can produce and immediately release songs worldwide. Consumers can access information about their favorite artist and even buy his/her songs despite the geographical distance. However, even though the progress of the globalization of music industry was expected to promote the trade of music, from 2000 to 2006 only 18% of trade paths traded music compact discs (CDs), whereas 65% of trade paths were active in terms of total goods trade.

Standard trade theory predicts that trade volume is determined by cost, productivity, factor

[1] UNESCO (2009) defines cultural good : "Consumer goods that convey ideas, symbols and ways of life, i.e. books, magazines, multimedia products, software, recordings, films, videos, audio–visual programmes, crafts and fashion."

endowment, etc.. In the case of cultural goods, including music, we also consider "cultural differences" as important determinants of trade volumes; however, the relationship between the trade of cultural goods and cultural differences is unclear. The purpose of this study is to define cultural differences and to assess whether such differences affect the trade of cultural goods. To this end, we use a large dataset of traded music CDs and the gravity model of trade. While Felbermayr and Toubal (2010) and Holloway (2014) investigate the relation between the trade of cultural goods and cultural differences using a gravity type model, this kind of approach to the cultural good trade is relatively rare.

When analyzing the international trade, we address the existence of the zero–trade path, which causes a sample selection bias. In addition, we discuss the omitted variable bias that may arise due to the lack of producers' "productivity" data. To avoid these biases, we use the gravity model of trade proposed by Helpman et al. (2008). This model can correct the sample selection bias and control the effect of latent music "productivity," which can differ across countries. We disentangle the effect of cultural differences, using this type of gravity model to control the observable and unobservable determinants of trade.

Among the determining factors of trade appearing in usual gravity models, costs are the most important factor. In general, there are two kinds of trade costs: "transportation" cost as variable one and "entry" cost as fixed one. In the gravity model by Helpman et al. (2008), the transportation costs appear in both the selection and outcome equations, while the entry costs appear only in the selection equation [2]. In empirical studies, the transportation costs are represented as "distance between two countries" or "contiguousness dummy." The entry costs, on the other hand, are represented as "common language dummy," "religious proximity," or "FTA dummy [3]." When we analyze the total trade volume, these variables correctly represent the transporta-

[2] In Helpman et al.'s (2008) gravity model, countries firstly decide either to start trading or not (the first-stage selection equation), and then decide how much they trade (the second-stage outcome equation).

[3] Cultural variables are often used as measurements of entry costs.

tion and entry costs. Helpman et al. (2008) show that the distance between two countries has significant effects on both the probability of trade occurrence and the volume traded. This result implies that "distance" is a good measurement of transportation costs. They also indicate that variables that represent the entry costs have a significant effect on the probability of trade occurrence, but have no significant effect on trade volume. This implies that these variables are good measurements of entry costs.

However, when analyzing the cultural goods trade, this is not the case. Ferreira and Waldfogel (2013) analyze the trade of music using a gravity equation and show that the language dummy has significant effects on both the probability of trade occurrence and volume of music traded. If the language dummy represents the entry cost of trade, this variable might have a significant effect only on the probability of trade occurrence. From the estimation result, we can conclude that the language dummy does not indicate the entry cost in the case of cultural goods trade. Rather, we can consider that the language dummy indicates a variable cost of music trade. This consideration does not seem exaggerated. Considering lyrics, if a destination uses the same language as the origin, consumers can better understand the intent of the lyrics. Therefore, the language dummy has a significant positive effect on the music trade volume. Hence, we presume that the variables that seemed to indicate entry costs in previous studies indicate a variable cost when analyzing the trade of cultural goods, including music.

Regarding the costs, "cultural differences" must be considered in addition to the usual explanatory variables. We assume that some kind of cultural difference exists between two countries, and the differences affect the choice of consumers. "Country music" is a good example. "Country music" is very popular in the United States [4] and in those countries that share the American culture, such as Canada and Australia. However, in countries that do not share the

[4] The share of country music in the United States was about 15% in 2014. This is the third largest share. *Source*: *2014 Nielsen Music Report* (http://www.billboard.com/articles/business/6436399/nielsen-music-soundscan-2014-taylor-swift-republic-records-streaming?page=0%2C3)

American culture, this is not the case. Indeed, in the Asian region, country music is not a popular music genre [5]. Thus, it is natural to consider the cultural differences as trade cost.

The purpose of our study is to find cultural variables that capture the cultural differences and to reveal the relation between trade behaviors and cultural differences, supported by sound econometric method. An important and difficult aspect of our study is how to classify culture. We analyze only the trade of music as a representative of cultural goods; therefore, we can define the cultural differences in the context of musical culture. We find that country pairs that share the same culture tend to trade significantly more compared to the country pairs that do not. Moreover, one of our cultural variables helps us to satisfy the exclusion restriction of the two-stage estimation procedure.

This study is organized as follows. In section 2.2, we highlight the definition of cultural differences and its measurement method. In section 2.3, we introduce the gravity model of international trade and explain the parameter estimation technique. In section 2.4, we describe the data used for our analysis. In section 2.5, we show the estimation results, and section 2.6 concludes.

2.2 Cultural Differences

Here, we provide the definition of cultural difference and its measurement. Cultural differences are important determinants of trade volume that affect the consumer choice. However, only a few studies have examined the cultural differences because an accurate quantification of the differences in culture is difficult. In studies such as by Guiso et al. (2009), Disdier et al. (2010), Felbermayr and Toubal (2010), Tadesse and White (2010), Gokmen (2012), Giuliano et al. (2014), and Holloway (2014), they have attempted to capture the cultural difference and

[5] For example, Garth Brooks, one of the most successful country musicians, who charted in Billboard 200 in 2014, did not chart in Billboard Japan Hot Overseas chart in 2014.

perform analysis using cultural variables defined therein. In our study, we focus only on the music trade to capture the cultural difference correctly. Owing to this limitation of the subject of research, we can define the cultural difference in the context of music.

However, before defining the cultural difference, let us explain a cultural region, which is a basic concept when discussing cultural differences. As with other phenomena with broad classifications, we assume that culture can also be classified into several groups. Here, we call the cultural groups as "cultural regions", and define cultural difference as follows: If two countries are not in the same cultural region, there is a cultural difference between the two countries. Using this definition, we can deal with cultural differences if we classify the countries into several cultural regions.

The question is how to classify the various regions. Here, we consider two comprehensive and intuitive ways of classification: "ethnomusicology-based classification" by Lomax (1959) and "civilization-based classification" by Huntington (1996). Lomax (1959) uses the ethnomusicology-based classification to classify all musical styles into ten styles: American Indian, Pygmoid [6] , African, Australian, Melanesian, Polynesian, Malayan, Eurasian, Old European, and Modern European. This comprehensive classification explains the differences such as the melody structure, performance method, and social and religious meaning [7] . This classification captures the musical difference across cultures. We define these regions as "musical region" in this study. Huntington (1996) uses the civilization-based classification to categorize all countries into eleven regions: Western, Sinic, Islamic, Hindu, Orthodox, Latin American, African, Buddhist, Japan, Haiti, and Ethiopia. We consider that this classification captures the difference of mass culture. We define these regions as "civilization region" in this study. The lists of countries and corresponding classification of cultural regions are reported in Table 2.1

[6] We do not consider the Pygmoid region, as it is difficult to identify the countries that constitute this region.

[7] Note that, following this classification, some countries belong to two or three musical regions. For example, France and Spain belong to Eurasian, Old European, and Modern European regions.

and 2.2.

Using these classifications, we define two cultural dummy variables: *Culture1* and *Culture2*. If an origin and a destination country are in the same musical region, the *Culture1* dummy takes a value equal to 1, and 0 otherwise. This variable represents the cultural proximity (or lack of difference) in terms of traditional meaning. If two countries share the traditional music culture, *Culture1* takes a value equal to 1. Similarly, if both countries are in the same civilization region, the *Culture2* dummy takes a value equal to 1, and 0 otherwise. This variable represents the cultural proximity (or lack of difference) in terms of modish meaning. If two countries share the modern cultural attitude, *Culture2* takes a value equal to 1. For example, consider the case of Egypt and Italy. Egypt and Italy are in the same "Eurasian" musical region; hence, *Culture1* takes a value equal to 1 for Egypt–Italy and Italy–Egypt trade paths. On the other hand, Egypt is in the "Islamic" civilization cultural region and Italy is in the "Western" civilization cultural region; hence, *Culture2* takes a value equal to 0. Both *Culture1* and *Culture2* take a value equal to 1 if two countries share the corresponding culture, and 0 otherwise. The corresponding estimated coefficients become positive if our hypothesis is true.

In addition, we assume that there are two types of consumers: "devotee" and "mass" consumers. We define devotees as consumers who are keen on music. Since they are enthusiastic music consumers, they are sensitive to the musical and mass cultural differences, seek music from around the world and introduce it to their own country's market. On the other hand, we define masses as consumers who are not keen on music compared to devotees. Therefore, they do not pay a particular attention to the musical cultural differences and are only concerned with the mass cultural differences. From these definitions, we infer that devotees can be affected by *Culture1* and *Culture2* because *Culture1* captures the musical cultural proximity (or difference) and *Culture2* captures the mass cultural proximity. On the other hand, masses can be only affected by *Culture2* because they do not focus on the musical cultural differences, which are captured by *Culture1*. In addition, we also assume that the number of mass consumers is larger compared to devotees. This assumptions does not seem to be arbitrary, as most music consumers behave as masses rather than devotees, while only a few enthusiastic music consumers act as devotees. These are essential assumptions of our study and help us estimate the gravity equation. We will explain the importance of these assumptions in the next section.

2.3 Model

Here, we introduce the gravity model we used in this paper, which follows Helpman et al. (2008) [8]. To summarize, the model explains why some countries trade and others do not from the perspective of productivity heterogeneity. In this model, suppose that a producer-specific productivity a is distributed and can be described by a cumulative distribution function $G(a)$ with support $[a_L, a_H]$. In the case of cultural goods trade, "producer" corresponds to the artist (in the case of music trade, a singer or a band) and producer-specific productivity can be considered as an ability to make arts (e.g., Ferreira and Waldfogel (2013)).

Besides, we should pay attention to what represents the fixed cost of trade in the music trade. In the case of total trade, regulation cost of a firm entry, measured by the number of days and/or legal procedures, expresses the fixed cost of trade (e.g., Helpman et al. (2008)). These measurements affect the decision of trade entry but have no effect on trade volume. In the case of music trade, the entry cost of artists to participate in the foreign market (a kind of notification cost, which is required for artists to be recognized by consumers in foreign countries) could express the fixed cost. A part of such cost is measured by traditional relation of two countries in the context of music. If two countries are traditionally related, artists might enter the market in

[8] Most of the symbols that we use for variables correspond to those used by Helpman et al. (2008).

partner country at low cost.

In this study, the traditional cultural variable *Culture1* is good measurement of this fixed cost. On the other hand, as discussed in section 2.1, linguistic proximity, past colonial relations, religious proximity and modern cultural variable *Culture2* could be measurements of variable cost.

Consider a variable that represents the proportion of profit for the most productive producer to the common fixed cost to export:

$$Z_{ij} \equiv \frac{(1-\alpha)\left(\frac{\alpha P_i}{T_{ij}c_j}\right)^{\varepsilon-1} Y_i a_L^{1-\varepsilon}}{c_j f_{ij}}, \tag{2.1}$$

where Y_i is the income of country i, P_i is the price index in country i, ε is the elasticity of substitution across goods, α is the parameter that fulfills $0 < \alpha < 1$, and T_{ij}, c_j, f_{ij} represent the cost factors. T_{ij} express the variable costs including transportation costs; $T_{ij} > 1$ for all $i \neq j$ and $T_{ij} = 1$ for all trade within country j. $c_j f_{ij}$ express the fixed costs; c_j is country specific and f_{ij} is trade path i-j specific and$f_{ij} > 0$ for all trade paths $i \neq j$. We assume that the trade path i-j specific cost f_{ij} is stochastic. Let $f_{ij} \equiv \exp(\phi_{EX,j} + \phi_{IM,i} + \kappa\phi_{ij} - \iota_{ij})$, where ι_{ij} is an error term and $\iota_{ij} \sim N(0, \sigma_\iota^2)$, $\phi_{EX,j}$ is is the fixed export cost common across all export destinations, $\phi_{IM,i}$ is a fixed trade barrier, and ϕ_{ij} is a country-pair-specific observed fixed cost. Then, we assume that T_{ij} is also stochastic because there is unmeasured trade friction u_{ij}. We define $T_{ij}^{\varepsilon-1} \equiv D_{ij}^{\gamma} e^{-u_{ij}}$, where D_{ij} is the observed index of variable costs between country i and j, such as distance between two countries, and $u_{ij} \sim N(0, \sigma_u^2)$. The positive export from country j to i is observed only if $Z_{ij} > 1$.

Using these specifications, the logarithm of the variable Z_{ij} is

$$z_{ij} = \alpha_0 + \lambda_{1,j} + \chi_{1,i} - \gamma d_{ij} - \kappa\phi_{ij} + \eta_{ij}, \tag{2.2}$$

where $\eta_{ij} \equiv u_{ij} + \iota_{ij} \sim N(0, \sigma_u^2 + \sigma_\iota^2)$, $\lambda_{1,j}$ and $\chi_{1,i}$ represent the exporter and importer fixed effects, respectively (these contain the information of price index, income, importer/exporter fixed costs, etc.). The lowercase letters refer to the natural logarithm of their uppercase variables.

Then, assume that as $\sigma_u^2 + \sigma_\iota^2 = 1$, the probability that country j exports to country i conditional on observed variables can be expressed as

$$\begin{aligned} \rho_{ij} &= \Pr(I_{ij} = 1 | \text{ObservedVariables}) \\ &= \Phi(\alpha_0 + \lambda_{1,j} + \chi_{1,i} - \gamma d_{ij} - \kappa \phi_{ij}), \end{aligned} \tag{2.3}$$

where I_{ij} is the indicator function that takes a value equal to 1 if country j exports to country i and 0 otherwise, and $\Phi(\cdot)$ is the cumulative distribution function of standard normal distribution. Equation (2.3) estimates the probability that country j starts to export music to country i. It is not possible to observe z_{ij}, but we can calculate the value of z_{ij} using equation (2.3). We call equation (2.3) the first-stage selection equation.

Then, consider the volume of trade. The trade volume from country j to country i is expressed as

$$M_{ij} = \left(\frac{T_{ij} c_j}{\alpha P_i}\right)^{1-\varepsilon} Y_i N_j V_{ij}, \tag{2.4}$$

where N_j is the number of goods that are available in country j, and V_{ij} indicates the fraction of exporting producers. Suppose that the productivity $1/a$ follows a truncated Pareto distribution, and this assumption indicates that we can rewrite the expression as

$$V_{ij} = \theta W_{ij}, \ \ where \ \ W_{ij} = \max\left(\left(\frac{a_{ij}}{a_L}\right)^{k-\varepsilon-1} - 1, 0\right), \tag{2.5}$$

where θ is a constant parameter and k is the shape parameter of the truncated Pareto distribution.

Equation (2.4) can be expressed in a log-linear form as

$$m_{ij} = \beta_0 + \lambda_{2,j} + \chi_{2,i} - \gamma d_{ij} + w_{ij} + u_{ij}, \tag{2.6}$$

where β_0 is a constant term, and $\lambda_{2,j}$ and $\chi_{2,i}$ represent the exporter and importer fixed effects, respectively (these contain the information of price index, income, population, etc.). The lowercase letters refer to the natural logarithm of their uppercase variables.

To estimate the consistent estimator, we need to control the endogenous effect of the number of exporters, w_{ij}, and the selection bias. Taking conditional expectations, equation (2.6) can be rewritten as

$$m_{ij} = \beta_0 + \lambda_{2,j} + \chi_{2,i} - \gamma d_{ij} + h(\hat{z}_{ij}, \hat{\bar{\eta}}_{ij}) + \beta_{u\eta}\hat{\bar{\eta}}_{ij} + e_{ij} \tag{2.7}$$

where $\hat{\bar{\eta}}_{ij} = \phi(z_{ij})/\Phi(z_{ij})$, $\phi(\cdot)$ is probability density function of standard normal distribution, $\hat{z}_{ij} = \Phi^{-1}(\hat{\rho}_{ij})$, $h(\hat{z}_{ij}, \hat{\bar{\eta}}_{ij})$ is the third polynomial function [9] of $\hat{z}_{ij}$, and $\hat{\bar{\eta}}_{ij}$, $\beta_{u\eta} = corr(u_{ij}, \eta_{ij})(\sigma_u/\sigma_\eta)$, $corr(a,b)$ is a correlation coefficient between a and b, and e_{ij} is an error term with $e_{ij} \sim N(0, \sigma_e^2)$. We call equation (2.7) the second-stage outcome equation.

To summarize the estimation model, we use equations (2.3) and (2.7). First, we estimate equation (2.3) and calculate the values of $\hat{z}_{ij}$(estimated value of z_{ij}, the unobserved ratio of the export profit to the fixed costs) and $\hat{\bar{\eta}}_{ij}$(inverse Mills ratio, which corrects the sample selection bias) using the estimation result. Then, we estimate equation (2.7).

When we estimate the outcome equation, we need to exclude at least one variable from the equation, which does not appear in outcome equation such as observed fixed costs ϕ_{ij}. The choice of the variable that we exclude is crucial. The estimated coefficients and their variances

[9] w_{ij} is a concave function and have lower bias if we directly take an expectation. To avoid this bias, we first approximate w_{ij} with a polynomial in $\hat{z}_{ij}$ and $\hat{\bar{\eta}}_{ij}$, and then, we take an expectation of w_{ij} . The value is described as $E[w_{ij}|\cdot, I_{ij} = 1] = \omega_0 + \omega_1\hat{z}_{ij} + \omega_2\hat{z}_{ij}^2 + \omega_3\hat{z}_{ij}^3 + \hat{\bar{\eta}}_{ij}(\omega_4\hat{z}_{ij} + \omega_5\hat{z}_{ij}^2 + \omega_6\hat{z}_{ij}^3)$, and we define this as $h(\hat{z}_{ij}, \hat{\bar{\eta}}_{ij})$.

will be significantly biased if we exclude an inappropriate one [10] .

In our study, the variable *Culture1* can be viewed as the observed fixed cost ϕ_{ij}. From our assumption of devotees and masses in section 2.2, we suppose that *Culture1* affects only devotees and the number of devotees is small. In the case that *Culture1* equals to 1, devotees tend to import music from its trading partner compared to the case that *Culture1* equals to 0. However, once two countries start trade, the volume of music traded does not depend on *Culture1* since *Culture1* affects only devotees and the number of devotees is extremely smaller compared to masses. *Culture1* reduces the trade starting cost through the act of devotees but has no effect on trade volume. Thus, *Culture1* can be considered as fixed cost ϕ_{ij} in the model.

On the other hand, the variable *Culture2* can be viewed as the variable cost d_{ij}. If *Culture2* equals to 1, devotees and masses tend to import music from the trading partner. Recalling that the number of masses is larger in the market, the volume of music traded is promoted in the case that *Culture2* equals to 1. Therefore, *Culture2* can act as the variable cost d_{ij} in the model.

After estimating the parameters, we perform an additional bias correction. Panel data models using fixed effects can cause incidental parameter problem and the parameters become biased severely when the model is nonlinear. To correct this bias, we use the bias correction method proposed by Fernández-Val and Weidner (2016) and expand it to apply to our two-stage estimation model. The details of these correction methods are in appendix 2.7.

2.4 Data

We use the amount of traded CDs as a proxy of the traded music. The data employed in this study are from 2000 to 2006 and cover 188 countries. The list of these countries is provided

[10] In Helpman et al. (2008), they assume religious proximity as excluded variable in their dataset. Following this, Ferreira and Waldfogel (2013) also exclude the religious variable. However, we need to be more careful on the choice of excluded variable.

in Table 2.3. The trade data of music is from the United Nations Commodity Trade Statistics Database (http://comtrade.un.org/), which is the most comprehensive database [11]. We use an HS Code classification that is popular and detailed one. The commodity code is HS8524.32: discs for laser reading systems for reproducing sound only.

As we calculate an average value from 2000 to 2006 to avoid a year–specific effect, our dataset is essentially cross–sectional. The variables of our data contain two indexes, for importer i and exporter j, and the data can be arranged as if they were an $N \times N$ panel dataset [12]. The most significant difference between a general panel dataset and our data is that the diagonal elements M_{jj} (exports from some country j to the country j) are always omitted by definition. In addition, the trade data is asymmetric, that is, M_{ij} (export from a county j to a country i) need not be equal to M_{ji} (export from a county i to a country j), although some explanatory variables must be symmetric (for example, $Distance_{ij} = Distance_{ji}$).

The explanatory variables are geographic distance, common border dummy, common language dummy, colonial tie dummy, religious proximity and two cultural proximity dummies (*Culture1* and *Culture2*). These variables except *Culture1* represent the variable cost of trade and are included in the variable cost d_{ij} in the estimation model. On the other hand, as aforementioned in section 2.3, *Culture1* would represent the fixed cost and are included in ϕ_{ij} in the selection equation. The data for geographic distance, common border dummy, common language dummy and colonial tie dummy were obtained from the Centre d'Études Prospectives et d'Informations Internationales (http://www.cepii.fr/) database. The religious proximity variable is calculated in the same way as in Helpman et al. (2008), using the dataset introduced by Alesina et al. (2003). We also use the cultural dummy variables introduced in the previous section. The

[11] Other databases that provide trade data include NEBR-UN and CHELEM. However, Comtrade provides a higher level of sector disaggregation (6-digit) and covers a rather unlimited number of countries (Gaulier and Zignago, 2010).

[12] In this case, the row index assign to importer countries and the column index assign to exporter countries.

definitions of independent and dependent variables are provided in Table 2.4.

When using data of music traded, we need to take into account the effects of intellectual property right (IPR) protection levels (for example, IPRI (2017) and World Economic Forum (2017) provide such data respectively) on the trade volume. Shin et al. (2016) show that the IPR protection levels of the importing country have positive effect on total trade value. On the other hand, Aguiar and Waldfogel (2014) point out that copyright protection reduces the consumption choice of music in the foreign market. However, in either case, such country specific institutional effects can be controlled by country–specific fixed effect terms in our model, since the IPR protection levels of importing or exporting country are country–specific.

In addition, we need to consider how to treat the effects of digital piracy on the sales. There are many studies about the relationship between piracy and cultural goods sales (e.g., Oberholzer-Gee and Strumpf (2007); Rob and Waldfogel (2006); Zentner (2005)). However, the effect of piracy rate on the music sales is still unclear; moreover, there has been no conclusive theories or empirical studies. In this study, we consider that the effect of piracy on the volume of music traded is negligible. Oberholzer-Gee and Strumpf (2007) show that, in 2003, most of file sharing users were in large countries, such as the United States (30.9%), Germany (13.5%), Italy (11.1%), and Japan (8.4%) [13]. Aside from these large countries, this fact allows us that it is possible to ignore the effect of piracy on the music traded in small countries that occupy the major part of our sample. In large countries that have many file-sharing-software users, there is a possibility that the trade volume data reported from such large countries are smaller than the actual traded volume owing to the effect of illegal downloads. However, we can also avoid this possibility. Rob and Waldfogel (2006) state that the willingness to pay for music that is downloaded illegally is lower than music purchased. This implies that the sales of CDs

[13] The number of file sharing users in top 16 countries was about 93% in 2003.

do not depend on whether there is piracy, because the music download illegally would not be worth paying money. As mentioned above, we consider that the piracy does not affect the sales or trade volume of music regardless of countries size.

Similarly, the effect of digital content sales must be taken into consideration. Digital music became more significant in the current music industry; however, tracing the trade flow of digital contents is extremely difficult. The purpose of this study is to reveal the impact of cultural differences on music trade. For this purpose, comparing physical and digital music, physical contents seem desirable because they are traceable and widely traded around the world compared to digital contents [14]. In our sample period, we can confirm that digital media have negligible effects on trade. Based on the IFPI (2012) report, the market share of digital music is small [15] in our sample and is mainly concentrated in the United States and Canada. Furthermore, in our sample period, digital contents were not available in many countries [16]. This implies that there should not be an underestimation of the trade volume, which is caused by digital music sales, in almost all trade paths. Therefore, we conclude that the digital media do not have a significant impact on our estimation result and conclusions [17].

Column "All" in Table 2.5 shows the summary statistics of dependent and independent variables. From the table, only 2% of the country pairs share a border. The ratio of country pairs sharing a language is 15% and country pairs that were in a colonial relation are only 1%. The average religious proximity is 0.14. Of the country pairs, 22% are in the same music cultural region and 15% share the mass culture. Column "In Trade" in Table 2.5 shows the summary

[14] Moreover, IFPI (2015) reports that in 2014 physical music contents had 46% share, which is equivalent to the digital ones. Therefore, physical goods data do not seem to be outdated for investigating cultural trade.

[15] The global share of digital music was 0% from 2000 to 2003, 2% in 2004, 5% in 2005, and 10% in 2006.

[16] For example, iTunes Store, which is the pioneer of music download service, started their service in 2003 and had provided the service for only four countries in July 2004, and twenty countries in August 2006. *Source*: *Apple Press Info* (http://www.apple.com/pr/).

[17] Of course we should consider the digital music contents data if it is traceable. This is the further research topic of this study.

statistics only for country pairs that have traded at least one unit of music. Compared to the full sample summary, the mean values of all variables, except *Distance*, increase. For positive trade flows, 40% of the country pairs are in the same music cultural region, and about 27% of the country pairs are in the same mass cultural region. From this summary, it can be expected that, as the value of these variables increase, they will have a positive effect on the probability ρ_{ij}.

In addition to the full sample, we prepare subsamples for advanced analysis. We use "Western-Latin" sample and "Asian" sample. Columns "All" and "In Trade" in Table 2.6 respectively show the summary statistics of the Western-Latin sample and Western-Latin sample of only for the country pairs that have traded at least one unit of music. In the Western-Latin sample, the degree of cultural proximity is high compared to the full sample. Columns "All" and "In Trade" in Table 2.7 respectively show the summary statistics of Asian sample and Asian sample of only for country pairs that have traded at least one unit of music. In the Asian region, the degree of mass culture proximity is low, although the degree of musical culture proximity is high. These tendencies are in common with all samples and samples with positive trade.

2.5 Result

Table 2.8 reports our estimation results. Columns (1) and (2) in Table 2.8 show the estimation result using full sample. Column (1) shows the estimates of the selection equation, and column (2) represents the estimates of the gravity equation with endogeneity controlling variables. In column (2), we use only positive trade flow.

In column (1), all variables except *Border* and *Religion* have significant effects on ρ_{ij}. As standard gravity estimates indicate, the distance between two countries has a negative effect on the probability of trade occurrence, ceteris paribus. Similarly, the country pairs using the same language and were in the colonial ties are likely to start trade significantly more compared to other country pairs. In addition, the estimation results show that both *Culture1* and *Culture2* have significant positive effects on ρ_{ij}. These results support our hypothesis that consumers are likely to choose a trading partner that culturally resembles each other.

Column (2) shows the estimation result of the outcome equation. To estimate this equation, we use *Culture1* as the excluded variable. As we stated in the previous section, we consider that *Culture1* has no effect on masses; therefore, *Culture1* has a significant effect on ρ_{ij} and non-significant effect on the volume of music traded. Hence, this variable can be excluded to satisfy the exclusion restriction. In addition, we introduce endogeneity controlling variables, their polynomial terms, and cross terms in the second-stage estimation. Similar with the Probit estimation results in the first stage, all variables except *Religion* has a significant effect on music trade volume, while *Distance* has a negative effect on the trade volume. The variables *Border*, *Language*, and *Colony* have significant positive effects on trade volume. Other things being equal, a pair of countries trade music about two and a half times (= exp (0.962)) more if they are contiguous, two times (= exp (0.831)) more if they use the same language, and two and a half times (= exp (0.967)) more if the countries have colonial ties. The variable *Culture2* also has a significant positive effect on the music trade volume, although the impact on the trade volume is relatively small compared to border, language, or colonial tie dummies. Other things being the same, a country exports music about two times (= exp(0.585)) more if both countries belong to the same cultural region. Thus, we can assert the importance of the effect of cultural difference on the trade volume. Our intuitive hypothesis that cultural differences affect the consumer choice, ceteris paribus, is supported by our estimation results. We intuitively know that when we consume foreign music, we choose the one that is more familiar. However, we cannot specify whether the choice is a result of the cultural difference or, for example, of the linguistic difference. After controlling for other conditions, such as language, colonial relation, income, distance between two countries, etc., our estimation results show that cultural difference significantly affects the consumer choice.

Next, we show the estimation results using the subsamples. Columns (3) and (4) in Table 2.8 show the estimation result using the Western-Latin subsample. In column (3), all variables except *Border* and *Curture1* dummies have significant effects on ρ_{ij}. This result is similar to the one in the full sample. The main differences between the full sample result (column (1)) and the Western-Latin subsample result (column (3)) are (a) *Religion* has a significant effect on ρ_{ij}, and (b) *Culture1* dummy has no significant effect on ρ_{ij}. Within the Western-Latin region, the cultural difference of music does not have a significant effect on the probability of trade occurrence ρ_{ij}. Column (4) shows a very different result. Here, only *Border* dummy has a significant effect on the trade volume. Even the control variables $\hat{z}_{ij}$, $\hat{\bar{\eta}}_{ij}$, and their cross terms that represent the productivity (or export ability) have no significant effects on the trade volume. Besides, the standard errors of estimated coefficients take larger values. We conclude from this estimation result that we fail to estimate the parameters of outcome equation using the Western-Latin subsample. Within the Western-Latin region, the variable *Curture1* does not behave as we expected.

The estimation results using the Asian subsamples are in columns (5) and (6) in Table 2.8. Column (5) shows that only *Distance* and *Language* dummies have significant effects on ρ_{ij}. However, both the cultural variables do not have significant effects on the probability of trade occurrence. This result implies that, when Asian countries trade music within the region, these cultural variables do not act as trade barriers. For the estimation result in column (6), almost all the variables have the expected signs that the gravity model of trade usually yields. However, almost all the variables have larger estimated coefficient values. This is the typical case of mis-specification of model parameters. The variable *Curture1* also does not behave as we expected.

From these two estimation results using subsamples, we conclude that the cultural variables that are defined globally, as those used here, are inadequate when we analyze trade within the local regions. It is necessary for us to choose cultural differences defined globally or locally according to our careful analysis. In this study, we cannot define the cultural variables that are used for the subsamples. Further research is needed to clarify the effect of cultural differences within these subsample regions.

In addition to our main results, we confirm the validity of our excluded variable [18]. Table 2.9 reports the results for a robustness check. Column (1) reports the estimation result of selection equation. Columns (2) to (4) report the estimation result of outcome equation using *Culture1*, *Culture2*, and *Religion* as excluded variables respectively. Column (5) reports the estimation result of uncorrected selection and endogeneity biases (excludes all zero samples). We regard the estimation result in column (2) as our benchmark.

In column (3), we use *Culture2* as an excluded variable instead of *Culture1*. Observing the regression coefficient signs in column (3), we can verify that the estimation result is seriously misspecified. The coefficient signs of variable *Distance*, *Language*, and *Colony* are sign-reversed and become nonsignificant, and *Culture1* has a negative effect on trade volume. This result is not intuitive. If this is correct, the distance between two countries does not act as a proxy of transportation costs. The linguistic differences and colonial ties do not affect the consumers' choice. This unexpected result does not support the hypothesis that *Culture2* is the appropriate excluded variable. Moreover, we cannot explain why *Culture2* does not affect the volume of music traded using our assumption of devotees and masses. We conclude that *Culture2* is inappropriate to be used as an excluded variable, compared to *Culture1*.

In column (4), we exclude the *Religion* as in the Helpman et al. (2008) study. Here, the coef-

[18] We also check the robustness of estimation model. We do poisson pseudo maximum likelihood estimation and obtain similar result.

ficient values are overestimated and the standard errors are larger than benchmark ones, although coefficient signs are appropriate. This result implies that using *Religion* as an excluded variable causes exaggerates estimated coefficients. For example, the result in column (4) represents that two countries that share the same language trade about 13 times (=exp(2.618)) more on average compared to the two countries that do not share the same language. However, the average trade volume in a group that does not share same language is 188,637 copies, and the volume in a group that shares same language is 256,745 copies. The same tendency can be found in other variables. From this fact, we conclude that *Religion* cannot be utilized to satisfy the exclusion restriction in the case of music trade.

Choosing an adequate excluded variable is difficult empirical works. Our justification to use *Culture1* as an excluded variable is not strong. However, we show that it is inappropriate to exclude other variables. Compared to others, the estimation result when excluding *Culture1* appears to be reasonable. This validates our choice of the variable to exclude.

2.6 Conclusion

The purpose of this study is to reveal the relationship between cultural differences and trade of music. Cultural differences are an important determinant of music trade. We empirically confirm its effect by using a large dataset of music trade from about 188 countries.

To define the cultural differences, we review studies on ethnomusicology and politics, and identify cultural variables that represent the differences of music and mass culture. We use the modified gravity model of trade proposed by Helpman et al. (2008) to avoid the possible bias. We assume that music consumers can be classified as devotees and masses, and that the number of masses is much larger than devotees. This unique assumption helps *Culture1* to satisfy the exclusion restriction in our model.

From our estimation result, we find that the cultural differences play an important role when countries trade music, ceteris paribus. The cultural difference of music acts as a fixed cost, which has a positive effect on the probability of trade occurrence, but does not have a significant effect on the volume traded. The cultural difference of masses acts as a variable cost. If two countries share the same culture, they trade significantly more compared to the country pairs that do not share the same culture.

In addition to our full sample analysis, we also analyze the trade of music using the Western-Latin and Asian subsamples. In the Western-Latin region, the music culture variable *Culture1* does not have a significant effect on the probability of trade occurrence, and both the *Culture1* and *Culture2* have no significant effects on the volume of music traded. This result implies that in the Western-Latin region, people do not care about the cultural differences when they consume music. In the Asian region, both cultural variables have no significant effects on the probability of trade occurrence and the volume of music traded. In addition, the productivity term $\hat{z}_{ij}$, $\hat{\bar{\eta}}_{ij}$, and their cross terms have no significant effect on the music volume. We conjecture that people do not focus on the cultural proximity or productivity in the Asian region.

In conclusion, we show the importance of cultural differences. Our estimation results demonstrate that the cultural differences play an important role in music trade although they do not have a significant effect when we limit the subject of analysis to specific samples. Moreover, one cultural variable can be treated as excluded variable and this helps us to satisfy the exclusion restriction of our two-stage estimation procedure.

Our study sheds some light on the role of cultural differences in the trade of cultural goods; however, three issues remain open for future research.

Firstly, the results of this study cannot be directly applied to other cultural goods, such as movies or books, mainly because we define one cultural variable in the context of music. Nevertheless, our findings contribute to the literature by revealing the relationship between cultural differences and the trade of cultural goods. Further research on the relationship between cultural differences and other cultural goods is needed.

Secondly, we need to consider the effect of digital music trade and streaming service. Because of the difficulty to trace the complete digital music flows, we choose a sample period when digital music trade and streaming service do not have significant impact on our estimation results and conclusion. However, the share of digital market is equivalent to physical one in 2014 and has tended to increase through the year. Some studies treat the digital music sales and trade, for example, Gomez-Herrera et al. (2014) use digital music sales data in US, Canada and 16 European countries from 2006 to 2011 and investigates what drives digital trade patterns. Aguiar and Waldfogel (2015) obtain the volume of streams data from "Sportify" over the period of 2013–2015 and examine the impact on the physical goods sales and the digital piracy. Although in many countries the data of digital music and streaming service flow are not completely available, analysis and studies based on these data are helpful to reveal the role of cultural differences in cultural goods trade. Developing a way for tracing the digital music flows and analyzing them are topics for further research.

Finally, the effect of IPR protection (including copyright protection) must be investigated. Although Shin et al. (2016) show the relationship between trade value and IPR protection, the relationship between cultural goods trade and IPR protection is still unclear. In this paper, we control the effect of IPR protection using fixed effects. However, we cannot identify the effects themselves in the fixed effect terms. Investigating the relationship is also an important further research topic.

2.7 Appendix

In this section, we will explain how to treat the incidental parameter problem of our two-stage estimation procedure. Our estimation procedure contains two equations.

First, we estimate the trade decision equation. The problem is occurred because our model has fixed effects of importer and exporter. This is the typical case of incidental parameter problem. Fernández-Val and Weidner (2016) propose the bias correction way for nonlinear models that contain two-way fixed effects and we follow their way to correct the bias. The criterion function of first stage equation is

$$Q_1 = \sum_{i=1}^{I} \sum_{j=1}^{J} f_{1,ij}(\theta_1, \alpha_{1,i}, \gamma_{1,j}; X_{1,ij}), \tag{2.8}$$

where θ_1 is a $K \times 1$ parameter and $\alpha_{i,i}, \gamma_{1,j}$ are fixed effects country i and j respectively.

Fernández-Val and Weidner (2016) show that for the bias corrected estimator

$$\tilde{\theta}_1 = \hat{\theta}_1 - W_1^{-1}(B_{1,i} + B_{1,j}), \tag{2.9}$$

it is guaranteed that

$$\sqrt{IJ}(\tilde{\theta}_1 - \theta_{1,0}) \xrightarrow{d} N(0, \Sigma_1). \tag{2.10}$$

This is the strictly exogenous components of $X_{1,ij}$ case. For the detail of correction terms W_1, $B_{1,i}$, and $B_{1,j}$, see Fernández-Val and Weidner (2016).

Then, we estimate the outcome equation. The two-stage estimation bias correction way with one-way fixed effect is proposed in Fernández-Val and Vella (2011). We expand their way to our two-stage estimation with two-way fixed effects model. The criterion function of second stage equation is

$$Q_2 = \sum_{i=1}^{I} \sum_{j=1}^{J} f_{2,ij}(\theta_2, \zeta, \alpha_{2,i}, \gamma_{2,j}; X_{2,ij}, \lambda_{ij}) \tag{2.11}$$

where θ_2 is a $M \times 1$ parameter vector, λ_{ij} is a $L \times 1$ control variables vector, and ζ is a $L \times 1$ coefficient vector. In our case, λ_{ij} can be written as $\lambda_{ij} = (z_{ij}, z_{ij}^2, z_{ij}^3, z_{ij}\eta_{ij}, z_{ij}^2\eta_{ij}, z_{ij}^3\eta_{ij}, \eta_{ij})$. We can show that for the bias corrected estimator

$$\tilde{\theta}_2 = \hat{\theta}_2 - W_2^{-1}(B_{2,i} + B_{2,j}), \tag{2.12}$$

it is guaranteed that

$$\sqrt{IJ}(\tilde{\theta}_2 - \theta_{2,0}) \xrightarrow{d} N(0, \Sigma_2), \tag{2.13}$$

where

$$W_2 = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix}' \tag{2.14}$$

$$
\begin{aligned}
B_{2,i} = &- \mathbb{E}_J\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \frac{v_{2,ij}}{\mathbb{E}_I[d_{ij}]}\right] - \mathbb{E}_J\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \frac{v_{2,ij}}{\mathbb{E}_I[d_{ij}]} \cdot \zeta' \cdot \lambda_{ij,\pi} \cdot \psi_{1,i}^{(J)}\right] \\
&- \mathbb{E}_J\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \left(\zeta' \cdot \tilde{\lambda}_{ij,\pi} \cdot \beta_{1,i} + \zeta' \cdot \tilde{\lambda} ij, \pi\pi \cdot \frac{\sigma_{11,i}}{2}\right)\right] - \begin{pmatrix} 0 \\ \mathbb{E}_J[d_{ij} \cdot \tilde{\lambda}_{ij,\pi} \cdot \zeta' \cdot \tilde{\lambda}_{ij,\pi}] \end{pmatrix} \cdot \sigma_{11,i} \\
&+ \begin{pmatrix} 0 \\ \mathbb{E}_J\left[d_{ij} \cdot v_{2,it} \cdot \left(\tilde{\lambda}_{ij,\pi} \cdot (\psi_{1,ij}^{(J)} + \beta_{1,i}) + \tilde{\lambda}_{ij,\pi\pi} \cdot \frac{\sigma_{11,i}}{2}\right)\right] \end{pmatrix},
\end{aligned} \tag{2.15}
$$

$$
\begin{aligned}
B_{2,j} = &- \mathbb{E}_I\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \frac{v_{2,ij}}{\mathbb{E}_I[d_{ij}]}\right] - \mathbb{E}_I\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \frac{v_{2,ij}}{\mathbb{E}_I[d_{ij}]} \cdot \zeta' \cdot \lambda_{ij,\pi} \cdot \psi_{1,i}^{(I)}\right] \\
&- \mathbb{E}_I\left[d_{it} \cdot \begin{pmatrix} \tilde{X}_{2,ij} \\ \tilde{\lambda}_{ij} \end{pmatrix} \cdot \left(\zeta' \cdot \tilde{\lambda}_{ij,\pi} \cdot \beta_{1,j} + \zeta' \cdot \tilde{\lambda} ij, \pi\pi \cdot \frac{\sigma_{11,j}}{2}\right)\right] - \begin{pmatrix} 0 \\ \mathbb{E}_I[d_{ij} \cdot \tilde{\lambda}_{ij,\pi} \cdot \zeta' \cdot \tilde{\lambda}_{ij,\pi}] \end{pmatrix} \cdot \sigma_{11,j} \\
&+ \begin{pmatrix} 0 \\ \mathbb{E}_I\left[d_{ij} \cdot v_{2,it} \cdot \left(\tilde{\lambda}_{ij,\pi} \cdot (\psi_{1,ij}^{(I)} + \beta_{1,j}) + \tilde{\lambda}_{ij,\pi\pi} \cdot \frac{\sigma_{11,j}}{2}\right)\right] \end{pmatrix}.
\end{aligned} \tag{2.16}
$$

The "tilde" marks represent the regression residuals of the variables on the two-way fixed effects, d_{ij} is the indicator in the selection equation, and

$$
\begin{aligned}
\lambda_{ij,\pi} &= (1, 2z_{ij}, 3z_{ij}^2, \eta_{ij} + z_{ij}\eta_{ij,\pi}, 2z_{ij}\eta_{ij} + z_{ij}^2\eta_{ij,\pi}, 3z_{ij}^2\eta_{ij} + z_{ij}^3\eta_{ij,\pi}, \eta_{ij,\pi}), \\
\lambda_{ij,\pi\pi} &= (0, 2, 6z_{ij}, 2\eta_{ij,\pi} + z_{ij}\eta_{ij,\pi\pi}, 2\eta_{ij} + 4z_{ij}\eta_{ij,\pi} + z_{ij}^2\eta_{ij,\pi\pi}, 6z_{ij}\eta_{ij} + 6z_{ij}^2\eta_{ij,\pi} + z_{ij}^3\eta_{ij,\pi\pi}, \eta_{ij,\pi\pi}).
\end{aligned}
$$

$\eta_{ij,\pi}$ and $\eta_{ij,\pi\pi}$ are values of η_{ij} differentiated by fixed effects once and twice respectively. $\psi_{ij}^{(I)}$, $\psi_{ij}^{(J)}$, $\beta_{1,i}$, $\beta_{1,j}$, $\sigma_{11,i}$, and $\sigma_{11,j}$ are defined in a way similar to Fernández-Val and Vella (2011).

Table 2.1: Ethnomusicology Based Classification

American Indian			
Antigua and Barbuda	Costa Rica	Guyana	Paraguay
Aruba	Cuba	Haiti	Saint Lucia
Bahamas	Dominica	Honduras	Saint Vincent and the Grenadines
Barbados	Dominican Rep.	Jamaica	Suriname
Belize	El Salvador	Mexico	Trinidad and Tobago
Br. Virgin Isds	Grenada	Nicaragua	Uruguay
Canada	Guatemala	Panama	USA

African			
Algeria	Djibouti	Madagascar	Senegal
Angola	Egypt	Malawi	Seychelles
Benin	Ethiopia	Mali	Sierra Leone
Botswana	Gabon	Mauritania	Somalia
Burkina Faso	Gambia	Mauritius	South Africa
Burundi	Ghana	Morocco	Swaziland
Cameroon	Guinea	Mozambique	Togo
Cape Verde	Guinea-Bissau	Namibia	Tunisia
Central African Rep.	Kenya	Niger	Uganda
Chad	Lesotho	Nigeria	United Rep. of Tanzania
Congo	Liberia	Rwanda	Zambia
Côte d'Ivoire	Libya	Sao Tome and Principe	Zimbabwe
Democratic Republic of the Congo			

Australian			
Australia			

Melanesian			
Fiji	N. Mariana Isds	New Caledonia	Solomon Isds
Indonesia	Nauru	Papua New Guinea	Vanuatu

Polynesian			
French Polynesia	Samoa	Tonga	Tuvalu
New Zealand			

Malayan			
Brunei Darussalam	Malaysia	Singapore	Timor-Leste
Indonesia	Philippines		

Eurasian			
Afghanistan	France	Kuwait	Singapore
Albania	Greece	Lao People's Dem. Rep.	Slovenia
Bahrain	India	Lebanon	Spain
Bosnia Herzegovina	Indonesia	Maldives	Sri Lanka
Cambodia	Iran	Mongolia	Syria
China	Iraq	Nepal	Thailand
China, Hong Kong SAR	Ireland	Oman	Turkey
China, Macao SAR	Israel	Pakistan	United Arab Emirates
Croatia	Italy	Qatar	United Kingdom
Cyprus	Japan	Rep. of Korea	Viet Nam
Dem. People's Rep. of Korea	Kazakhstan	Saudi Arabia	Yemen
Egypt			

Old European			
Andorra	Finland	Lithuania	Serbia
Armenia	France	Luxembourg	Slovakia
Austria	Georgia	Malta	Slovenia
Azerbaijan	Germany	Netherlands	Spain
Belarus	Greece	Norway	Sweden
Belgium	Greenland	Poland	Switzerland
Bulgaria	Iceland	Portugal	TFYR of Macedonia
Croatia	Italy	Rep. of Moldova	Ukraine
Czech Rep.	Kyrgyzstan	Romania	United Kingdom
Denmark	Latvia	Russian Federation	Uzbekistan
Faeroe Isds			

Modern European			
Antigua and Barbuda	Chile	Guyana	Romania
Argentina	Colombia	Haiti	Saint Lucia
Aruba	Costa Rica	Honduras	Saint Vincent and the Grenadines
Bahamas	Cuba	Hungary	San Marino
Barbados	Dominica	Italy	Spain
Belize	Dominican Rep.	Jamaica	Suriname
Bolivia	Ecuador	Mexico	Trinidad and Tobago
Br. Virgin Isds	El Salvador	Nicaragua	United Kingdom
Brazil	France	Panama	Uruguay
Bulgaria	Grenada	Paraguay	USA
Canada	Guatemala	Peru	Venezuela

Table 2.2: Civilization Based Classification

Western			
Andorra	Finland	Latvia	San Marino
Australia	France	Lithuania	Slovakia
Austria	Germany	Luxembourg	Slovenia
Barbados	Greenland	Malta	Solomon Isds
Belgium	Grenada	Netherlands	Spain
Canada	Hungary	New Zealand	Sweden
Croatia	Iceland	Norway	Switzerland
Czech Rep.	Ireland	Papua New Guinea	Trinidad and Tobago
Denmark	Israel	Philippines	United Kingdom
Dominica	Italy	Poland	USA
Estonia	Jamaica	Portugal	Vanuatu

Sinic			
China	China, Macao SAR	Rep. of Korea	Viet Nam
China, Hong Kong SAR	Dem. People's Rep. of Korea		

Hindu			
Guyana	Nepal	India	

Islamic			
Afghanistan	Egypt	Lebanon	Saudi Arabia
Albania	Gambia	Libya	Senegal
Algeria	Guinea	Malaysia	Somalia
Azerbaijan	Guinea-Bissau	Mali	Syria
Bahrain	Indonesia	Mauritania	Timor-Leste
Bangladesh	Iran	Morocco	Tunisia
Bosnia Herzegovina	Iraq	Niger	Turkey
Brunei Darussalam	Jordan	Oman	United Arab Emirates
Burkina Faso	Kuwait	Pakistan	Uzbekistan
Chad	Kyrgyzstan	Qatar	Yemen
Djibouti			

Orthodox			
Armenia	Georgia	Rep. of Moldova	Serbia
Belarus	Greece	Romania	TFYR of Macedonia
Bulgaria	Kazakhstan	Russian Federation	Ukraine
Cyprus			

Latin			
Antigua and Barbuda	Paraguay	Guatemala	Costa Rica
Belize	Saint Vincent and the Grenadines	Nicaragua	Ecuador
Chile	Argentina	Peru	Honduras
Cuba	Bolivia	Uruguay	Panama
El Salvador	Colombia	Bahamas	Saint Lucia
Mexico	Dominican Rep.	Brazil	Venezuela

African			
Angola	Côte d'Ivoire	Malawi	South Africa
Benin	Democratic Republic of the Congo	Mauritius	Suriname
Botswana	Gabon	Mozambique	Swaziland
Burundi	Ghana	Namibia	Togo
Cameroon	Kenya	Nigeria	Uganda
Cape Verde	Lesotho	Rwanda	United Rep. of Tanzania
Central African Rep.	Liberia	Sao Tome and Principe	Zambia
Congo	Madagascar	Sierra Leone	Zimbabwe

Buddhist			
Bhutan	Lao People's Dem. Rep.	Myanmar	Sri Lanka
Cambodia	Mongolia	Singapore	Thailand

Ethiopia
Ethiopia

Haiti
Haiti

Japan
Japan

Table 2.3: Country List

Afghanistan	Cyprus	Kyrgyzstan	Rwanda
Albania	Czech Rep.	Lao People's Dem. Rep.	Saint Lucia
Algeria	Dem. People's Rep. of Korea	Latvia	Saint Vincent and the Grenadines
Andorra	Democratic Republic of the Congo	Lebanon	Samoa
Angola	Denmark	Lesotho	San Marino
Antigua and Barbuda	Djibouti	Liberia	Sao Tome and Principe
Argentina	Dominica	Libya	Saudi Arabia
Armenia	Dominican Rep.	Lithuania	Senegal
Aruba	Ecuador	Luxembourg	Serbia
Australia	Egypt	Madagascar	Seychelles
Austria	El Salvador	Malawi	Sierra Leone
Azerbaijan	Estonia	Malaysia	Singapore
Bahamas	Ethiopia	Maldives	Slovakia
Bahrain	Faeroe Isds	Mali	Slovenia
Bangladesh	Fiji	Malta	Solomon Isds
Barbados	Finland	Mauritania	Somalia
Belarus	France	Mauritius	South Africa
Belgium	French Polynesia	Mexico	Spain
Belize	Gabon	Mongolia	Sri Lanka
Benin	Gambia	Morocco	Suriname
Bermuda	Georgia	Mozambique	Swaziland
Bhutan	Germany	Myanmar	Sweden
Bolivia	Ghana	N. Mariana Isds	Switzerland
Bosnia Herzegovina	Greece	Namibia	Syria
Botswana	Greenland	Nauru	TFYR of Macedonia
Br. Virgin Isds	Grenada	Nepal	Thailand
Brazil	Guatemala	Netherlands	Timor-Leste
Brunei Darussalam	Guinea	New Caledonia	Togo
Bulgaria	Guinea-Bissau	New Zealand	Tonga
Burkina Faso	Guyana	Nicaragua	Trinidad and Tobago
Burundi	Haiti	Niger	Tunisia
Côte d'Ivoire	Honduras	Nigeria	Turkey
Cambodia	Hungary	Norway	Tuvalu
Cameroon	Iceland	Oman	Uganda
Canada	India	Pakistan	Ukraine
Cape Verde	Indonesia	Panama	United Arab Emirates
Central African Rep.	Iran	Papua New Guinea	United Kingdom
Chad	Iraq	Paraguay	United Rep. of Tanzania
Chile	Ireland	Peru	Uruguay
China	Israel	Philippines	USA
China, Hong Kong SAR	Italy	Poland	Uzbekistan
China, Macao SAR	Jamaica	Portugal	Vanuatu
Colombia	Japan	Qatar	Venezuela
Congo	Jordan	Rep. of Korea	Viet Nam
Costa Rica	Kazakhstan	Rep. of Moldova	Yemen
Croatia	Kenya	Romania	Zambia
Cuba	Kuwait	Russian Federation	Zimbabwe

Table 2.4: Definition of Variables

Trade Volume of Music:	Amount of traded products that are coded HS8524.32, that is, discs for laser reading systems for reproducing sound only.
Distance:	Distance between the capital cities of country i and country j (in km and expressed in logarithm).
Border:	Binary variable that takes 1 if country i and country j are contiguous, and 0 otherwise.
Language:	Binary variable that takes 1 if both country i and country j use the same language, and 0 otherwise.
Colony:	Binary variable that takes 1 if country i and country j possess colonial ties, and 0 otherwise.
Religion:	Following the way in Helpman et al. (2008), Religion is calculated as follows:
$\text{Religion}_{ij} =$	$\{(\% \text{ of Protestant in country i}) \times (\% \text{ of Protestant in country j})\}$ $+(\% \text{ of Catholics in country i}) \times (\% \text{ of Catholics in country j})$ $+(\% \text{ of Muslims in country i}) \times (\% \text{ of Muslims in country j})$
Culture1:	Binary variable that takes 1 if both country i and country j are in the same cultural region according to the Ethnomusicology-Based Classification, and 0 otherwise.
Culture2:	Binary variable that takes 1 if both country i and country j are in the same cultural region according to the Civilization-Based Classification, and 0 otherwise.

Table 2.5: Summary Statistics (full sample)

	All				In Trade			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Trade Volume (Log)	–	–	–	–	5.49	3.89	-1.95	17.95
Distance (Log)	8.77	0.78	2.35	9.90	8.40	0.98	4.09	9.89
Border	0.02	0.12	0.00	1.00	0.05	0.21	0.00	1.00
Language	0.15	0.36	0.00	1.00	0.18	0.38	0.00	1.00
Colony	0.01	0.10	0.00	1.00	0.04	0.21	0.00	1.00
Religion	0.14	0.22	0.00	1.00	0.15	0.24	0.00	1.00
Culture1	0.22	0.42	0.00	1.00	0.40	0.49	0.00	1.00
Culture2	0.15	0.36	0.00	1.00	0.27	0.44	0.00	1.00

Note: Number of observation is 35,156 and 6,390 country pairs are in trade.

Table 2.6: Summary Statistics (Latin–Western)

	All				In Trade			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Trade Volume (Log)	–	–	–	–	6.74	4.20	-1.95	17.95
Distance (Log)	8.50	1.04	4.09	9.88	8.16	1.13	4.09	9.88
Border	0.03	0.17	0.00	1.00	0.06	0.24	0.00	1.00
Language	0.20	0.40	0.00	1.00	0.22	0.41	0.00	1.00
Colony	0.03	0.16	0.00	1.00	0.05	0.22	0.00	1.00
Religion	0.30	0.28	0.28	0.89	0.31	0.28	0.00	0.89
Culture1	0.44	0.50	0.00	1.00	0.56	0.50	0.00	1.00
Culture2	0.54	0.50	0.00	1.00	0.66	0.47	0.00	1.00

Note: Number of observation is 4,556 and 2,076 country pairs are in trade

Table 2.7: Summary Statistics (Asian)

	All				In Trade			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Trade Volume (Log)	–	–	–	–	6.34	4.24	-1.95	16.10
Distance (Log)	7.84	0.61	4.11	8.83	7.81	0.72	4.11	8.83
Border	0.11	0.31	0.00	1.00	0.16	0.37	0.00	1.00
Language	0.07	0.26	0.00	1.00	0.14	0.35	0.00	1.00
Colony	0.01	0.10	0.00	1.00	0.02	0.13	0.00	1.00
Religion	0.04	0.14	0.00	0.84	0.04	0.12	0.00	0.84
Culture1	0.51	0.50	0.00	1.00	0.65	0.48	0.00	1.00
Culture2	0.19	0.39	0.00	1.00	0.20	0.40	0.00	1.00

Note: Number of observation is 380 and 165 country pairs are in trade

Table 2.8: Estimation Results

	Full Sample		Western-Latin		Asian	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Probit	Volume	Probit	Volume	Probit	Volume
Distance	-0.698***	-1.167***	-0.869***	0.570	-1.420***	-8.347*
	(0.026)	(0.340)	(0.062)	(1.603)	(0.380)	(4.850)
Border	0.100	0.962***	-0.185	1.460***	0.306	-0.039
	(0.103)	(0.203)	(0.242)	(0.465)	(0.427)	(1.299)
Language	0.491***	0.831***	0.606***	-0.644	1.568**	11.985**
	(0.046)	(0.248)	(0.127)	(1.123)	(0.677)	(5.216)
Colony	0.635***	0.967***	0.855***	-1.324	-1.111	-11.599***
	(0.100)	(0.316)	(0.272)	(1.553)	(0.868)	(3.995)
Religion	-0.112	0.333	0.682**	-0.596	1.311	16.530***
	(0.079)	(0.206)	(0.301)	(1.255)	(1.355)	(2.757)
Culture1	0.202***		0.079		0.193	
	(0.039)		(0.116)		(0.300)	
Culture2	0.310***	0.585***	0.184**	0.384	-0.292	-1.253
	(0.047)	(0.181)	(0.091)	(0.370)	(0.450)	(1.269)
$\hat{z}_{ij}$		4.489**		4.130		30.861***
		(1.811)		(2.659)		(10.063)
$\hat{z}_{ij}^2$		-0.819**		-0.249		-7.541
		(0.402)		(0.351)		(1.904)
$\hat{z}_{ij}^3$		0.045		0.006		0.482***
		(0.029)		(0.024)		(0.119)
$\hat{z}_{ij}\hat{\hat{\eta}}_{ij}$		-1.534***		-0.767		5.105
		(0.418)		(0.694)		(4.278)
$\hat{z}_{ij}^2\hat{\hat{\eta}}_{ij}$		-0.250		-0.114		-0.731
		(0.299)		(0.463)		(4.095)
$\hat{z}_{ij}^3\hat{\hat{\eta}}_{ij}$		-0.042		-0.004		-0.843
		(0.043)		(0.078)		(1.337)
$\hat{\hat{\eta}}_{ij}$		5.758*		2.964		75.828***
		(3.099)		(3.199)		(19.333)
Observations	35,156	6,390	4,556	2,076	380	165
R-squared		0.629		0.732		0.570

Note. Estimated coefficients are reported for Probit. Robust standard errors are in parentheses. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. All specification includes exporter and importer fixed effects.

Table 2.9: Check the Validity of Excluded Variable

	(1) Probit	(2) Exclude(Culture1)	(3) Exclude(Culture2)	(4) Exclude(Religion)	(5) Simplest
Distance	-0.698***	-1.167***	0.137	-3.719***	-1.474***
	(0.026)	(0.340)	(0.247)	(1.265)	(0.064)
Border	0.100	0.962***	0.777***	1.325***	0.918***
	(0.103)	(0.203)	(0.204)	(0.260)	(0.198)
Language	0.491***	0.831***	-0.086	2.618***	0.805***
	(0.046)	(0.248)	(0.206)	(0.880)	(0.118)
Colony	0.635***	0.967***	-0.219	3.291***	1.336***
	(0.100)	(0.316)	(0.247)	(1.157)	(0.170)
Religion	-0.112	0.333	0.546***		0.395*
	(0.079)	(0.206)	(0.194)		(0.222)
Culture1	0.202***		-0.369***	0.745**	0.125
	(0.039)		(0.118)	(0.373)	(0.095)
Culture2	0.310***	0.585***		1.704***	0.960***
	(0.047)	(0.181)		(0.536)	(0.105)
$\hat{z}_{ij}$		4.489**	6.357***	0.812	
		(1.811)	(1.790)	(2.567)	
$\hat{z}_{ij}^2$		-0.819**	-0.819**	-0.814**	
		(0.402)	(0.402)	(0.402)	
$\hat{z}_{ij}^3$		-0.045	-0.045	-0.044	
		(0.029)	(0.029)	(0.029)	
$\hat{z}_{ij}\hat{\hat{\eta}}_{ij}$		-1.534***	-1.531***	-1.534***	
		(0.418)	(0.418)	(0.418)	
$\hat{z}_{ij}^2\hat{\hat{\eta}}_{ij}$		-0.250	-0.250	-0.252	
		(0.299)	(0.299)	(0.299)	
$\hat{z}_{ij}^3\hat{\hat{\eta}}_{ij}$		-0.042	-0.042	-0.042	
		(0.043)	(0.043)	(0.043)	
$\hat{\hat{\eta}}_{ij}$		5.758*	5.764*	5.729*	
		(3.099)	(3.099)	(3.099)	
Observations	35,156	6,390	6,390	6,390	6,390
R-squared		0.629	0.629	0.629	0.618

Note. Estimated coefficients are reported for Probit. Robust standard errors are in parentheses. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. All specification includes exporter and importer fixed effects.

Chapter 3

A Bias Correction Method of Two-Step Estimator for Panel Data Sample Selection Model with Two-Way Fixed Effects

3.1 Introduction

This study considers a bias correction method in a two-step estimator of a sample selection model with two-way fixed effects. The sample size of cross-section and time series are denoted by N and T respectively. We consider an asymptotic theory that both N and T go to infinity at the same rate. Such a setting appears in empirical studies of finance (e.g., Bai (2009)), macroeconomics (e.g., Maddala and Wu (1999)), trade and network effects using dyadic data (e.g., Cameron and Miller (2014)). In particular, Helpman et al. (2008) focus the intensive margin and extensive margin of international trade based upon their theoretical model and derive a sample-selection-like estimation model with two-way fixed effects to examine the empirical implications, where the model consists of two equations; the first equation explains the decision of export and the second one explains the volume of export.

When both cross-sectional and time-series sample size are sufficiently large, estimators are believed to be free from the the incidental parameter problem (Neyman and Scott (1948)), where all parameter estimators are biased in general due to the presence of the incidental parameters. Helpman et al. (2008) implicitly assume that they could avoid the bias problem in their two-step estimator since the data set they use contains a large number of countries' information. However, it is not well investigated how the finite sample properties of their estimator is. Moreover, recent studies of nonlinear panel data estimation clarify that the biases in the mean vector of the asymptotic distribution are non-negligible even asymptotically as long as N and T grow to infinity at the same rate. The reason is that, since the leading term of the asymptotic bias is of order N^{-1}, or T^{-1} and the normalized term is $\sqrt{NT}$ (the asymptotic variance of the estimator is standardized by $\sqrt{NT}$), the order of bias terms are $\sqrt{NT}/T = \sqrt{N/T}$ or $\sqrt{NT}/N = \sqrt{T/N}$. These terms do not disappear even asymptotically as long as N and T grow to infinity at the same rate.

This study proposes the analytical bias correction formula for two-step estimation of sample selection model and clarify the finite sample property of the bias corrected estimator through Monte Carlo simulations.

3.2 Model

Denote the fixed effect parameter vector as $\phi_j = (\alpha'_{j,1}, \alpha'_{j,2}, \ldots, \alpha'_{j,N}, \gamma'_{j,1}, \gamma'_{j,2}, \ldots, \gamma'_{j,T})'$ ($j = 1,2$), where j is the index indicating the first- and second-step estimation. The objective functions of the two-step estimation are given as follows:

$$Q_{1,NT}(\theta_1,\phi_1) = \sum_{i=1}^{N}\sum_{t=1}^{T} q_{1,it}(\theta_1, \underbrace{\alpha_{1,i}+\gamma_{1,t}}_{\pi_{1,it}:M_1\times 1}), \qquad \eta_1 = (\underbrace{\theta_1'}_{1\times K_1}, \underbrace{\alpha_1'}_{1\times NM_1}, \underbrace{\gamma_1'}_{1\times TM_1})' \tag{3.1}$$

$$Q_{2,NT}(\theta_2,\phi_2;\lambda(\eta_1)) = \sum_{i=1}^{N}\sum_{t=1}^{T} q_{2,it}(\theta_2, \underbrace{\alpha_{2,i}+\gamma_{2,t}}_{\pi_{2,it}:M_2\times 1}; \underbrace{\lambda_{it}(\eta_1)}_{L\times 1}), \;\; \eta_2 = (\underbrace{\theta_2'}_{1\times K_2}, \underbrace{\alpha_2'}_{1\times NM_2}, \underbrace{\gamma_2'}_{1\times TM_2})', \tag{3.2}$$

where $\lambda_{it}(\boldsymbol{\eta_1})$ is the control function based upon the estimated results in the first-step estimation. For example, the standard sample selection model (for example, Heckman (1979); Wooldridge (2010)), the model consists of two equations,

$$\begin{aligned} d_{it} &= \mathbb{1}\{\mathbf{x}_{1,it}'\delta + \alpha_{1,i} + \gamma_{1,t} + u_{1,it}\},\ u_{1,it} \sim N(0,1),\ \ i=1,2,\ldots,N,\ t=1,2,\ldots,T. \\ y_{it}^* &= \mathbf{x}_{2,it}'\beta + \alpha_{2,i} + \gamma_{2,t} + u_{2,it},\ u_{2,it} \sim N(0,\sigma^2),\ \mathbb{E}[u_{1,it}u_{2,it}] = \rho\cdot\sigma. \end{aligned}$$

The former is called "the selection equation" and the later "the outcome equation". The dependent variable y_{it}^* is only observed when $d_{it} = 1$. Then the objective functions of two-step estimation are given as,

$$q_{1,it} = d_{it}\cdot\log\Phi(\mathbf{x}_{1,it}'\delta + \alpha_{1,i} + \gamma_{1,t}) + (1-d_{it})\cdot\log\Phi(-\mathbf{x}_{1,it}'\delta - \alpha_{1,i} - \gamma_{1,t}) \tag{3.3}$$

$$q_{2,it} = -\frac{1}{2}(y_{it} - \mathbf{x}_{2,it}'\beta - \zeta\cdot\lambda(\mathbf{x}_{1,it}'\delta + \alpha_{1,i} + \gamma_{1,t}) - \alpha_{2,i} - \gamma_{2,t})^2. \tag{3.4}$$

where $\zeta = \rho\sigma$, $\lambda(z) = \phi(z)/\Phi(z)$, $\phi(z)$ is the probability density function of the standard normal distribution and $\Phi(z)$ is the cumulative distribution function of the standard normal distribution. This is a special case of equation (3.1) and (3.2) that $\theta_1 = \delta$, $\theta_2 = (\beta,\zeta)$. Other models that are applicable to the above frame work are Fernández-Val and Vella (2011) and Helpman et al.

(2008).[1].

The estimators in the first-step are given as follows,

$$\hat{\phi}(\theta_1) = \underset{\phi_1}{\operatorname{argmax}}\, Q_{1,NT}(\theta_1, \phi_1)$$

$$\hat{\theta}_1 = \underset{\theta_1}{\operatorname{argmax}}\, Q_{1,NT}(\theta_1, \hat{\phi}_1(\theta_1))$$

The estimator of θ_1 is denoted as $\tilde{\theta}_1$ and define $\tilde{\phi}_1 = \hat{\phi}_1(\tilde{\theta}_1)$ and $\tilde{\eta}_1 = (\tilde{\theta}_1, \tilde{\phi}_1)$. The second-step estimators of are given as

$$\hat{\phi}(\theta_2) = \underset{\phi_2}{\operatorname{argmax}}\, Q_{2,NT}(\theta_2, \phi_2; \lambda(\tilde{\eta}_1))$$

$$\hat{\theta}_2 = \underset{\theta_2}{\operatorname{argmax}}\, Q_{2,NT}(\theta_2, \hat{\phi}_2(\theta_2); \lambda(\tilde{\eta}_1))$$

It is impossible to estimate all $N+T$ fixed effect parameters simultaneously due to exact multicollinearity. Fernández-Val and Weidner (2016) propose the estimation procedure that imposes the restrictions, $\sum_{i=1}^{N} \alpha_{j,i} = \sum_{t=1}^{T} \gamma_{j,t}$, for $j = 1, 2$, to estimate the $N+T-1$ fixed effect parameters. This is the algebraically same approach as dropping one parameter from α and γ and adding a constant term and estimate the parameters. Along this way, we can restore all $N+T$ fixed effect parameters using the estimated constant term, the restriction condition, and the estimated $(N-1)+(T-1)$ fixed effect parameters: $1+1+(N-1)+(T-1) = N+T$.

[1] Another extension of the model is the one with interactive fixed effects and/or both additive and interactive fixed effects. The models with interactive fixed effects is closely related to factor analysis in multivariate analysis. The interpretation of the estimated fixed effects is not straightforward, but the effects also could be interpreted as factors related to spatial or cross-sectional correlation in panel data settings (e.g. Chudik and Pesaran (2015)). Chen et al. (2014) propose a bias correction method for the probit model with interactive fixed effects, and we could extend our analysis to the case of the two-step estimation of the sample selection model with interactive fixed effects. Identification of both additive and interactive fixed effects is attained in the similar way to Bai (2009).

3.3 Bias correction

Hahn and Newey (2004) discuss the bias correction methods for the maximum likelihood estimator (MLE) for possibly nonlinear panel data models with one-way fixed effect. They propose two types of bias correction methods: the analytical and the resampling-based bias correction method. Arellano and Hahn (2016) extend them to the nonlinear dynamic panel models with multiple fixed effects. Fernández-Val (2009) provide the detailed analysis of the bias-corrected MLEs for the probit model. Hahn and Kuersteiner (2011) investigate the theoretical properties of existing bias corrected methods.

The biases of the MLE for the sample selection model could be corrected by the method of Arellano and Hahn (2016). However, researchers often employ the two-step estimation procedure by Heckman (1976) owing to its computational ease. Fernández-Val and Vella (2011) propose the bias correction method for the two-step estimator with one-way fixed effects.

While Fernández-Val and Weidner (2016) discuss the order N^{-1} and T^{-1} bias correction for the nonlinear model with the two-way fixed effects, there are no existing study that cover the case of the two-step estimation with two-way fixed effects. We show the explicit bias terms for the case and analyze its properties. The symbols we use correspond to those used by Fernández-Val and Weidner (2016) and the assumptions for the data generating processes also follow those of Fernández-Val and Weidner (2016).

Note that we treat the fixed effects as if they were constant and the expectation operator $\mathbb{E}$ calculate the expected value conditional on the fixed effects. The bias corrected estimator of the first-step parameters θ_1 and the second-step parameters θ_2 are given by

$$\tilde{\theta}_1 \equiv \hat{\theta}_1 - \mathscr{W}_1^{-1}\mathbf{b}_1, \;\; \tilde{\theta}_2 \equiv \hat{\theta}_2 - \mathscr{W}_2^{-1}\mathbf{b}_2,$$

where $\hat{\theta}_1$ and $\hat{\theta}_2$ are defined in section 2, and $\mathscr{W}_1$ and $\mathscr{W}_2$ can be written as

$$\mathscr{W}_1 = \mathbb{E}[Q_{1,\theta\theta} + \Xi_1' Q_{1,\phi\phi} \Xi_1] = \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbb{E}\left[\frac{\partial^2 q_{1,it}}{\partial \theta_1 \partial \theta_1'} + (\Xi_{1,i\bullet} + \Xi_{1,\bullet t})' \frac{\partial^2 q_{1,it}}{\partial \pi_{1,it} \partial \pi_{1,it}'} (\Xi_{1,i\bullet} + \Xi_{1,\bullet t}) \right]$$

$$\mathscr{W}_2 = \mathbb{E}[Q_{2,\theta\theta} + \Xi_2' Q_{2,\phi\phi} \Xi_2] = \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbb{E}\left[\frac{\partial^2 q_{2,it}}{\partial \theta_2 \partial \theta_2'} + (\Xi_{2,i\bullet} + \Xi_{2,\bullet t})' \frac{\partial^2 q_{2,it}}{\partial \pi_{2,it} \partial \pi_{2,it}'} (\Xi_{2,i\bullet} + \Xi_{2,\bullet t}) \right].$$

The parameter in the subscript of matrices represents the derivative of the matrix with respect to the parameter in the subscript. For Ξ_j, $\Xi_j = \bar{\mathscr{H}}_j^{-1} \mathbb{E}[Q_{j,\phi\theta}]$ and the dimension is $(M_j \cdot N + M_j \cdot T) \times K_j$. The first N block of Ξ_j is given as $\Xi_{j,i\bullet}$, ($j = 1,2$, $i = 1,2,\ldots,N$) and the remaining T block of Ξ_j is $\Xi_{j,\bullet t}$, ($j = 1,2$, $t = 1,2,\ldots,T$). The Hessian matrices of the fixed effects parameters are $\bar{\mathscr{H}}_1$ for the first-step criterion function and $\bar{\mathscr{H}}_2$ for the second-step one.

We define $\Psi_1 \equiv Q_{1,\theta} + \Xi_1' Q_{1,\phi}$ and the bias of order N^{-1} and T^{-1} in the first-step estimation is given as$\mathscr{W}_1^{-1}\mathbf{b}_1$, where

$$\begin{aligned} \mathbf{b}_1 &= \mathbb{E}\left[\tilde{\Psi}_{1,\phi} \cdot \Delta_{1,NT}\right] + \mathbb{E}\left[\Psi_{1,\phi\phi}\right] \cdot \frac{\sigma_{11}}{2} \\ &= \sum_{i=1}^{N} \mathbf{b}_{1,i\bullet} + \sum_{t=1}^{T} \mathbf{b}_{1,\bullet t} + o_p\left((NT)^{-1/2}\right). \end{aligned} \tag{3.5}$$

The tilde means the deviation from the mean, for $\Delta_{1,NT}$, $\Delta_{1,NT} = \bar{\mathscr{H}}_1^{-1} Q_{1,\phi}$ and σ_{11} is defined as $\sigma_{11} \equiv \mathbb{E}\left[\Delta_{1,NT} \otimes \Delta_{1,NT}\right]$. And the $\mathbf{b}_{1,i\bullet}$ and $\mathbf{b}_{1,\bullet t}$ are

$$\begin{aligned} \mathbf{b}_{1,i\bullet} &= \mathbb{E}\left[\left(\sum_{t=1}^{T} \frac{\partial \tilde{\Psi}_{1,it}}{\partial \pi_{it}}\right) \cdot \Delta_{1,i\bullet}\right] + \mathbb{E}\left[\sum_{t=1}^{T} \frac{\partial^2 \tilde{\Psi}_{1,it}}{\partial \pi_{it} \partial \pi_{it}'}\right] \cdot \frac{\mathbb{E}[\Delta_{1,i\bullet} \otimes \Delta_{1,i\bullet}]}{2}, \\ \mathbf{b}_{1,\bullet t} & \quad \mathbb{E}\left[\left(\sum_{i=1}^{N} \frac{\partial \tilde{\Psi}_{1,it}}{\partial \pi_{it}}\right) \cdot \Delta_{1,\bullet t}\right] + \mathbb{E}\left[\sum_{i=1}^{N} \frac{\partial^2 \tilde{\Psi}_{1,it}}{\partial \pi_{it} \partial \pi_{it}'}\right] \cdot \frac{\mathbb{E}[\Delta_{1,\bullet t} \otimes \Delta_{1,\bullet t}]}{2}. \end{aligned}$$

Next, we consider the bias correction for the second-step estimation. We define $\Psi_2 \equiv Q_{2,\theta} +$

$\Xi'_{2,NT} \cdot Q_{2,\phi}$. The bias of order N^{-1} and T^{-1} in the second stage equation is $\mathscr{W}_2^{-1}\mathbf{b}_2$, where

$$
\begin{aligned}
\mathbf{b}_2 &= \mathbb{E}\left[\Psi_{2,\lambda}\Lambda_\phi\right]\cdot\beta_1 + \mathbb{E}\left[\tilde{\Psi}_{2,\phi}\cdot\Delta_{2,NT}\right] + \mathbb{E}\left[\left(\tilde{\Psi}_{2,\lambda} + \tilde{\Psi}_{2,\phi}\bar{\mathscr{H}}_2^{-1}\mathbb{E}[Q_{2,\phi\lambda}]\right)\cdot\Lambda_\phi\cdot\Delta_{1,NT}\right] \\
&\quad + \mathbb{E}\left[\Psi_{2,\phi\phi}\right]\cdot\frac{\sigma_{22}}{2} + \mathbb{E}\left[\Psi_{2,\phi\lambda}(\mathbf{I}_{N+T}\otimes\Lambda_\phi)\right]\cdot\sigma_{21} + \mathbb{E}\left[\Psi_{2,\lambda}\Lambda_{\phi\phi} + \Psi_{2,\lambda\lambda}(\Lambda_\phi\otimes\Lambda_\phi)\right]\cdot\frac{\sigma_{11}}{2} \\
&= \sum_{i=1}^{N}\mathbf{b}_{2,i\bullet} + \sum_{t=1}^{T}\mathbf{b}_{2,\bullet t} + o_p\left((NT)^{-1/2}\right), \qquad (3.6)
\end{aligned}
$$

where $\Lambda_\phi = \partial\lambda/\partial\phi_1'$, $\Lambda_{\phi\phi} = \partial^2\lambda/(\partial\phi_1\otimes\partial\phi_1)'$, $\Delta_{2,NT} = \bar{\mathscr{H}}_2^{-1}Q_{2,\phi}$ and $\sigma_{\ell m} \equiv \mathbb{E}[\Delta_{\ell,NT}\otimes\Delta_{m,NT}]$.

The $\mathbf{b}_{2,i\bullet}$, $\mathbf{b}_{2,\bullet t}$ and β_1 are given as follows,

$$
\begin{aligned}
\mathbf{b}_{2,i\bullet} &= \sum_{t=1}^{T}\mathbb{E}\left[\frac{\partial\Psi_{2,it}}{\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right]\cdot\beta_{1,i\bullet} + \mathbb{E}\left[\left(\sum_{t=1}^{T}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\pi_{2,it}'}\right)\cdot\Delta_{2,i\bullet}\right] + \mathbb{E}\left[\left(\sum_{t=1}^{T}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\cdot\Delta_{1,i\bullet}\right] \\
&\quad + \mathbb{E}\left[\left(\sum_{t=1}^{T}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\pi_{1,it}'}\right)\cdot\left(\sum_{t=1}^{T}\left(\sum_{s=1}^{T}\frac{\partial^2 q_{2,is}}{\partial\pi_{2,is}\partial\pi_{2,is}'}\right)^{-1}\frac{\partial^2 q_{2,it}}{\partial\pi_{2,it}\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}}\right)\cdot\Delta_{1,i\bullet}\right] \\
&\quad + \left(\sum_{t=1}^{T}\mathbb{E}\left[\frac{\partial^2\Psi_{2,it}}{(\partial\pi_{2,it}\otimes\partial\pi_{2,it})'}\right]\right)\cdot\frac{\mathbb{E}\left[\Delta_{2,i\bullet}\otimes\Delta_{2,i\bullet}\right]}{2} \\
&\quad + \left(\sum_{t=1}^{T}\mathbb{E}\left[\frac{\partial^2\Psi_{2,it}}{(\partial\pi_{2,it}\otimes\partial\lambda_{it})'}\left(\mathbf{I}_{M_1}\otimes\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\right]\right)\cdot\mathbb{E}\left[\Delta_{2,i\bullet}\otimes\Delta_{1,i\bullet}\right] \\
&\quad + \left(\sum_{t=1}^{T}\mathbb{E}\left[\frac{\partial\Psi_{2,it}}{\partial\lambda_{it}'}\frac{\partial^2\lambda_{it}}{(\partial\pi_{1,it}\otimes\partial\pi_{1,it})'} + \frac{\partial^2\Psi_{2,it}}{(\partial\lambda_{it}\otimes\partial\lambda_{it})'}\left(\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\otimes\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\right]\right)\cdot\frac{\mathbb{E}\left[\Delta_{1,i\bullet}\otimes\Delta_{1,i\bullet}\right]}{2}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{b}_{2,\bullet t} &= \sum_{i=1}^{N}\mathbb{E}\left[\frac{\partial\Psi_{2,it}}{\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right]\cdot\beta_{1,\bullet t} + \mathbb{E}\left[\left(\sum_{i=1}^{N}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\pi_{2,it}'}\right)\cdot\Delta_{2,\bullet t}\right] + \mathbb{E}\left[\left(\sum_{i=1}^{N}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\cdot\Delta_{1,\bullet t}\right] \\
&\quad + \mathbb{E}\left[\left(\sum_{i=1}^{N}\frac{\partial\tilde{\Psi}_{2,it}}{\partial\pi_{1,it}'}\right)\cdot\left(\sum_{i=1}^{N}\left(\sum_{j=1}^{N}\frac{\partial^2 q_{2,jt}}{\partial\pi_{2,jt}\partial\pi_{2,jt}'}\right)^{-1}\frac{\partial^2 q_{2,it}}{\partial\pi_{2,it}\partial\lambda_{it}'}\frac{\partial\lambda_{it}}{\partial\pi_{1,it}}\right)\cdot\Delta_{1,\bullet t}\right] \\
&\quad + \left(\sum_{i=1}^{N}\mathbb{E}\left[\frac{\partial^2\Psi_{2,it}}{(\partial\pi_{2,it}\otimes\partial\pi_{2,it})'}\right]\right)\cdot\frac{\mathbb{E}\left[\Delta_{2,\bullet t}\otimes\Delta_{2,\bullet t}\right]}{2} \\
&\quad + \left(\sum_{i=1}^{N}\mathbb{E}\left[\frac{\partial^2\Psi_{2,it}}{(\partial\pi_{2,it}\otimes\partial\lambda_{it})'}\left(\mathbf{I}_{M_1}\otimes\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\right]\right)\cdot\mathbb{E}\left[\Delta_{2,\bullet t}\otimes\Delta_{1,\bullet t}\right] \\
&\quad + \left(\sum_{i=1}^{N}\mathbb{E}\left[\frac{\partial\Psi_{2,it}}{\partial\lambda_{it}'}\frac{\partial^2\lambda_{it}}{(\partial\pi_{1,it}\otimes\partial\pi_{1,it})'} + \frac{\partial^2\Psi_{2,it}}{(\partial\lambda_{it}\otimes\partial\lambda_{it})'}\left(\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\otimes\frac{\partial\lambda_{it}}{\partial\pi_{1,it}'}\right)\right]\right)\cdot\frac{\mathbb{E}\left[\Delta_{1,\bullet t}\otimes\Delta_{1,\bullet t}\right]}{2}
\end{aligned}
$$

$$
\begin{aligned}
\beta_1 &= \bar{\mathscr{H}}_1^{-1}\mathbb{E}\left[\tilde{\mathscr{H}}_1 \cdot \Delta_{1,NT}\right] + \bar{\mathscr{H}}_1^{-1}\mathbb{E}\left[Q_{1,\phi\phi\phi}\right] \cdot \frac{\mathbb{E}\left[\Delta_{1,NT} \otimes \Delta_{1,NT}\right]}{2} \\
&\approx \left(\begin{array}{c}
\left\{ \begin{array}{l}
\left(\sum_{t=1}^{T}\left(\sum_{s=1}^{T} \frac{\partial q_{1,is}^2}{\partial \pi_{1,is}\partial \pi_{1,is}'}\right)^{-1} \cdot \frac{\partial q_{1,it}^2}{\partial \pi_{1,it}\partial \pi_{1,it}'}\right) \cdot \Delta_{1,i\bullet} \\
+\left(\sum_{t=1}^{T}\left(\sum_{s=1}^{T} \frac{\partial q_{1,is}^2}{\partial \pi_{1,is}\partial \pi_{1,is}'}\right)^{-1} \cdot \frac{\partial^2 q_{1,it}}{\partial \pi_{1,it}(\partial \pi_{1,it}^{\otimes 2})'}\right) \cdot \frac{\mathbb{E}[\Delta_{1,i\bullet} \otimes \Delta_{1,i\bullet}]}{2}
\end{array} \right\}_{i=1}^{N} \\
\\
\left\{ \begin{array}{l}
\left(\sum_{i=1}^{N}\left(\sum_{j=1}^{N} \frac{\partial q_{1,jt}^2}{\partial \pi_{1,jt}\partial \pi_{1,jt}'}\right)^{-1} \cdot \frac{\partial q_{1,it}^2}{\partial \pi_{1,it}\partial \pi_{1,it}'}\right) \cdot \Delta_{1,\bullet t} \\
+\left(\sum_{i=1}^{N}\left(\sum_{j=1}^{N} \frac{\partial q_{1,jt}^2}{\partial \pi_{1,jt}\partial \pi_{1,jt}'}\right)^{-1} \cdot \frac{\partial^2 q_{1,it}}{\partial \pi_{1,it}(\partial \pi_{1,it}^{\otimes 2})'}\right) \cdot \frac{\mathbb{E}[\Delta_{1,\bullet t} \otimes \Delta_{1,\bullet t}]}{2}
\end{array} \right\}_{t=1}^{T}
\end{array} \right)
\end{aligned}
$$

Finally, we apply the above formula to a specific case, the sample selection model with two-way fixed effects. The bias correction method for the selection equation is already shown as Example 1 in Fernández-Val and Weidner (2016). We show the bias correction method for the outcome equation. Assume that $L = M_1 = M_2 = 1$ and the error terms have the bivariate normal distribution, the correction terms are

$$
\begin{aligned}
b_{2,i\bullet} &= -\bar{\mathbb{E}}_T\left[\left(d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\right)\cdot\frac{v_{2,is}}{\mathbb{E}_T[d_{it}]}\right]-\bar{\mathbb{E}}_T\left[\left(d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\cdot\zeta\cdot\tilde{\lambda}_{it,\pi}\right)\cdot\psi_{1,is}^{(T)}\right]\\
&\quad-\mathbb{E}_T\left[d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\cdot\left(\tilde{\lambda}_{it,\pi}\zeta\cdot\beta_{1,i\bullet}+\tilde{\lambda}_{it,\pi\pi}\zeta\cdot\frac{\sigma_{11,i\bullet}}{2}\right)\right]\\
&\quad-\begin{pmatrix}\mathbf{0}\\ \mathbb{E}_T\left[d_{it}\cdot\tilde{\lambda}_{it,\pi}\tilde{\lambda}_{it,\pi}\cdot\zeta\right]\end{pmatrix}\cdot\sigma_{11,i\bullet}\\
&\quad+\begin{pmatrix}\mathbf{0}\\ \bar{\mathbb{E}}_T\left[\left(d_{it}\cdot\tilde{\lambda}_{it,\pi}v_{2,it}\right)\cdot\psi_{1,is}^{(T)}\right]\end{pmatrix}+\begin{pmatrix}\mathbf{0}\\ \mathbb{E}_T\left[d_{it}\cdot v_{2,it}\cdot\left(\tilde{\lambda}_{it,\pi}\cdot\beta_{1,i\bullet}+\tilde{\lambda}_{it,\pi\pi}\cdot\frac{\sigma_{11,i\bullet}}{2}\right)\right]\end{pmatrix}\\
b_{2,\bullet t} &= -\mathbb{E}_N\left[\left(d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\right)\cdot\frac{v_{2,it}}{\mathbb{E}_T[d_{it}]}\right]-\mathbb{E}_N\left[\left(d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\cdot\zeta\cdot\tilde{\lambda}_{it,\pi}\right)\cdot\psi_{1,it}^{(N)}\right]\\
&\quad-\mathbb{E}_N\left[\left(d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\cdot\left(\tilde{\lambda}_{it,\pi}\zeta\cdot\beta_{1,\bullet t}+\tilde{\lambda}_{it,\pi\pi}\zeta\cdot\frac{\sigma_{11,\bullet t}}{2}\right)\right)\right]\\
&\quad-\begin{pmatrix}\mathbf{0}\\ \mathbb{E}_N\left[d_{it}\cdot\tilde{\lambda}_{it,\pi}\tilde{\lambda}_{it,\pi}\cdot\zeta\right]\end{pmatrix}\cdot\sigma_{11,\bullet t}\\
&\quad+\begin{pmatrix}\mathbf{0}\\ \mathbb{E}_N\left[\left(d_{it}\cdot\tilde{\lambda}_{it,\pi}v_{2,it}\right)\cdot\psi_{1,it}^{(N)}\right]\end{pmatrix}+\begin{pmatrix}\mathbf{0}\\ \mathbb{E}_N\left[d_{it}\cdot v_{2,it}\cdot\left(\tilde{\lambda}_{it,\pi}\cdot\beta_{1,\bullet t}+\tilde{\lambda}_{it,\pi\pi}\cdot\frac{\sigma_{11,\bullet t}}{2}\right)\right]\end{pmatrix},
\end{aligned}
$$

where $\tilde{\mathbf{x}}_{it}$ is the residuals from the regression of $\mathbf{x}_{it}$ on a constant term and $(N-1)+(T-1)$ fixed effects, $\tilde{\lambda}_{it,T}=\lambda_{it}-(\mathbb{E}_T[d_{is}\lambda_{is}]/\mathbb{E}_T[d_{is}])$ and $\tilde{\lambda}_{it,N}=\lambda_{it}-(\mathbb{E}_N[d_{is}\lambda_{is}]/\mathbb{E}_N[d_{is}])$. $\mathbb{E}_T$ is the probability limit along the time series dimension and $\mathbb{E}_N$ is the probability limit along the cross sectional dimension. $\bar{\mathbb{E}}_T[f_t g_s]$ is the one-sided long-run variance ($\sum_{s=0}^{\infty}\operatorname{cov}(f_t,g_{t-s})$). The last two terms in both $b_{2,i\bullet}$ and $b_{2,\bullet t}$ is zero if the explanatory variables are exogenous. For the explicit forms of $v_{2,it}$, $\psi_{1,it}^{(T)}$ and $\psi_{1,it}^{(N)}$ are,

$$\begin{aligned}
v_{2,it} &= y_{it} - \mathbf{x}'_{2,it}\beta - \zeta\cdot\lambda(\mathbf{x}'_{1,it}\delta + \alpha_{1,i} + \gamma_{1,t}) - \alpha_{2,i} - \gamma_{2,t} \\
\psi_{1,it}^{(T)} &= \varphi_{it}\cdot(d_{it} - \Phi_{it})/\mathbb{E}_T[\varphi_{it}\phi_{it}] \\
\psi_{1,it}^{(N)} &= \varphi_{it}\cdot(d_{it} - \Phi_{it})/\mathbb{E}_N[\varphi_{it}\phi_{it}],
\end{aligned}$$

where $\varphi_{it} \equiv \phi_{it}/\{\Phi_{it}(1-\Phi_{it})\}$, $\sigma_{11,i\bullet} = \mathbb{E}_T[(\psi_{1,it}^{(T)})^2]$ and $\sigma_{11,\bullet t} = \mathbb{E}_N[(\psi_{1,it}^{(N)})^2]$.

From these results, the bias corrected term for the θ_2 is given as,

$$\mathscr{B}_2 = \left\{\sum_{i=1}^{N}\sum_{t=1}^{T}\mathscr{W}_{2,it}\right\}^{-1}\left(\sum_{i=1}^{N}\mathbf{b}_{2,i\bullet} + \sum_{t=1}^{T}\mathbf{b}_{2,\bullet t}\right),\ \mathscr{W}_{2,it} = -\mathbb{E}\left[d_{it}\cdot\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}\begin{pmatrix}\tilde{\mathbf{x}}_{it}\\ \tilde{\lambda}_{it}\end{pmatrix}'\right]. \quad (3.7)$$

3.4 Monte Carlo experiments

We conduct Monte Carlo experiments to investigate finite sample properties of the bias corrected estimator. While our main interest is in the second stage estimator θ_2, we also need to consider θ_1 since the estimated values of θ_2 depend on the estimated values of θ_1. We use two types of data generating process in the experiments.

The first data generating process is the model with a static structure in the selection and the outcome equation. Consider the following simple selection model,

$$d_{it} = \mathbb{1}\{x_{1,it}\delta_1 + x_{2,it}\delta_2 + \alpha_{1,i} + \gamma_{1,t} + u_{1,it} \geq 0\} \tag{3.8}$$

$$y^*_{it} = x_{1,it}\beta_1 + \alpha_{2,i} + \gamma_{2,t} + u_{2,it}. \tag{3.9}$$

where $i = 1,2,...,N$ and $t = 1,2,...,T$. The observational rule is given as

$$y_{it} = \begin{cases} y^*_{it} & \text{if } d_{it} = 1 \\ \text{not observed} & \text{if } d_{it} = 0 \end{cases}$$

For the observations with $d_{it} = 1$, we consider the regression model of the outcome equation:

$$y_{it} = x_{1,it}\beta_1 + \zeta \cdot \lambda(x_{1,it}\delta_1 + x_{2,it}\delta_2 + \alpha_{1,i} + \gamma_{1,t}) + \alpha_{2,i} + \gamma_{2,t} + v_{2,it}. \tag{3.10}$$

The fixed effects are generated with $\alpha_{j,i} \sim$ i.i.d. $N(0,1/16)$ and $\gamma_{j,t} \sim$ i.i.d. $N(0,1/16)$, the explanatory variables are generated with $x_{j,it} = \frac{1}{2}x_{j,i,t-1} + \alpha_{1,i} + \gamma_{1,t} + v_{j,it}$ and the error terms are generated with $v_{j,it} \sim$ i.i.d. $N(0,3/4)$.

For the estimation of the selection and the outcome equation, we exclude the $\alpha_{j,1}$ and $\gamma_{j,1}$ and add a constant term to avoid exact multicollinearity. The sample size is $(N,T) = (56,14),(56,28),(56,56),(100,20),(100,50),(100,100)$ in each experiment. The experiments are replicated 1000 times in each case. The estimated one-sided long-run variance is always positive by using the method of Newey and West (1987).

Table 3.1 shows the summary of the first experiment. The "corrected" row shows the bias-corrected simulation results and "naive" row shows the uncorrected ones. First of all, we focus on the results of the naive estimation. The biases remain about 5% for δ_1 and δ_2 in the case of $N = T = 56$ and about 3% in the case of $N = T = 100$, although the asymptotic theory indicates that the biases in the naive estimator will disappear when both N and T are sufficiently large. To see the result of outcome equation, at most 5% bias of β_1 and about 4.6% ($N = T = 56$) and 3.3% ($N = T = 100$) bias of ζ remain. These biases have an increasing tendency when the sample size of T decreases.

Next, we focus on the bias-corrected results. With the exception of ζ, the biases of the corrected estimation are at most 1%, and are much smaller than those of the naive estimation results. The biases of ζ are about 6.1% to 7.3% when there is a large gap between the size of N and T. The biases of ζ also tend to decrease as the sample size increases. The estimation of ζ is known to be difficult due to near multicollinearity between the control variable λ and the explanatory variables in the outcome equation. Since we use exclusion restrictions to control the near multicollinearity, our simulation results are stable ones.

The second data generating process contains the state-dependency (the lagged dependent variable) in the selection equation. The selection model with state-dependency is given as

$$d_{it} = \mathbb{1}\{x_{1,it}\delta_1 + d_{i,t-1}\delta_2 + \alpha_{1,i} + \gamma_{1,t} + u_{1,it} \geq 0\} \qquad (3.11)$$

$$y_{it}^* = x_{1,it}\beta_1 + \alpha_{2,i} + \gamma_{2,t} + u_{2,it}, \qquad (3.12)$$

The outcome equation is given as follows, under the same observational rule,

$$y_{it} = x_{1,it}\beta_1 + \zeta \cdot \lambda(x_{1,it}\delta_1 + d_{i,t-1}\delta_2 + \alpha_{1,i} + \gamma_{1,t}) + \alpha_{2,i} + \gamma_{2,t} + v_{2,it}. \qquad (3.13)$$

The selection process at the time $t = 0$ is given by

$$d_{i0} = \mathbb{1}\{x_{1,i0}\delta_1 + \alpha_{1,i} + \gamma_{1,0} + u_{1,i0} \geq 0\},\ x_{j,i0} \sim N(0,1)\gamma_{1,0} \sim N(0,1/16),\ u_{1,i0} \sim N(0,1).$$

The sample size and replication number is the same as the first experiment.

Table 3.2 shows the summary of the second experiment. We focus on δ_2 and ζ. For δ_2, the estimation bias depends on the size of T. There remains negligible bias when the size of T is larger than 50. For ζ, the estimation bias depends on the ratio of the size of T to N. While there remains bias in the case of $N = 100$ and $T = 50$, the bias is negligible in the case of $N = T = 56$.

3.5 Conclusions

This study discusses a bias correction method for the two-step estimation of the panel data sample selection model with two–way fixed effects. We propose a general bias correction formula for two-step estimation models and investigate finite sample properties of the bias corrected estimator for the sample selection model. The bias corrected estimators dominate the naive estimators in terms of both bias and efficiency, although the degree of the correction largely depends on the estimated model and the sample size, especially for the case of the model with state-dependency.

The empirical topics, for example, the bias correction methods for treatment effect parameters (e.g., Heckman et al. (2003)), the robust standard error estimation (e.g. Cameron and Miller (2015)) are left as future topics. The investigation of the bias properties of semiparametric models using panel data (e.g., Li and Racine (2006)) is also required owing to their empirical importance.

Table 3.1: Simulation Result: Sample Selection Model with Static Selection Equation

		Selection eq.(3.8)		Outcome eq.(3.10)		Selection eq.(3.8)		Outcome eq.(3.10)	
Parameters		δ_1	δ_1	β	ζ	δ_1	δ_1	β	ζ
True Value		1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Sample Size		(N,T)=(56,14)				(N,T)=(100,20)			
corrected	mean	1.008	1.006	0.988	0.939	1.004	1.005	0.989	0.927
(naive)	(mean)	(1.158)	(1.159)	(0.949)	(0.857)	(1.111)	(1.113)	(0.970)	(0.901)
	std.dev.	0.107	0.105	0.113	0.236	0.065	0.064	0.058	0.131
	(std.dev.)	(0.130)	(0.128)	(0.104)	(0.203)	(0.075)	(0.074)	(0.056)	(0.121)
	RMSE	0.107	0.105	0.114	0.243	0.065	0.064	0.059	0.150
	(RMSE)	(0.205)	(0.204)	(0.116)	(0.249)	(0.134)	(0.136)	(0.063)	(0.157)
Ratio of d=1		0.504				0.578			
Sample Size		(N,T)=(56,28)				(N,T)=(100,50)			
corrected	mean	1.005	1.001	0.998	0.987	1.003	1.003	0.997	0.986
(naive)	(mean)	(1.090)	(1.087)	(0.977)	(0.935)	(1.050)	(1.050)	(0.986)	(0.954)
	std.dev.	0.069	0.065	0.071	0.141	0.039	0.038	0.037	0.076
	(std.dev.)	(0.077)	(0.073)	(0.069)	(0.132)	(0.041)	(0.041)	(0.037)	(0.073)
	RMSE	0.069	0.065	0.071	0.142	0.039	0.038	0.038	0.077
	(RMSE)	(0.119)	(0.114)	(0.073)	(0.147)	(0.065)	(0.064)	(0.040)	(0.087)
Ratio of d=1		0.493				0.514			
Sample Size		(N,T)=(56,56)				(N,T)=(100,100)			
corrected	mean	1.000	1.001	1.000	1.004	1.000	1.002	1.000	0.999
(naive)	(mean)	(1.054)	(1.054)	(0.986)	(0.954)	(1.033)	(1.035)	(0.991)	(0.967)
	std.dev.	0.049	0.049	0.052	0.103	0.026	0.027	0.024	0.054
	(std.dev.)	(0.052)	(0.052)	(0.051)	(0.097)	(0.027)	(0.028)	(0.024)	(0.052)
	RMSE	0.049	0.049	0.052	0.103	0.026	0.027	0.024	0.054
	(RMSE)	(0.075)	(0.075)	(0.053)	(0.108)	(0.043)	(0.045)	(0.025)	(0.061)
Ratio of d=1		0.449				0.535			

Table 3.2: Simulation Result: Sample Selection Model with State-dependent Selection Equation

		Selection eq.(3.11)		Outcome eq.(3.13)		Selection eq.(3.11)		Outcome eq.(3.13)	
Parameters		δ_1	δ_1	β	ζ	δ_1	δ_1	β	ζ
True Value		1.0	0.5	1.0	1.0	1.0	0.5	1.0	1.0
Sample Size		(N,T)=(56,14)				(N,T)=(100,20)			
corrected	mean	1.029	0.423	0.953	0.887	1.020	0.439	0.976	0.915
(naive)	(mean)	(1.177)	(0.300)	(0.870)	(0.685)	(1.125)	(0.341)	(0.934)	(0.815)
	std.dev.	0.105	0.128	0.180	0.415	0.064	0.081	0.076	0.186
	(std.dev.)	(0.123)	(0.138)	(0.148)	(0.329)	(0.072)	(0.085)	(0.070)	(0.168)
	RMSE	0.109	0.149	0.186	0.430	0.067	0.101	0.080	0.205
	(RMSE)	(0.215)	(0.243)	(0.197)	(0.455)	(0.144)	(0.180)	(0.097)	(0.250)
Ratio of d=1		0.581				0.634			
Sample Size		(N,T)=(56,28)				(N,T)=(100,50)			
corrected	mean	1.010	0.471	0.989	0.977	1.006	0.485	0.994	0.981
(naive)	(mean)	(1.093)	(0.407)	(0.933)	(0.843)	(1.053)	(0.447)	(0.970)	(0.919)
	std.dev.	0.067	0.084	0.125	0.269	0.033	0.049	0.055	0.121
	(std.dev.)	(0.073)	(0.087)	(0.111)	(0.232)	(0.035)	(0.050)	(0.052)	(0.113)
	RMSE	0.067	0.089	0.125	0.270	0.034	0.052	0.055	0.123
	(RMSE)	(0.118)	(0.128)	(0.130)	(0.280)	(0.063)	(0.073)	(0.061)	(0.139)
Ratio of d=1		0.562				0.583			
Sample Size		(N,T)=(56,56)				(N,T)=(100,100)			
corrected	mean	1.003	0.486	0.997	1.001	1.002	0.493	0.997	0.997
(naive)	(mean)	(1.055)	(0.458)	(0.960)	(0.909)	(1.032)	(0.475)	(0.979)	(0.945)
	std.dev.	0.046	0.059	0.087	0.175	0.025	0.035	0.037	0.082
	(std.dev.)	(0.049)	(0.062)	(0.081)	(0.157)	(0.026)	(0.036)	(0.035)	(0.078)
	RMSE	0.046	0.061	0.087	0.175	0.025	0.036	0.037	0.082
	(RMSE)	(0.073)	(0.074)	(0.090)	(0.182)	(0.041)	(0.044)	(0.041)	(0.095)
Ratio of d=1		0.535				0.600			

Chapter 4

Measuring the Asymmetric Effects of Cultural Relations on Music Trade Using a Sample Selection Model with Additive and Interactive Fixed Effects

4.1 Introduction

Between two countries, cultural relations, whether observable such as linguistic (e.g., Melitz (2008)) or unobservable such as values (e.g., Kristjansdottir et al. (2017)), are important determinants of international trade in cultural goods. In general, the familiarity with, and approval of, one country's cultural goods by consumers in another country represent a positive relation. This relation could promote the import and the domestic consumption of the other country's cultural goods. Theoretically, cultural proximities or differences can be sources of trade friction in various respects (e.g., Melitz (2008)), provide comparative advantage through the effects on productivity (e.g., Belloc and Bowles (2017)), and create demand for cross-cultural varieties (see Helpman and Krugman (1985) for the "love of variety" model). In other words, cultural proximity could increase trading volume because of reduced trading costs regarding international business administration or publicity campaigns (i.e., special treatment of prohibited goods and no need for translation) if countries share a common language or religious background. However, there could also be a strong demand for foreign goods from culturally different countries in terms of cross–cultural perceptual experience.

The current study measures the effect of cultural relations on the trade in cultural goods, specifically recorded music. In order to introduce cultural relations as unobserved heterogeneous relations in our econometric trade model, we include multiple interactive terms of fixed effects to extract the features of unobserved relations (including cultural relations) between two countries. Through panel data analyses, the interactive effects capture the heterogeneous impacts of time effects on cross-sectional units (e.g., Gobillon and Magnac (2016); Shi and Lee (2017)). We include these interactive effects with the dyadic data between an exporter and importer (e.g., Cameron and Miller (2014); Cameron and Miller (2015)), where the interactive fixed term is a multiplicative term of fixed effects specific to an importer and exporter after controlling for traditional explanatory variables and the factors used in the empirical trade literature that successfully account for the economic statuses of two countries and the trading costs between them (for recent surveys using the gravity model, see Anderson (2011) and Head and Mayer (2014)). We interpret the estimated interactive fixed effects as quantitative cultural relations, referring to the results based on ethnomusicology (e.g., Lomax (1959)) and political science (e.g., Huntington (1996)). Based on the estimation results, we point out that the major unexplained part of the cultural goods trade in the context of traditional econometric models of trade (the gravity models) is attributable to cultural relations between countries. Further, the interactive terms in our model can reflect the effect of such relations on trade.

One feature of our framework is the asymmetry of the effect of cultural relations on trade. For example, the effect of cultural factors on the exports of country A to country B could differ from that of B to A after controlling for each country's economic condition. Asymmetry is naturally introduced because of the multiplicative nature of the interactive term. For example, the product of the fixed effect of A as an exporter and that of B as an importer could differ from the product of the fixed effect of B as an exporter and that of A as an importer; moreover, the fixed effects of an exporting country are not always the same as those of an importing country. We attempt to capture the asymmetric, unobserved heterogeneities in the cultural relations between two countries through the interactive terms of the importer– and exporter–specific fixed effects. We discuss this asymmetric structure in the next section.

Asymmetry helps to explain the difference in trading volumes between two equipollent countries in terms of asymmetric unobserved heterogeneous relations such as cultural relations. Most pairs of countries in our data set show asymmetric trade flows. For example, the exports from country A to country B are much larger (smaller) than those from B to A. Institutional differences such as tariff and copyright systems (e.g., Towse (2017)) account for some of the asymmetry. However, such differences are not always observable, at least in a unified way. We expect that the product forms of importer– and exporter–specific fixed effects can capture unobservable heterogeneities in the relations between two countries.

Although such asymmetry in trade is commonly observed (we also discuss the asymmetry of trade relations in our data set in section 4.2), most literature on the cultural effects of trade does not refer to it. For example, Tadesse and White (2010), Giuliano et al. (2014), and Takara (2017) confirm the effect of cultural factors on trade. Their methodology is to construct the proxy variable(s) of the cultural proximity or difference between two countries and regress the volume of trade on the variable(s). In this regard, Tadesse and White (2010) use the World Values Survey and the European Values Survey, Giuliano et al. (2014) employ gene data, and Takara (2017) uses country classifications based on ethnomusicology and political science. Although these noteworthy proxy variables have their own inherent values, one common limitation of the authors' analyses is that "the cultural distance" between two countries is always symmetrically measured. In other words, the marginal effect of the cultural variable on the exports from country A to country B must be the same as that from B to A while regression analysis is used. Except for a few studies (e.g., Disdier et al. (2010); Felbermayr and Toubal (2010); Shin and McKenzie (2016)), "the cultural distance" from A to B is usually treated in the same way as that from B to A. Moreover, the construction of symmetric cultural distance measures completely depends on the authors' exogenous ideas of the definition of "culture," with the results sensitive to differences in the definitions. Concerning these points, we generalize the authors' method by using a factor structure in the form of interactive fixed effects. This structure can flexibly capture the asymmetric, unobserved heterogeneous relations between trading countries; then, the results can be interpreted by referring to various factors including cultural one.

Our interactive terms can also capture two conflicting effects separately. As aforementioned, cultural proximities can have positive and negative effects on trading volume because of the reduction effects on trading costs and a demand for novel cross–cultural goods. These conflicting effects can mask the precise impacts of cultural factors on cultural goods trade and yield–biased coefficient estimates of cultural factors. Our interactive terms are multiple and multiplicative; thus, one factor could explain the positive effect and another could explain the negative effect of unobserved relations. This is one of our specification's advantages.

Our study offers several contributions. First, we develop a statistical model that incorporates additive and interactive terms of fixed effects with sample selectivity in order to consider the presence of zero trade paths. Second, we interpret estimated factors in terms of cultural relations and measure asymmetric cultural relations between countries empirically. Finally, we visualize a novel world map of cultural relations based on the estimated interactive terms. Our estimation result for traditional economic determinants is consistent with international trade theories and empirical evidence from prior research (e.g., Helpman et al. (2008)). Thus, we conclude that our interaction terms capture asymmetric cultural relations between countries successfully.

4.2 Asymmetry in Cultural Goods Trade Data

In their research, Helpman et al. (2008) derive a slightly modified gravity model, with importer– and exporter–specific factors as additive two–way fixed effects. The model consists of two equations. The first determines whether the j–th country exports to the i–th (the selection equation); the second determines the trading volume (the outcome equation). The model is a generalized version of a sample selection model (Heckman (1979)). Positive trade flow is selective because of the fixed costs of serving a specific market; moreover, low productivity is insufficient to serve a specific destination. The sources of selectivity induce linear and nonlinear selection correction terms into the outcome equation. Since the derivation of the correction terms heavily depends on the underlying assumptions, the validity of the inferences cannot be extended to cases with non-i.i.d. (independent and identically distributed) unobservable factors.

It is certain that heteroskedasticity in error terms can be partially alleviated by adding two-way fixed effects. However, the misspecifications of the unobserved terms' properties stem from the misspecified relations between the importer and the exporter; thus, the additive fixed effects have only limited mitigation effects on the misspecifications. Several remarks about the foregoing inference procedure are also noted by Santos Silva and Tenreyro (2015). With regard to the cultural goods trade, such misspecifications of unobserved terms are more serious because striking asymmetries in trading flows are found in our data set. These asymmetries cannot be explained by only the economic or related scales of trading countries or additive fixed effects. In the following, we first present the summary of our data set and then reveal the features of trading flows in cultural goods in order to discuss the possibility of misspecifications.

We employ the amount of exported compact discs (HS8524.32: discs for laser reading systems for reproducing sound only) as representative of cultural goods[1]. Our data cover 187 countries from 2000 to 2006 and use averages by year. Table 4.1 lists the countries in our sample. The sample size of our data is 34,782 and 6,238 country pairs that trade cultural goods. The explanatory variables are the *distance between two countries*, *a border sharing dummy*, *a linguistic proximity dummy*, *a past colonial relation dummy*, and *religious proximity*. These variables are from the data set of Takara (2017). The precise definitions of each explanatory variable are in Table 4.2. Each variable, x_{ij}, can be arranged as if it is N$\times$N panel data. In this case, the row index i represents the origin country and the column index j represents the destination country. However, unlike ordinary panel data settings, the diagonal elements (the exports of country j to country j) in our data are always omitted because these values do not exist by definition. Thus, we pay attention to the omitted elements when we estimate the parameters. The summary statistics of all observations and in–trade observations are shown in Table 4.3.

One important feature of our cultural goods trade data is the asymmetric trading flows between a pair of countries. In this regard, a large difference between the exports of country i to country j and those of j to i is often found. The gravity model of trade claims that the cause of such asymmetry is the difference between the economic conditions of two countries. We confirm the degree of trade asymmetry and the corresponding difference of gross domestic product per capita (GDPPC) between trading pairs. There are two types of asymmetric trade: (a) one country exports to another but the latter does not export to the former and (b) two countries export to each other but the volume is asymmetric. Approximately 36% of in-trade pairs correspond to (a). The average value of trade asymmetry, $y_{ij} - y_{ji}$, is approximately 1,800; moreover, pairs of economically large countries are not seen in the case of (a). With regard to (b), we prepare

[1] The data is from the United Nations Commodity Trade Statistics Database (http://comtrade.un.org/).

lists of highly asymmetric and symmetric pairs in Table 4.4 and Table 4.5 respectively. The column "Asymmetry" represents the value of $y_{ij} - y_{ji}$ and "Asymratio" represents y_{ij}/y_{ji}. We fix larger values to y_{ji}. The columns "GDPPC1" and "GDPPC2" represent the average values of GDPPC from 2000 to 2006[2] in countries 1 and 2 respectively. The "GDPPC_Ratio" is the value of GDPPC1/GDPPC2.

We arrange the absolute values of "Asymmetry" in decreasing order and place the top 30 pairs in Table 4.4. With the exception of China, the Czech Republic, and Poland, Table 4.4 lists countries that have large GDPPC values. It is expected that the values of "Asymmetry" become greater when both countries have larger GDPPC values. We also check the values of "Asymratio" to avoid the effect of trade volume size on "Asymmetry." With regard to "Asymratio," more than half of the pairs show five to ten times trade asymmetry. However, the values of "GDPPC_Ratio" are not too asymmetric compared with the values of "Asymratio." In particular, the UK–Netherlands and France–Germany pairs have remarkable trade asymmetry, although they have almost the same GDPPC values. Symmetric pairs (where the value of "Asymratio" is close to 1) are listed in Table 4.5. With regard to "GDPPC_Ratio" in Table 4.5, no trend is evident. Moreover, the pairs in Table 4.5 are highly asymmetric in "GDPPC_Ratio," although their trade volumes are symmetric. In the usual gravity model setting, the asymmetry of trade is explained by the difference in the economic conditions between two countries. This difference can be captured by additive fixed-effect terms. However, as can be seen in Tables 4.4 and 4.5, we confirm that economically equipollent countries do not necessarily export the same amount of cultural goods. This finding implies that additive fixed effects may not fully capture unobserved heterogeneity.

In addition to additive fixed effects, the empirical trade literature uses a variant of the grav-

[2] Source: International Monetary Fund (*http://www.imf.org/external/index.htm*)

ity model to successfully explain trade flows with observed explanatory variables for relevant countries. These variables include *linguistic relation*, *religious proximity*, *past colonial relation*, and *geographical relation* (e.g., Anderson (2011); Head and Mayer (2014)). However, many possible misspecifications remain in the outcome and selection equations when there is trade asymmetry. Indeed, it is pointed out here that the use of symmetric variables in many empirical studies of trade causes misspecifications (Shenkar (2001); Tung and Verbeke (2010); Fiorini et al. (2018)). Nevertheless, most variables that are generally used are perfectly symmetric (e.g., *the distance between two countries*). Some studies use asymmetric relational variables. Disdier et al. (2010) employ the volume of cultural goods traded as an index of cultural proximity that acts as an asymmetric relational variable. The traded volume of cultural goods can be a good measure of cultural proximity between two countries; however, this measure cannot be applied to the trade in cultural goods. Other asymmetric measurements of cultural proximity between two countries that studies use are Eurovision Song Contest scores[3] (Felbermayr and Toubal (2010)), differences in box office revenues, and tourist arrival statistics (Shin and McKenzie (2016)). Although these variables apply to the cultural goods trade, they can cover only some countries worldwide. Li et al. (2017) construct an asymmetric cultural attractiveness index using survey data. However, this index also covers only a few countries.

In the current study, we introduce an estimation model of trading flows between a pair of countries that incorporates the asymmetric effects of unobserved relations. The model consists of generalized empirical gravity equations of bilateral trade and applies to a situation with frequent zero trade flows. Our estimated model of trading flows from an exporting country j to an

[3] Budzinski and Pannicke (2017) shows new evidences on culturally biased voting behavior in the Eurovision Song Contest Contest, where biases are closely related to geographical closeness, political relations, ethical and linguistic affinity.

importing country i is as follows:

$$
\begin{aligned}
d_{ij}^* &= \underbrace{\mathbf{z}_{ij}'\delta}_{\text{observed heterogeneity}} + \underbrace{\alpha_{d,i} + \gamma_{d,j} + \mathscr{A}_{d,i}'\mathscr{G}_{d,j}}_{\text{unobserved heterogeneity}} + v_{ij} && (4.1)\\
y_{ij}^* &= \underbrace{\mathbf{x}_{ij}'\beta}_{\text{observed heterogeneity}} + \underbrace{\alpha_{y,i} + \gamma_{y,j} + \mathscr{A}_{y,i}'\mathscr{G}_{y,j}}_{\text{unobserved heterogeneity}} + u_{ij} && (4.2)\\
y_{ij} &= y^* \quad \text{if } d_{ij} \equiv \mathbb{1}\{d_{ij}^* \geq 0\} = 1. && (4.3)
\end{aligned}
$$

The first equation takes into account the extensive margin (the decision of country j to export j to country i); the second takes into account the intensive margin (the export volume from country j to country i given the export decision). The standard sample selection model is extended to one with additive and interactive fixed effects, where $\mathbf{x}_{ij}$ and $\mathbf{z}_{ij}$ are $K_y \times 1$ and $K_d \times 1$ vectors of observable explanatory variables respectively, and β and δ are their coefficient vectors. $\alpha_{y,i}$ and $\alpha_{d,i}$ ($\gamma_{y,j}$ and $\gamma_{d,j}$) are additive fixed effects of the importer i (the exporter j) in the outcome equation (the volume-of-export equation, (4.2)) and the selection equation (the decision-of-export equation, (4.1)). Further, $\mathscr{A}_{y,i}$ and $\mathscr{G}_{y,j}$ ($\mathscr{A}_{d,i}$ and $\mathscr{G}_{d,j}$) are $R \times 1$ vectors that are included in the outcome (the selection) equation in their multiplicative forms:

$$
\underbrace{\mathscr{A}_{y,i}'\mathscr{G}_{y,j}}_{(1\times R)(R\times 1)} = \sum_{r=1}^{R} \underbrace{\mathscr{A}_{y,i,r} \times \mathscr{G}_{y,j,r}}_{1\times 1}
$$

where $\mathscr{A}_{y,i,r}$ ($\mathscr{G}_{y,j,r}$) is the r-th unobserved factor of the importer (the exporter) in the outcome equation. We temporarily assume that the number of included factors, R, is known to us; however, the estimation from our data set is discussed in Section 4.4. Lastly, equation (4.3) is the observational rule of the volume of export if the countries are engaged in exporting.

The most distinctive feature of our model is the inclusion of the interactive fixed effects in addition to the usual additive fixed effects. The additive fixed effects incorporate country–specific heterogeneities such as economic and demographic characteristics (an explanation based on a theoretical model is in Helpman et al. (2008), in particular equation (9)), whereas the interactive fixed effects are multiples of importer– and exporter–specific heterogeneity between two countries. Aside from the effects of the observed relations ($\mathbf{x}_{ij}$ or $\mathbf{z}_{ij}$) between the importer and the exporter and their unobserved but country–specific additive terms (α_i or γ_j), the interactive terms ($\mathscr{A}_i' \times \mathscr{G}_j$) capture the effects of unobserved interactions between them on the dependent variable, which in our empirical context is an important determinant. An example of an important but unobserved interaction in cultural goods trade is cultural relations, which is this study's main focus.

There are several advantages to using interactive fixed–effect terms. First, the interactive term is generically asymmetric because the product, $\mathscr{A}_{y,i,r} \times \mathscr{G}_{y,j,r}$, usually differs from $\mathscr{A}_{y,j,r} \times \mathscr{G}_{y,i,r}$: The fixed effect of country i as an importer, $\mathscr{A}_{y,i,r}$, is not restricted to be the same as the fixed effect of the country as an exporter, $\mathscr{G}_{y,i,r}$. Second, the degree of asymmetry (the difference between $\mathscr{A}_{y,i,r} \times \mathscr{G}_{y,j,r}$ and $\mathscr{A}_{y,j,r} \times \mathscr{G}_{y,i,r}$) can be adaptively estimated from data. Thus, asymmetry helps to explain asymmetric trade flows, even between two equipollent countries. Third, if omitted heterogeneous relations in the outcome and selection equations are driven by a small number of dominant factors, as in traditional factor analyses, the estimated number of included interactive terms also remains relatively small, which makes the interpretation of results easier.

In addition, we can estimate the effects of standard explanatory variables more precisely because the effects of unobserved relations are controlled by the interactive terms. Certainly, the multiplicative form is a restrictive one for fully capturing double–indexed omitted factors. However, this specification enables us to make simplified inferences about the system; moreover, the use of multiple terms gathers omitted heterogeneous relations in the model. We especially focus on the interpretation of interactive terms with regard to music traditions and trend. Further, in Section 4.4 we investigate the connections between the estimated interactive terms and the cultural relation variables used in the previous literature.

4.3 Estimation Procedure

To implement the inference of the system (4.1), (4.2), and (4.3), we also assume that the joint distribution of the error terms is the bivariate normal[4]:

$$\begin{pmatrix} u_{ij} \\ v_{ij} \end{pmatrix} \sim N(\mathbf{0},\Sigma),\ \ \Sigma = \begin{pmatrix} \sigma^2 & \rho\cdot\sigma \\ \rho\cdot\sigma & 1 \end{pmatrix}. \tag{4.4}$$

Denote the structural parameters (the coefficient vectors in (4.1) and (4.2), the variance and the correlation coefficient parameter) as $\theta' = (\beta', \delta', \sigma, \rho)$ and the incidental parameters (the additive and the interactive fixed effect parameters) as,

$$\underbrace{\pi'_{ij}}_{1\times 2(2+2r)} = (\underbrace{a'_i}_{1\times(2+2r)}, \underbrace{g'_j}_{1\times(2+2r)}),\ i = 1,2,\ldots,N,\ j = 1,2,\ldots,N, j \neq i. \tag{4.5}$$

where

$$\begin{aligned} a_i &= (a_{y,i}, a_{d,i}) = (\underbrace{\alpha_{y,i}, \mathscr{A}'_{y,i}}_{1+r}, \underbrace{\alpha_{d,i}, \mathscr{A}'_{d,i}}_{1+r}) \\ g_j &= (g_{y,j}, g_{d,j}) = (\underbrace{\gamma_{y,j}, \mathscr{G}'_{y,j}}_{1+r}, \underbrace{\gamma_{d,j}, \mathscr{G}'_{d,j}}_{1+r}). \end{aligned}$$

[4] The normality assumption can be extended to the distribution with fat-tails and/or with skewness (e.g., Chen et al. (2014)) at the cost of computational simplicity.

To achieve the identification, we employ the same restrictions as Bai (2009):

$$\sum_{i=1}^{N}\alpha_{y,i}=\sum_{i=1}^{N}\alpha_{d,i}=\sum_{j=1}^{N}\gamma_{y,j}=\sum_{j=1}^{N}\gamma_{d,j}=0,\ \sum_{i=1}^{N}\mathscr{A}_{y,i}=\sum_{i=1}^{N}\mathscr{A}_{d,i}=\sum_{j=1}^{N}\mathscr{G}_{y,j}=\sum_{j=1}^{N}\mathscr{G}_{d,j}=\underbrace{0}_{R\times 1},$$

$$\mathscr{A}_y'\mathscr{A}_y=\mathscr{A}_d'\mathscr{A}_d=I_R,\ \mathscr{G}_y'\mathscr{G}_y=\Lambda_y,\ \mathscr{G}_d'\mathscr{G}_d=\Lambda_d,$$

where I_R is the $R\times R$ identity matrix, and Λ_y and Λ_d are $R\times R$ diagonal matrices.

We employ an expectation-maximization (EM) algorithm (e.g., Dempster et al. (1977)) to obtain the maximum likelihood estimate of the unknown parameters in (4.1), (4.2), (4.3) and (4.5). The procedure consists of the two-step procedure: the expectation-step (the conditional expectation of the complete likelihood function given the observations) and the maximization-step (the maximization of the expected likelihood with respect to unknown parameters). The actual procedure to obtain the MLE by the EM algorithm is given as follows[5]:

E-step: Given initial values of the parameters $\{\beta^{(s)},\, a_y^{(s)}, g_y^{(s)}\}$, $\{\delta^{(s)},\, a_d^{(s)}, g_d^{(s)}\}$, $\rho^{(s)},\sigma^{(s)}$, define the conditional means and variances of the latent dependent variables, y^*_{ij} and d^*_{ij},

$\mathbb{E}_{y^*_{ij}|d=0}[y^*_{ij}]$, $\mathbb{E}_{d^*_{ij}|y_{ij},d_{ij}=1}[d^*_{ij}]$, $\mathbb{E}_{d^*_{ij}|d_{ij}=0}[d^*_{ij}]$, $\mathbb{V}_{y^*_{ij}|d_{ij}=0}[y^*_{ij}]$, $\mathbb{V}_{d^*_{ij}|y_{ij},d_{ij}=1}[d^*_{ij}]$, and $\mathbb{V}_{d^*_{ij}|d_{ij}=0}[d^*_{ij}]$

and define

$$\begin{aligned}\tilde{y}_{ij} &= d_{ij}\cdot y_{ij}+(1-d_{ij})\cdot\mathbb{E}_{y^*_{ij}|d_{ij}=0}[y^*_{ij}]\\ \tilde{d}_{ij} &= d_{ij}\cdot\mathbb{E}_{d^*_{ij}|y_{ij},d_{ij}=1}[d^*_{ij}]+(1-d_{ij})\cdot\mathbb{E}_{d^*_{ij}|d_{ij}=0}[d^*_{ij}]\end{aligned}$$

M-step: This step utilizes three conditional maximization sub-steps (e.g., Meng and Rubin (1993);

[5] Ruud (1991) proposes another estimation scheme via EM algorithm for the standard sample selection model. The proposed estimation procedure here is an extension of the ECM algorithm proposed by Chen (2016) for the probit model with interactive fixed effect terms.

McLachlan and Krishnan (2008)):

1. Given $\{\beta^{(s)}, a_y^{(s)}, g_y^{(s)}\}, \{\delta^{(s)}, a_d^{(s)}, g_d^{(s)}\}, \rho^{(s)}, \sigma^{(s)}$, define

$$\hat{\tilde{y}}_{ij}^{(s)} \equiv \tilde{y}_{ij}^{(s)} - \rho^{(s)}\sigma^{(s)}(\tilde{d}_{ij}^{(s)} - \mathbf{z}_{ij}'\delta^{(s)} - \alpha_{d,i}^{(s)} - \gamma_{d,j}^{(s)} - \mathscr{A}_{d,i}^{(s)}(\mathscr{G}_{d,j}^{(s)})').$$

   Then update $\{\beta, a_y, g_y\}$ by the minimizer of the following criterion function:

$$(\beta^{(s+1)}, a_y^{(s+1)}, g_y^{(s+1)}) = \arg\min_{\beta, a_y, g_y} \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\hat{\tilde{y}}_{ij}^{(s)} - \mathbf{x}_{ij}'\beta - \alpha_{y,i} - \gamma_{y,j} - \mathscr{A}_{y,i}\mathscr{G}_{y,j}'\right)^2.$$

2. Given $\{\beta^{(s+1)}, a_y^{(s+1)}, g_y^{(s+1)}\}$, $\{\delta^{(s)}, a_d^{(s)}, g_d^{(s)}\}$, $\rho^{(s)}, \sigma^{(s)}$, define

$$\hat{\tilde{d}}_{ij}^{(s)} \equiv \tilde{d}_{ij}^{(s)} - \frac{\rho^{(s)}}{\sigma^{(s)}}(\tilde{y}_{ij}^{(s)} - \mathbf{x}_{ij}'\beta^{(s+1)} - \alpha_{y,i}^{(s)} - \gamma_{y,j}^{(s)} - \mathscr{A}_{y,i}^{(s)}(\mathscr{G}_{y,j}^{(s)})').$$

   Then update $\{\delta^{(s)}, a_d^{(s)}, g_d^{(s)}\}$ by the minimizer of the following criterion function:

$$(\delta^{(s+1)}, a_d^{(s+1)}, g_d^{(s+1)}) = \arg\min_{\delta, a_d, g_d} \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\hat{\tilde{d}}_{ij}^{(s)} - \mathbf{z}_{ij}'\delta - \alpha_{d,i} - \gamma_{d,j} - \mathscr{A}_{d,i}\mathscr{G}_{d,j}'\right)^2.$$

3. Given $\{\beta^{(s+1)}, a_y^{(s+1)}, g_y^{(s+1)}\}, \{\delta^{(s+1)}, a_d^{(s+1)}, g_d^{(s+1)}\}, \rho^{(s)}, \sigma^{(s)}$, update ρ and σ by

$$\sigma^{(s+1)} = \left(T_{yy}^{(s)} + \frac{(T_{yd}^{(s)})^2}{T_{dd}^{(s)}} \cdot (1 - T_{dd}^{(s)})\right)^{1/2}, \quad \rho^{(s+1)} = \frac{1}{\sigma^{(s+1)}} \cdot \frac{T_{yd}^{(s)}}{T_{dd}^{(s)}}$$

where ($\pi_{y,it} \equiv \alpha_{y,i} - \gamma_{y,t} - \mathscr{A}_{y,i}\mathscr{G}'_{y,t}$, $\pi_{d,it} \equiv \alpha_{d,i} - \gamma_{d,t} - \mathscr{A}_{d,i}\mathscr{G}'_{d,t}$), and

$$
\begin{aligned}
T_{yy}^{(s)} &= \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \left\{ (\tilde{y}_{ij}^{(s)} - \mathbf{x}'_{ij}\beta^{(s+1)} - \pi_{y,ij}^{(s+1)})^2 + (1-d_{ij}) \cdot \mathbb{V}_{y^*|d=0}^{(s)}[y_{ij}^*] \right\} \\
T_{yd}^{(s)} &= \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \left\{ (\tilde{y}_{ij}^{(s)} - \mathbf{x}'_{ij}\beta^{(s+1)} - \pi_{y,ij}^{(s+1)})(\tilde{d}_{ij}^{(s)} - \mathbf{z}'_{ij}\delta^{(s+1)} - \pi_{d,ij}^{(s+1)}) \right. \\
&\qquad \left. + (1-d_{ij}) \cdot \rho^{(s)}\sigma^{(s)} \cdot \mathbb{V}_{d^*|d=0}^{(s)}[d_{ij}^*] \right\} \\
T_{dd}^{(s)} &= \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \left\{ (\tilde{d}_{ij}^{(s)} - \mathbf{z}'_{ij}\delta^{(s+1)} - \pi_{d,ij}^{(s+1)})^2 \right. \\
&\qquad \left. + d_{ij} \cdot \mathbb{V}_{d^*|y,d=1}^{(s)}[d_{ij}^*] + (1-d_{ij}) \cdot \mathbb{V}_{d^*|d=0}^{(s)}[d_{ij}^*] \right\}
\end{aligned}
$$

The procedure proposed here is easy to implement: the minimization problems in the first two conditional maximization sub-steps can be solved by the same way as Bai (2009), the third sub-step has closed-form solutions.

The asymptotic distribution of the maximum likelihood estimator has a non-zero mean vector since we are facing at the situation where the sample sizes of exporting countries and importing countries simultaneously go to infinity at the same rate. The asymptotic properties of the biased-corrected estimator can be derived along the same lines as Hahn and Kuersteiner (2002), Arellano and Hahn (2007) and Fernández-Val and Weidner (2017): the bias corrected estimator is defined as:

$$\tilde{\theta} = \hat{\theta} - \mathbf{b}_N - \mathbf{d}_N$$

where $\hat{\theta}$ is the maximum likelihood estimator, and $\mathbf{b}_N$ and $\mathbf{d}_N$ are bias correction terms defined in (4.8) and (4.9) in the appendix of this chapter. The asymptotic distribution of the estimator is given as follows,

$$\sqrt{N^2}\left(\tilde{\theta} - \theta_0\right) \xrightarrow{d} N(\mathbf{0},\ \mathscr{W}_{NN}^{-1}\Psi_{NN}\mathscr{W}_{NN}^{-1})$$

where details of the asymptotic variance are also discussed in the appendix of this chapter.

4.4 Estimation Results

In this section, we discuss the estimation results of the number of included factors, the structural parameters, and the additive and interactive fixed effect parameters. We confirm the implications of the estimates, referring to Helpman et al. (2008) and Takara (2017). The differences between our implications and the implications of these two studies are caused by the models' specifications. The models of Helpman et al. (2008) and Takara (2017) adopt the control function approach, which account for the selective exporting behavior based on the exporters' productivity of music CDs that are in high demand. They include only the importer– the exporter–specific additive fixed effects in order to mitigate the effects of unobserved heterogeneities. However, we control for the selectivity from zero trade flows in accordance with the standard sample selection model (Heckman (1979)) and introduce the importer– and exporter–specific additive and interactive fixed effects to alleviate unobserved heterogeneous relations between countries.

First, we discuss the estimation of the number of the factors, R, included in the model. There are several model selection criteria, such as information criteria (e.g., Bai and Ng (2002), Choi and Jeong (2018)), the eigenvalue based test (e.g., Ahn and Horenstein (2013)) for the standard factor model of large dimensions (e.g., Bai and Wang (2016)). However, these methods are only applicable to pure factor structures without regressors and without selectivity (e.g., Lu and Su (2016)). Thus, we use a traditional model selection procedure in factor analyses: the contribution ratio. We calculate the eigenvalues of cross-product matrices of residuals to account for the presence of regressors in the first and second steps of conditional maximization. In this regard, the eigenvalues are obtained as by–products of estimating interactive fixed effect parameters because the eigenvectors are used for the estimates of factors (Bai (2009)). The contribution ratio of a factor is defined as the ratio of the corresponding eigenvalue to the sum of all eigenvalues. We select the minimum number of factors so that the cumulative contribution ratio is stabilized.

Table 4.6 shows the contribution ratios in the outcome equation. The results of the selection equation is similar; thus they are omitted. A candidate for the estimated number of included factors is four ($R = 4$). When the included number is less than four, the cumulative contribution ratios up to R rapidly increase. However, more than four factors gradually add to the cumulative ratio of approximately 95%. In other words, the additional contribution of the fifth and subsequent factors is approximately 5%. We select the first four factors as the major part of the contributed factors.

4.4.1 Interpretation of Additive Fixed Effect Parameters

Base on their theoretical setting, Helpman et al. (2008) derive the empirical gravity model with exporter– and importer–specific additive fixed effects, into which the economic status of each country, in terms of GDP, population, price level and other (possibly unobserved) country–specific trade frictions, are merged. These factors are assumed to be country–specific and independent of trading partners. Figure 4.1 and Figure 4.2 is the choropleth maps, where countries are colored based on the additive fixed effect estimates from the outcome and the selection equation. $\alpha_{y,i}$ ($\alpha_{d,i}$) is the fixed effect parameter of the i-th as an importer in the outcome equation (the selection equation) and $\gamma_{y,j}$ ($\gamma_{d,j}$) is the fixed effect parameter of the j-th as an exporter in the outcome equation (the selection equation). Warm (cold) colors indicate positive (negative) values of estimates. The transition to soft, white colors implies that the value is approaching to zero.

Glancing at the maps, the additive fixed estimates look proportional to their economic scales.

This tendency is shared to both estimates of exporter- and importer-specific fixed effect parameters in both equations, the outcome and the selection. These findings are consistent with the theoretical implications about additive fixed effect parameters obtained in Helpman et al. (2008). Some country-specific, partner-independent factors such as economic scales are important determinants but non–identitifiable determinants of trade in gravity models when we only use the dyadic, cross-sectional dataset. It is true that the additive fixed effects can control for them, but there remain other factors that are not accounted for by the explanatory variables and the additive fixed effects in the gravity equation. Then, those factors could be interpreted as unobserved, heterogeneous institutional relations or cultural relations between the importing and the exporting country.

4.4.2 Interpretation of Interactive Fixed Effect Parameters

In our estimation model, we incorporate not only additive fixed effect terms to control for unobserved heterogeneities specific to each country; we also include interactive fixed effect terms to control for unobserved heterogeneous relations between trading countries. In this subsection, we discuss interpretations of the estimation results of the interactive fixed effect parameters, with reference to the relation based on music culture. Our major conclusions are as follows. The first factor of four interactive fixed effect terms can be interpreted as the one that captures the effect of raising the consumption of cultural goods in terms of cultural proximity (this is closely related to the home consumption bias in Ferreira and Waldfogel (2013)). The second factor that embodies the preference to engage with the cross-cultural experience introduced by cultural goods from culturally distant countries.

At this point, it should be recalled that the interactive fixed effect terms take the form of the product of an exporter– and importer–specific fixed effect; thus the effect of the j-th (origin) country's exporter fixed effect parameter, $\mathscr{G}_{y,j}$ or $\mathscr{G}_{d,j}$, on the trade volume or trade probability is not determined without taking into consideration of the i-th (destination) country's importer fixed effect parameter, $\mathscr{A}_{y,i}$ or $\mathscr{A}_{d,i}$. Both the sign and the degree of the parameter is important

First, we analyze the relationship between the estimated interactive fixed effect terms and the cultural proximity indices used in Takara (2017): these indices based on the ethnomusicological classification by Lomax (1959) and the political scientific classification by Huntington (1996). The former reflects the affinity of traditional musical backgrounds between two countries (approximately corresponding to the similarity in the musical structure of traditional musics: *the music tradition* variable) and the latter reflects some of shared societal values between two countries (approximately corresponding to the similarity in the music trends: *the music trend* variable).

We regress each binary variable index on the estimated four interactive terms ($R = 4$) using the probit link function. The regression result using the interactive terms from the selection (outcome) equation is presented in Table 4.7 (Table 4.8). In the regression analysis, we also add two-way additive fixed effects in the right-hand side to control for unobserved heterogeneities and check the results' robustness.

The interactive terms from the selection equation show positive signs in all significant cases except one in Table4.7. The exception is the coefficient of the second factor in the regression of the *music trend* variable. Most of the interactive terms is positively correlated with the *music tradition* variable and the *music trend* variable. Thus, the positive correlations imply that the interactive terms can be regarded as proxies of the cultural proximity; moreover, cultural proximity, as reflected in the terms, affects positively on the probability with a trade relationship (the trade probability).

The coefficients of all interactive terms from the outcome equation show negative signs in the regression of the *music tradition* variable in Table4.8, whereas the coefficient of the first (the third and fourth) term shows a positive (negative) sign in the regression of the *music trend* variable in Table4.8. These results indicate that the estimated interactive terms can be interpreted as the effects of music culture on the trading volume of cultural goods. In the following, we explain the detailed implications of each factor in the interactive terms on the music trade, especially focusing on the first and the second factor: the first one is consistent with the literature on the home consumption bias (e.g., Ferreira and Waldfogel (2013)). The second is new evidence about capturing the demand for cross-cultural goods. This evidence can be found by our novel specification of the model with interactive fixed effects.

With regard to the first factor of the interactive terms $\mathscr{A}_{1y,i} \times \mathscr{G}_{1y,j}$, this is positively correlated with the *music trend* variable based on Huntington (1996) but negatively correlated with the *music tradition* variable based on Lomax (1959). A feature of this factor is that consumers are sensitive to music trends but value music traditions to lesser extent. Thus, consumers tend to import music products from countries with cultural proximity in terms of music trends but spend less money on international music goods with cultural proximity in terms of music traditions. As many authors such as Holloway (2014) and Takara (2017) discover, the positive effect of cultural proximity on trade in cultural goods is consistent with our finding about the positive effect of music trend proximity. The reduction in export if both are similar only in music tradition is also consistent with the discussion of home consumption bias in Ferreira and Waldfogel (2013): if other countries' music is similar to its own in terms of music tradition, domestic consumers choose music goods produced in their own country and buy fewer imported music goods from countries with similar music tradition.

Further supportive evidence on this point is provided by the choropleth map (see Figure 4.3) of the fixed effects that are specific to exporter ($\mathscr{G}_{1y,j}$) and importer ($\mathscr{A}_{1y,i}$). In this regard, higher values of the fixed effects tend to be found in countries with matured, large-scale music markets[6]. In other words, consumers in a country with a matured music market can select their domestic music products from an abundant choice within the country to satisfy their preference for traditional music; however, music products that have similar music trend could internationally traded especially between countries with large-scale music markets.

With regard to the second factor of the interactive terms, this is negatively correlated with the *music tradition* variable; however, it is insignificantly correlated with the *music trend* variable. A direct interpretation of this result is that it represents the demand for cross-cultural goods in terms of music tradition. One of the driving forces of engagement with cross-cultural experiences through foreign music is embodied in this factor. Most studies that regress the proxy variable of *cultural proximity* on the trading volume in order to confirm the effect of cultural factor cannot separately identify both the effect of cultural goods as an aspect of cultural proximity and the effect of such goods as an aspect of cross-cultural value in international trade. Our interactive fixed effect terms could overcome the identification problem of the conflicting effects of cultural factor. As an important by-product, other estimates of observed explanatory variables are also estimated more precisely. Such estimates are consistent with the interpretation of those variables as trade frictions (see subsection 4.4.3).

In addition, this second factor shows interesting asymmetries as the product form of estimates. Figure 4.4 provides an explanation of asymmetric trading flows between European countries and a part of Asian countries based on the cross-cultural demand interpretation. In the figure, the second factor in the exporter-specific ($\mathscr{G}_{2y,j}$) and the importer-specific ($\mathscr{A}_{2y,i}$) fixed effects are depicted as a choropleth map. The fixed effects of European countries as importers are positive, and those of a part of Asian countries as exporters are also positive overall. Exports

[6] Recording Industry Association of Japan (2006) reports the market size of music CDs in each country.

from Asian to European countries is positively boosted up by the multiplicative effect of the fixed effects. This finding could be interpreted as a sort of “Orientalism.”

However, the reverse trading flow requires another explanation. The fixed effects of European countries as exporters are negative, while those of Asian countries as exporters are positive overall. The negativity of European fixed effects as exporters may be partly because of the prevailing piracy of physical CDs worldwide during the sample period. The interactive effects regarding the direction of trade suppress the volume of the trade. This suppression is partly due to the relatively small market share of traditional European music CDs (not performing arts), such as classical music, compared with that of popular music CDs. However it may also be partly due to the piracy of physical music CDs among some Asian countries. In sum, though, the asymmetric effects by the two fixed effect parameters produce or accelerate the asymmetric trading flows.

The explanatory powers of the third and the fourth factor is not as great as those of the first two factors; however, they capture other aspects of asymmetric trading flows. In Figure 4.5 and Figure 4.6, a bit fragmented values of estimated fixed effects are depicted in colopleth maps. The detailed interpretation of these maps requires more information on local music markets and bilateral relationships worldwide. Such an interpretation is left for future studies.

4.4.3 Parameter Estimates

Next, we discuss parameter estimates of the sample selection model. The results are presented in Tables 4.9 and 4.10. In gravity models, the total trade between two countries becomes more active in a way that is proportional to the product of the trading countries’ economic scales. However, trading costs such as transportation costs, business administration costs, and other frictions may reduce opportunities for international trade and the consequent volumes that are traded. The observed explanatory variables included in our estimation, *sharing a common language* (Language), *distance between two countries* (Distance), *border sharing* (Border), *past colonial relation* (Colony), and *religious proximity* (Religion), possess the meanings of proxy variables of trade frictions (trading costs) and cultural affinity between the exporter and the importer.

The sign of the coefficient estimate of *Distance* is expected to be negative when it is regarded as a proxy variable of transportation costs. The sign is actually negative in both Table 4.9, and 4.10: Countries that are more distant are less involved in a trade relationship and export less. Compared with those in Takara (2017) (-0.698 in the selection equation, -1.167 in the outcome equation) the estimated parameters in the current study are larger. If, as discussed in the prior sections, one of the interactive terms shows strong demand for the novelty of cross–cultural goods, the interactive term would be positive in the equations. Given the tendency for the distances between two countries of different cultural backgrounds to be larger, the coefficient estimate of transportation costs is partially offset by the reverse effects of demands for distant, cross–cultural goods if the model does not include the interactive fixed–effect terms. Indeed, the coefficient of *Distance* in Takara (2017) may be estimated with bias toward zero. Thus, we have more precise estimates of the effect of transportation costs on trade by including the interactive fixed–effect terms.

Similarly, the tendency of cross-cultural novelty is captured by one of the interactive fixed–effect terms. It is also possible to say that the coefficient estimates of *Border* have smaller values in the outcome equation and those of *Language*, *Colony*, and *Religion* have larger values in both equations. The dummy variable *Border* accounts for two countries sharing the same national border. With regard to the economizing indicator of trade costs such as transportation costs, the coefficient is expected to be positive in the selection and outcome equations. However, this expectation implies that countries often share not only a border but also various aspects of their cultural backgrounds. Thus, the effect of being neighbors has negative effects on cross–culture–oriented trades. Using the estimation model without accounting for cross–cultural preferences provides an underestimated coefficient of the variable *Border* in the selection equation. However, the effect is not so large as to increase the probability of being in a new cross-cultural trade relationship (see Table 4.9).

The variables *Religion*, *Language*, and *Colony* also reflect aspects of cultural backgrounds common to trading countries. While using a common language reduces trading costs by assisting direct communication, two countries that do not share a common language and common cultural background often do not have an overlapping variety of cultural goods. With such a relation, the volume of trade in cultural goods increases based on strong cross–cultural issues. Thus, *Language* has negative and positive effects on trade. Tables 4.9 and 4.10 show that the inclusion of interactive fixed-effect terms regains the positive values of the coefficients of *Language* and *Colony*, which are offset by the effects of preferences for cross-cultural goods. The variable *Religion* also has larger, positive effects on trading volume but insignificant effects on trade probabilities after accounting for cross-cultural engagement in accordance with the interactive terms. As seen in the foregoing, we conclude that interactive fixed-effect terms separate the effects of cross–cultural demands from trade frictions or trade costs for which the explanatory variables in gravity models act as proxies.

4.5 Conclusions

This study's aim is to measure the effect of asymmetric cultural relations on the trade in cultural goods. In this regard, we introduced additive and interactive fixed effects to the standard sample selection model. We also presented an estimation procedure for the model using an expectation-conditional-maximization algorithm.

Based on an exploratory regression analysis, the estimated interactive terms are significantly correlated with two cultural proximity indices, the *music tradition* variable and the *music trend* variable. We found that the first factor of estimated four interactive fixed effect terms captured the effect of the increased consumption of cultural goods in terms of cultural proximity regarding music trends. Further, the second factor embodied the preference for engaging with the cross-cultural experiences introduced by cultural goods from culturally distant countries.

We also showed that commonly observed trade asymmetries are explained by our interactive fixed effects, whereby some asymmetric flows stem from the discrepancy in each fixed estimate in the second factor or the asymmetric preference for cross-cultural goods between European and a part of Asian countries.

Some standard explanatory variables in gravity models are interpreted as proxies of not only trade frictions but also the cultural relations between two countries. By incorporating the interactive terms, the coefficients are more precisely estimated as proxies of trade frictions because of cultural aspects that those variables have are absorbed into the interactive terms. The estimated values of the additive terms are also consistent with trade theory: the additive terms successfully capture economic statuses such as GDP, population, and price index.

While this study provides novel knowledge of the effect of cultural relations on trade, limitations exist and topics for further research remain. Primarily, we created cultural maps and discussed the properties of cultural relations using some of these. However, more information about the music market at country level is needed to investigate the maps in detail.

Appendix

Conditional expectation of the latent variables

The conditional means and variances of the latent variables, y^*_{ij} and d^*_{ij}, given observations, y_{ij} and $d_{ij}=1$, or $d_{ij}=0$ are,

$$
\begin{aligned}
\mathbb{E}_{y^*_{ij}|d_{ij}=0}[y^*_{ij}] &= \mathbf{x}'_{ij}\beta + \pi_{y,it} - \rho\sigma_u \cdot \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \\
\mathbb{E}_{d^*_{ij}|y_{ij},d_{ij}=1}[d^*_{ij}] &= (1-\rho^2)^{1/2} \cdot \left\{ \frac{\eta_{ij}}{(1-\rho^2)^{1/2}} + \frac{\phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)}{\Phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)} \right\} \\
\mathbb{E}_{d^*_{ij}|d_{ij}=0}[d^*_{ij}] &= \mathbf{z}'_{ij}\gamma + \pi_{d,it} - \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}
\end{aligned}
$$

and

$$
\begin{aligned}
\mathbb{V}_{y^*_{ij}|d_{ij}=0}[y^*_{ij}] &= \sigma_u^2 \left\{ 1 + \rho^2 \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \left\{ \mathbf{z}'_{ij}\gamma + \pi_{d,it} - \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \right\} \right\} \\
\mathbb{V}_{d^*_{ij}|y_{ij},d_{ij}=1}[d^*_{ij}] &= (1-\rho^2) \cdot \left\{ 1 - \frac{\phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)}{\Phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)} \left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}} + \frac{\phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)}{\Phi\left(\frac{\eta_{ij}}{(1-\rho^2)^{1/2}}\right)} \right) \right\} \\
\mathbb{V}_{d^*_{ij}|d_{ij}=0}[d^*_{i}] &= 1 + \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \left(\mathbf{z}'_{ij}\gamma + \pi_{d,it} - \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \right) \\
\mathrm{cov}(y^*_{ij}, d^*_{ij}) &= \rho\sigma_u \left\{ 1 + \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \cdot \left(\mathbf{z}'_{ij}\gamma + \pi_{d,it} - \frac{\phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)}{1-\Phi\left(\mathbf{z}'_{ij}\gamma + \pi_{d,it}\right)} \right) \right\} \\
&= \rho\sigma_u \cdot \mathbb{V}_{d^*_{ij}|d=0}[d^*_{ij}]
\end{aligned}
$$

where

$$\eta_{ij} = \mathbf{z}'_{ij}\gamma + \pi_{d,it} + \rho \cdot \frac{y^*_{ij} - \mathbf{x}'_{ij}\beta - \pi_{y,it}}{\sigma_u}.$$

Asymptotic properties of the bias-corrected estimator

Denote

$$\mu_{y,ij} \equiv \mathbf{x}'_{ij}\beta + \alpha_{y,i} + \gamma_{y,j} + \mathscr{A}'_{y,i}\mathscr{G}_{y,j}$$

and

$$\mu_{d,ij} \equiv \mathbf{z}'_{ij}\gamma + \alpha_{d,i} + \gamma_{d,j} + \mathscr{A}'_{d,i}\mathscr{G}_{d,j}.$$

The likelihood function of the sample $\{ \{ y_{ij}, d_{ij} \}_{j=1,j\neq i}^{N} \}_{i=1}^{N}$ is

$$\log L(\theta, a_y, g_y, a_d, g_d) = \sum_{i}^{N} \sum_{j=1,j\neq i}^{N} \ell_{ij}(\theta, a_{y,i}, g_{y,j}, a_{d,i}, g_{d,j})$$

where ℓ_{ij} is the log-likelihood contribution of the (i,j)-th observation:

$$\ell_{ij} = d_{ij} \cdot \log \frac{1}{\sigma}\phi\left(\frac{y_{ij} - \mu_{y,ij}}{\sigma}\right) + d_{ij} \cdot \log \Phi\left(\frac{\mu_{z,ij} + \rho \cdot (y_{ij} - \mu_{y,ij})/\sigma}{(1-\rho^2)^{1/2}}\right) + (1 - d_{ij}) \cdot \log \Phi\left(\mu_{z,ij}\right).$$

The asymptotic variance of the bias corrected estimator is $\mathscr{W}_{NN}^{-1}\Psi_{NN}\mathscr{W}_{NN}^{-1}$, where

$$\begin{aligned}
\Psi_{NN} &= \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\left(\frac{\partial \ell_{ij}}{\partial \theta} - \Xi'_{i\bullet}\frac{\partial \ell_{ij}}{\partial a_i} - \Xi'_{\bullet j}\frac{\partial \ell_{ij}}{\partial g_j}\right)\cdot\left(\frac{\partial \ell_{ij}}{\partial \theta} - \Xi'_{i\bullet}\frac{\partial \ell_{ij}}{\partial a_i} - \Xi'_{\bullet j}\frac{\partial \ell_{ij}}{\partial g_j}\right)' \\
&= \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\psi_{ij}(\theta,\pi_{ij})\cdot\psi'_{ij}(\theta,\pi_{ij}) \qquad (4.6) \\
\mathscr{W}_{NN} &= \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\left\{\frac{\partial^2 \ell_{ij}}{\partial\theta\partial\theta'} - \Xi'_{i\bullet}\frac{\partial^2 \ell_{ij}}{\partial a_i \partial a'_i}\Xi_{i\bullet} - \Xi'_{\bullet j}\frac{\partial^2 \ell_{ij}}{\partial g_j\partial g'_j}\Xi_{\bullet j}\right\} \qquad (4.7)
\end{aligned}$$

and

$$\begin{aligned}
\underbrace{\Xi_{i\bullet}}_{(2+2r)\times K} &= -\left(-\sum_{j=1,j\neq i}^{N}\frac{\partial^2 \ell_{it}}{\partial a_i\partial a'_i}\right)^{-1}\left(\sum_{j=1,j\neq i}^{N}\frac{\partial^2 \ell_{ij}}{\partial a_j\partial\theta'}\right) \\
\underbrace{\Xi_{\bullet j}}_{(2+2r)\times K} &= -\left(-\sum_{i=1,i\neq j}^{N}\frac{\partial^2 \ell_{ij}}{\partial g_j\partial g'_j}\right)^{-1}\left(\sum_{i=1,i\neq j}^{N}\frac{\partial^2 \ell_{ij}}{\partial g_j\partial\theta'}\right)
\end{aligned}$$

The k-th element of the bias correction terms are derived as follows (note that we use the following abbreviations, $\sum_{j\neq i}^{N}$ and $\sum_{i\neq j}^{N}$ for $\sum_{j=1,j\neq i}^{N}$ and $\sum_{i=1,i\neq j}^{N}$, respectively),

$$\begin{aligned}
b_{k,N} = &-\frac{1}{N}\sum_{i=1}^{N}\text{trace}\left[\left(\sum_{j\neq i}^{N}\frac{\partial^2 \ell_{ij}}{\partial a_i\partial a'_i}\right)^{-1}\left(\sum_{j\neq i}^{N}\frac{\partial \ell_{ij}}{\partial a_i}\frac{\partial \psi_{k,ij}}{\partial a'_i}\right)\right] \\
&+\frac{1}{2N}\sum_{i=1}^{N}\text{trace}\left[\left(\sum_{j\neq i}^{N}\frac{\partial^2 \psi_{k,ij}}{\partial a_i\partial a'_i}\right)\left(\sum_{j\neq i}^{N}\frac{\partial^2 \ell_{ij}}{\partial a_i\partial a'_i}\right)^{-1}\left(\sum_{j\neq i}^{N}\frac{\partial \ell_{ij}}{\partial a_i}\frac{\partial \ell_{ij}}{\partial a'_i}\right)\left(\sum_{j\neq i}^{N}\frac{\partial^2 \ell_{ij}}{\partial a_i\partial a'_i}\right)^{-1}\right]
\end{aligned} \qquad (4.8)$$

$$
\begin{aligned}
d_{k,N} &= -\frac{1}{N}\sum_{j=1}^{N}\text{trace}\left[\left(\sum_{i\neq j}^{N}\frac{\partial^2 \ell_{ij}}{\partial g_j \partial g_j'}\right)^{-1}\left(\sum_{i\neq j}^{N}\frac{\partial \ell_{ij}}{\partial g_j}\frac{\partial \psi_{k,ij}}{\partial g_j'}\right)\right] \\
&\quad +\frac{1}{2N}\sum_{j=1}^{N}\text{trace}\left[\left(\sum_{i\neq j}^{N}\frac{\partial \psi_{k,ij}}{\partial g_j \partial g_j'}\right)\left(\sum_{i\neq j}^{N}\frac{\partial^2 \ell_{ij}}{\partial g_j \partial g_j'}\right)^{-1}\left(\sum_{i\neq j}^{N}\frac{\partial \ell_{ij}}{\partial g_j}\frac{\partial \ell_{ij}}{\partial g_j'}\right)\left(\sum_{i\neq j}^{N}\frac{\partial^2 \ell_{ij}}{\partial g_j \partial g_j'}\right)^{-1}\right] \\
k &= 1,2,\ldots,K. \qquad (4.9)
\end{aligned}
$$

where $\psi_{k,ij}$ is the k-th element of ψ_{ij} defined in (4.6) ($\psi_{ij} \equiv \frac{\partial \ell_{ij}}{\partial \theta} - \Xi_{i\bullet}' \frac{\partial \ell_{ij}}{\partial a_i} - \Xi_{\bullet j}' \frac{\partial \ell_{ij}}{\partial g_j}$). The partial derivatives in these formula are given as follows ($\eta_{ij} \equiv \mu_{d,ij} - \rho(y_{ij} - \mu_{yij})/\sigma$, $\zeta_{ij} \equiv \mu_{d,ij}$),

$$
\underbrace{\frac{\partial \ell_{ij}}{\partial a_i}}_{(2+2r)\times 1} = \begin{pmatrix} d_{ij}\cdot\frac{1}{\sigma}\cdot\left\{\frac{y_{ij}-\mu_{y,ij}}{\sigma} - \lambda(\eta_{ij})\cdot\frac{\rho}{(1-\rho^2)^{1/2}}\right\}\cdot\begin{pmatrix}1\\ \mathscr{G}_{y,j}\end{pmatrix} \\ \left\{d_{ij}\cdot\lambda(\eta_{ij})\cdot\frac{1}{(1-\rho^2)^{1/2}} - (1-d_{ij})\cdot\lambda(-\zeta_{ij})\right\}\cdot\begin{pmatrix}1\\ \mathscr{G}_{d,j}\end{pmatrix}\end{pmatrix}
$$

$$
\underbrace{\frac{\partial^2 \ell_{ij}}{\partial a_i \partial a_i'}}_{(2+2r)\times(2+2r)} = \begin{pmatrix} \left\{-1-\cdot\frac{\rho^2\cdot\xi_+(\eta_{ij})}{1-\rho^2}\right\}\cdot\frac{d_{ij}}{\sigma^2}\cdot\Delta_{yy,j}^{\mathscr{G}} & \frac{\rho\cdot\xi_+(\eta_{ij})}{1-\rho^2}\cdot\frac{d_{ij}}{\sigma}\cdot\Delta_{yd,j}^{\mathscr{G}} \\ \frac{\rho\cdot\xi_+(\eta_{ij})}{1-\rho^2}\cdot\frac{d_{ij}}{\sigma}\cdot\Delta_{dy,j}^{\mathscr{G}} & -\left\{\frac{d_{it}\cdot\xi_+(\eta_{ij})}{1-\rho^2} - (1-d_{ij})\cdot\xi_-(\zeta_{ij})\right\}\Delta_{dd,j}^{\mathscr{G}}\end{pmatrix},
$$

$$
\frac{\partial \ell_{ij}}{\partial g_j} = \begin{pmatrix} d_{ij}\cdot\frac{1}{\sigma}\cdot\left\{\frac{y_{ij}-\mu_{y,ij}}{\sigma} - \lambda(\eta_{ij})\cdot\frac{\rho}{(1-\rho^2)^{1/2}}\right\}\cdot\begin{pmatrix}1\\ \mathscr{A}_{y,i}\end{pmatrix} \\ \left\{d_{ij}\cdot\lambda(\eta_{ij})\cdot\frac{1}{(1-\rho^2)^{1/2}} - (1-d_{ij})\cdot\lambda(-\zeta_{ij})\right\}\cdot\begin{pmatrix}1\\ \mathscr{A}_{d,i}\end{pmatrix}\end{pmatrix}
$$

$$
\frac{\partial^2 \ell_{ij}}{\partial g_j \partial g_j'} = \begin{pmatrix} \left\{-1-\frac{\rho^2\cdot\xi_+(\eta_{ij})}{1-\rho^2}\right\}\cdot\frac{d_{ij}}{\sigma^2}\cdot\Delta_{yy,i}^{\mathscr{A}} & \xi_+(\eta_{ij})\cdot\frac{\rho}{1-\rho^2}\cdot\frac{d_{ij}}{\sigma}\cdot\Delta_{yy,i}^{\mathscr{A}} \\ \frac{\rho\cdot\xi_+(\eta_{ij})}{1-\rho^2}\cdot\frac{d_{ij}}{\sigma}\cdot\Delta_{dy,i}^{\mathscr{A}} & -\left\{d_{ij}\cdot\frac{\xi_+(\eta_{ij})}{1-\rho^2} - (1-d_{ij})\cdot\xi_-(\zeta_{ij})\right\}\Delta_{dd,i}^{\mathscr{A}}\end{pmatrix}
$$

where $\Delta_{uv,j}^{\mathscr{G}} = \begin{pmatrix}1\\ \mathscr{G}_{u,j}\end{pmatrix}\begin{pmatrix}1\\ \mathscr{G}_{v,j}\end{pmatrix}'$ and $\Delta_{uv,i}^{\mathscr{A}} = \begin{pmatrix}1\\ \mathscr{A}_{u,i}\end{pmatrix}\begin{pmatrix}1\\ \mathscr{A}_{v,i}\end{pmatrix}'$, $u,v = y,d$, and

$$
\lambda(\eta_{ij}) = \frac{\phi(\eta_{ij})}{\Phi(\eta_{ij})},\ \xi_+(\eta_{ij}) = \lambda(\eta_{ij})\left\{\eta_{ij} + \lambda(\eta_{ij})\right\},\ \xi_-(\zeta_{ij}) = \lambda(-\zeta_{ij})\left\{\zeta_{ij} - \lambda(-\zeta_{ij})\right\}.
$$

Other partial derivatives, $\frac{\partial^3 \ell_{it}}{\partial \theta_k \partial a_i \partial a_i'}$, $\frac{\partial^2 \ell_{ij}}{\partial \theta_k \partial a_i'}$, $\frac{\partial^2 \ell_{it}}{\partial \theta_k \partial g_t'}$, and $\frac{\partial^3 \ell_{it}}{\partial \theta_k \partial g_t \partial g_t'}$ are also derived in the similar way.

Table 4.1: Country List

Afghanistan	Cyprus	Kyrgyzstan	Rwanda
Albania	Czech Rep.	Lao People's Dem. Rep.	Saint Lucia
Algeria	Dem. People's Rep. of Korea	Latvia	Saint Vincent and the Grenadines
Andorra	Democratic Republic of the Congo	Lebanon	Samoa
Angola	Denmark	Lesotho	San Marino
Antigua and Barbuda	Djibouti	Liberia	Sao Tome and Principe
Argentina	Dominica	Libya	Saudi Arabia
Armenia	Dominican Rep.	Lithuania	Senegal
Aruba	Ecuador	Luxembourg	Seychelles
Australia	Egypt	Madagascar	Sierra Leone
Austria	El Salvador	Malawi	Singapore
Azerbaijan	Estonia	Malaysia	Slovakia
Bahamas	Ethiopia	Maldives	Slovenia
Bahrain	Faeroe Isds	Mali	Solomon Isds
Bangladesh	Fiji	Malta	Somalia
Barbados	Finland	Mauritania	South Africa
Belarus	France	Mauritius	Spain
Belgium	French Polynesia	Mexico	Sri Lanka
Belize	Gabon	Mongolia	Suriname
Benin	Gambia	Morocco	Swaziland
Bermuda	Georgia	Mozambique	Sweden
Bhutan	Germany	Myanmar	Switzerland
Bolivia	Ghana	N. Mariana Isds	Syria
Bosnia Herzegovina	Greece	Namibia	TFYR of Macedonia
Botswana	Greenland	Nauru	Thailand
Br. Virgin Isds	Grenada	Nepal	Timor-Leste
Brazil	Guatemala	Netherlands	Togo
Brunei Darussalam	Guinea	New Caledonia	Tonga
Bulgaria	Guinea-Bissau	New Zealand	Trinidad and Tobago
Burkina Faso	Guyana	Nicaragua	Tunisia
Burundi	Haiti	Niger	Turkey
Côte d'Ivoire	Honduras	Nigeria	Tuvalu
Cambodia	Hungary	Norway	Uganda
Cameroon	Iceland	Oman	Ukraine
Canada	India	Pakistan	United Arab Emirates
Cape Verde	Indonesia	Panama	United Kingdom
Central African Rep.	Iran	Papua New Guinea	United Rep. of Tanzania
Chad	Iraq	Paraguay	Uruguay
Chile	Ireland	Peru	USA
China	Israel	Philippines	Uzbekistan
China, Hong Kong SAR	Italy	Poland	Vanuatu
China, Macao SAR	Jamaica	Portugal	Venezuela
Colombia	Japan	Qatar	Viet Nam
Congo	Jordan	Rep. of Korea	Yemen
Costa Rica	Kazakhstan	Rep. of Moldova	Zambia
Croatia	Kenya	Romania	Zimbabwe
Cuba	Kuwait	Russian Federation	

Table 4.2: Definition of Explanatory Variables

Trade Volume of Music:	Amount of traded products that are coded HS8524.32, that is, discs for laser reading systems for reproducing sound only.
Distance:	Distance between the capital cities of country i and country j (in km and expressed in logarithm).
Border:	Binary variable that takes 1 if country i and country j are contiguous, and 0 otherwise.
Language:	Binary variable that takes 1 if both country i and country j use the same language, and 0 otherwise.
Colony:	Binary variable that takes 1 if country i and country j possess colonial ties, and 0 otherwise.
Religion:	Following the way in Helpman et al. (2008), Religion is calculated as follows:

$$\text{Religion}_{ij} = \{(\%\text{ of Protestant in country i}) \times (\%\text{ of Protestant in country j})\} + (\%\text{ of Catholics in country i}) \times (\%\text{ of Catholics in country j}) + (\%\text{ of Muslims in country i}) \times (\%\text{ of Muslims in country j})$$

Table 4.3: Summary Statistics

	All				In Trade			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max
Trade Volume(Log)	-	-	-	-	5.52	3.94	-1.95	17.82
Distance(Log)	8.77	0.78	2.35	9.9	8.41	0.98	4.09	9.89
Border	0.02	0.12	0	1	0.05	0.21	0	1
Language	0.15	0.36	0	1	0.18	0.38	0	1
Colony	0.01	0.1	0	1	0.04	0.2	0	1
Religion	0.14	0.22	0	1	0.15	0.24	0	1

Note: Number of observations is 34,782 and 6,238 country pairs are in trade.

Table 4.4: Asymmetric Country Pairs

Rank	Country1	Country2	Asymmetry	Asymratio	GDPPC1(US$)	GDPPC2(US$)	GDPPC_Ratio
1	United Kingdom	Netherlands	-46,419,096	0.05	31,118	32,196	0.97
2	USA	Canada	-40,900,000	0.24	38,637	29,011	1.33
3	France	Netherlands	-27,744,740	0.10	28,449	32,196	0.88
4	France	Austria	-24,425,000	0.07	28,449	31,065	0.92
5	France	Germany	-21,800,000	0.60	28,449	28,915	0.98
6	Germany	Czech Rep.	-21,493,880	0.19	28,915	9,187	3.15
7	Belgium	Netherlands	-15,926,488	0.08	29,523	32,196	0.92
8	Italy	Germany	-15,146,773	0.09	25,450	28,915	0.88
9	United Kingdom	Czech Rep.	-14,688,532	0.01	31,118	9,187	3.39
10	France	Belgium	-14,048,012	0.16	28,449	29,523	0.96
11	United Kingdom	Poland	-13,312,494	0.03	31,118	6,209	5.01
12	Ireland	United Kingdom	-10,405,041	0.11	38,545	31,118	1.24
13	United Kingdom	Germany	-9,800,000	0.63	31,118	28,915	1.08
14	Switzerland	Germany	-9,757,083	0.30	43,480	28,915	1.50
15	Sweden	Germany	-9,264,179	0.02	33,455	28,915	1.16
16	USA	China, Hong Kong SAR	-9,119,023	0.03	38,637	24,764	1.56
17	USA	China	-8,964,447	0.01	38,637	1,361	28.40
18	Norway	Sweden	-8,900,131	0.21	51,013	33,455	1.52
19	Italy	Austria	-8,830,225	0.02	25,450	31,065	0.82
20	Spain	Netherlands	-8,820,569	0.01	21,420	32,196	0.67
21	Spain	United Kingdom	-8,456,604	0.41	21,420	31,118	0.69
22	United Kingdom	Austria	-8,391,598	0.02	31,118	31,065	1.00
23	Netherlands	Austria	-7,883,073	0.17	32,196	31,065	1.04
24	Germany	Austria	-7,500,000	0.62	28,915	31,065	0.93
25	Portugal	Spain	-7,493,972	0.09	14,581	21,420	0.68
26	Spain	Germany	-6,788,284	0.23	21,420	28,915	0.74
27	Sweden	Netherlands	-6,208,189	0.05	33,455	32,196	1.04
28	Germany	Netherlands	-5,900,000	0.73	28,915	32,196	0.90
29	New Zealand	Australia	-5,698,775	0.06	19,552	27,030	0.72
30	United Kingdom	Israel	-5,364,118	0.02	31,118	18,814	1.65

Table 4.5: Symmetric Country Pairs

Rank	Country1	Country2	Asymmetry	Asymratio	GDPPC1(US$)	GDPPC2(US$)	GDPPC_Ratio
1	Azerbaijan	Finland	0	1	1,147	31,227	0.04
1	Ireland	Cameroon	0	1	38,545	800	48.19
1	Finland	Azerbaijan	0	1	31,227	1,147	27.22
4	Ireland	Spain	-595	1.00	38,545	21,420	1.80
5	Barbados	Canada	0	0.99	10,290	29,011	0.35
6	USA	Bulgaria	-23	0.99	38,637	2,585	14.95
7	USA	Grenada	-2	0.99	38,637	4,290	9.01
8	India	France	-446	0.99	575	28,449	0.02
9	Israel	Greece	-193	0.99	18,814	15,815	1.19
10	Guatemala	Italy	0	0.99	1,868	25,450	0.07
11	Kazakhstan	Belgium	0	0.98	2,533	29,523	0.09
12	France	China, Hong Kong SAR	-3,897	0.98	28,449	24,764	1.15
13	Greece	Hungary	-13	0.98	15,815	7,920	2.00
14	Spain	Croatia	-28	0.98	21,420	6,675	3.21
15	United Arab Emirates	New Zealand	-11	0.98	24,266	19,552	1.24
16	Argentina	South Africa	-5	0.98	5,150	3,831	1.34
17	USA	France	-34,212	0.97	38,637	28,449	1.36
18	Ethiopia	Ghana	0	0.97	134	390	0.34
19	USA	Sweden	-8,808	0.97	38,637	33,455	1.15
20	Ecuador	Panama	-59	0.96	2,222	4,351	0.51
21	Poland	Australia	-23	0.96	6,209	27,030	0.23
22	Lithuania	Greece	-2	0.96	5,507	15,815	0.35
23	Bosnia Herzegovina	Australia	-2	0.95	1,879	27,030	0.07
24	Finland	Norway	-1,404	0.95	31,227	51,013	0.61
25	Germany	Maldives	-2	0.95	28,915	2,309	12.52
26	United Kingdom	Turkey	-4,269	0.95	31,118	3,687	8.44
27	Spain	Canada	-1,313	0.94	21,420	29,011	0.74
28	Georgia	Finland	-6	0.94	1,069	31,227	0.03
29	Denmark	Brazil	-22	0.94	39,521	3,529	11.20
30	Australia	Italy	-1,950	0.94	27,030	25,450	1.06

Table 4.6: Contribution Ratio of Each Factor in Outcome Equation

	R=1	R=2	R=3	R=4	R=5	R=6	R=7	R=8	R=9	R=10
up to R	0.61	0.83	0.90	0.94	0.94	0.95	0.96	0.96	0.97	0.98
1st	0.61	0.50	0.32	0.28	0.23	0.24	0.23	0.23	0.22	0.21
2nd	0.02	0.33	0.31	0.24	0.22	0.17	0.15	0.14	0.13	0.12
3rd	0.02	0.01	0.26	0.22	0.17	0.15	0.14	0.12	0.12	0.11
4th	0.02	0.01	0.01	0.19	0.16	0.14	0.12	0.11	0.11	0.10
5th	0.01	0.01	0.00	0.00	0.15	0.13	0.12	0.10	0.09	0.09
6th	0.01	0.01	0.00	0.00	0.00	0.12	0.11	0.09	0.08	0.08
7th	0.01	0.01	0.00	0.00	0.00	0.00	0.09	0.09	0.08	0.07
8th	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.08	0.08	0.07
9th	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.07
10th	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
others	0.26	0.12	0.08	0.05	0.05	0.04	0.04	0.03	0.03	0.02

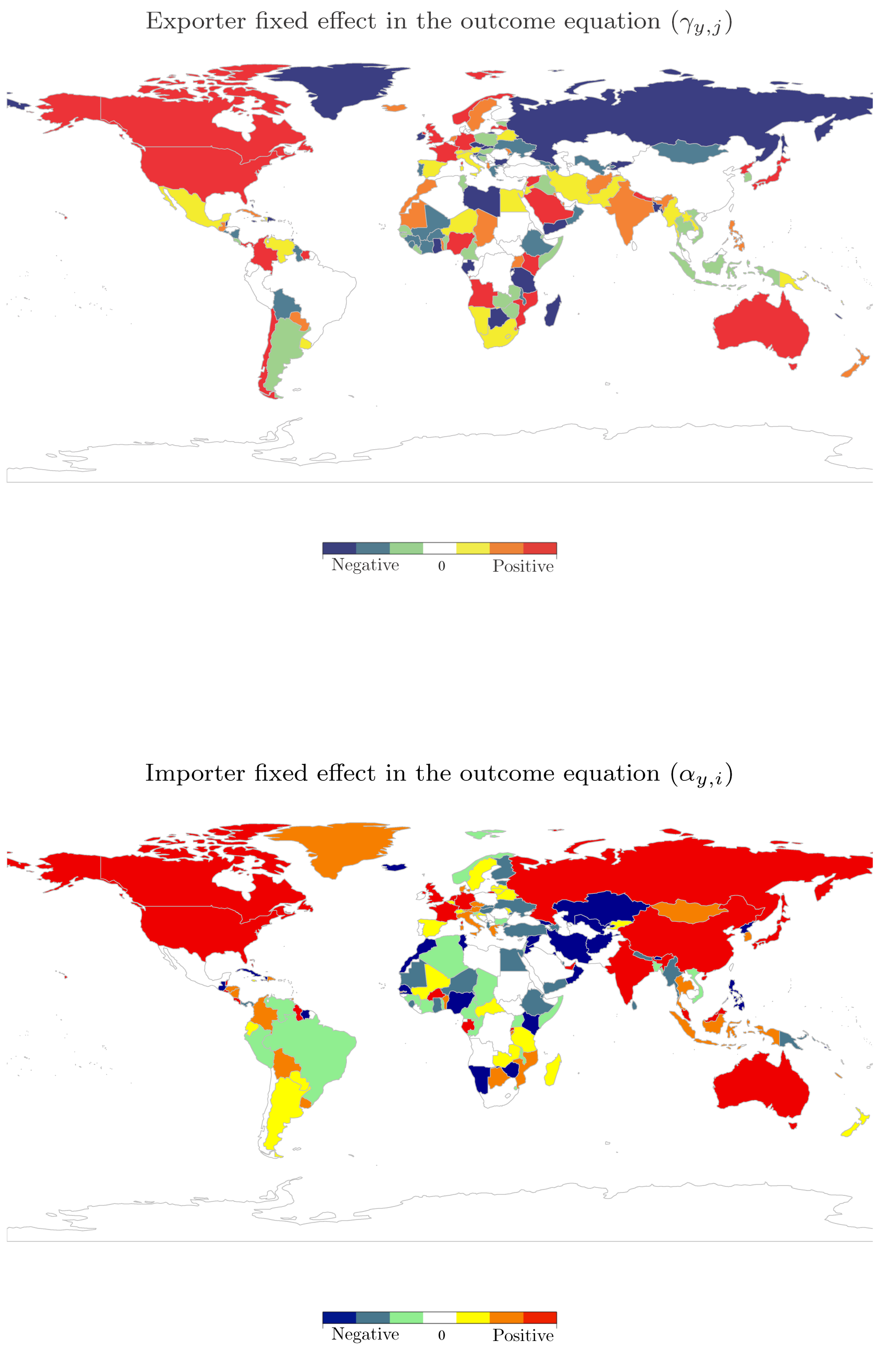
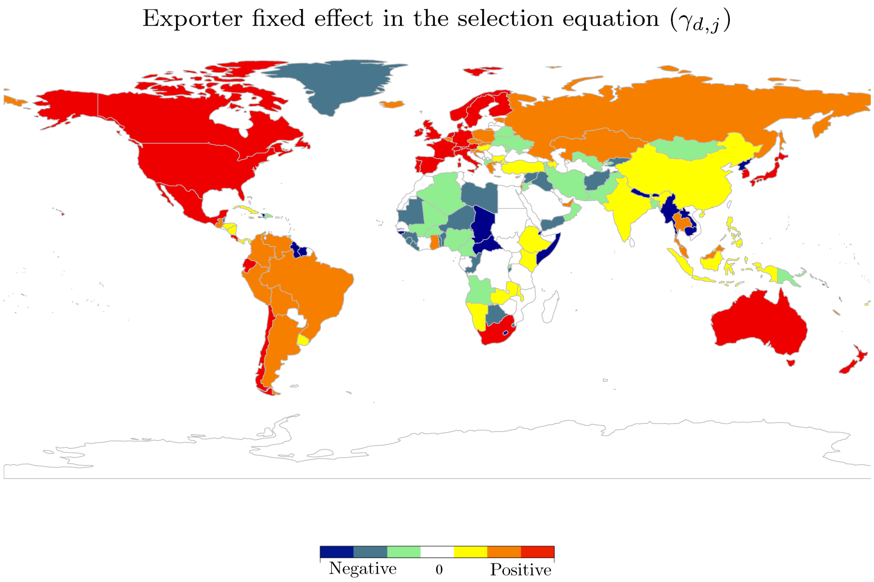


Figure 4.1: Additive Fixed Effects of the Outcome Equation on the World Map



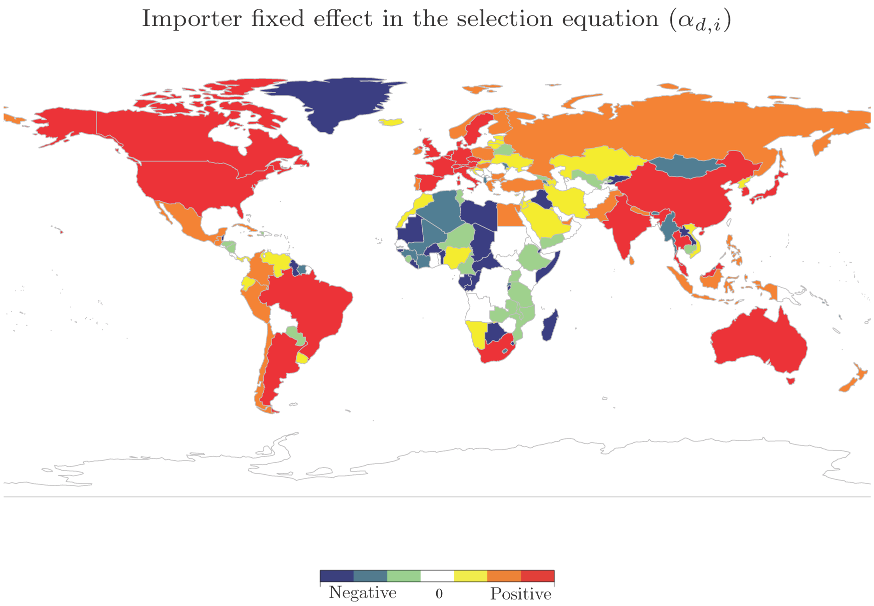


Figure 4.2: Additive Fixed Effects of the Selection Equation on the World Map

Table 4.7: Regression results of cultural variables on estimated interactive effects in the selection equation

VARIABLES	Lomax (1959)	Lomax (1959)	Huntington (1996)	Huntington (1996)
$\mathscr{A}_{1d,i}\mathscr{G}_{1d,j}$	0.140***	0.164***	0.152***	0.175***
	(0.007)	(0.007)	(0.007)	(0.009)
$\mathscr{A}_{2d,i}\mathscr{G}_{2d,j}$	0.003	-0.004	-0.016	-0.024**
	(0.009)	(0.010)	(0.010)	(0.009)
$\mathscr{A}_{3d,i}\mathscr{G}_{3d,j}$	0.012	0.013	0.044***	0.057***
	(0.012)	(0.013)	(0.013)	(0.015)
$\mathscr{A}_{4d,i}\mathscr{G}_{4d,j}$	0.047***	0.057***	0.028**	0.037**
	(0.013)	(0.013)	(0.014)	(0.015)
Fixed Effects	No	Yes	No	Yes
Observations	34,782	32,220	34,782	28,730

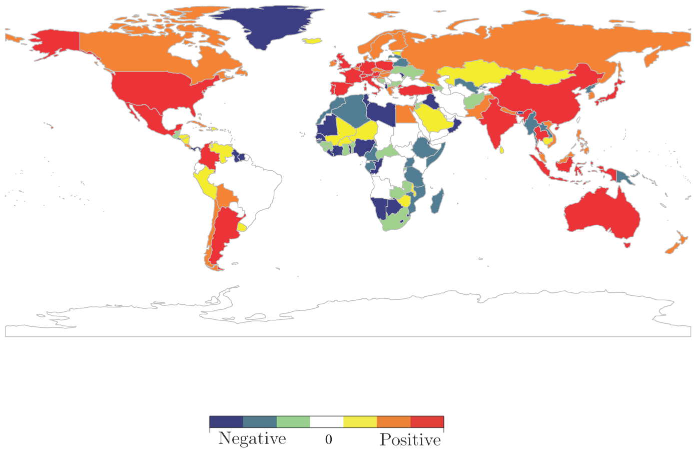
Note: Standard-errors in parentheses; * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Table 4.8: Regression results of cultural variables on estimated interactive effects in the outcome equation

VARIABLES	Lomax (1959)	Lomax (1959)	Huntington (1996)	Huntington (1996)
$\mathscr{A}_{1y,i}\mathscr{G}_{1y,j}$	-0.009**	-0.010**	0.015***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
$\mathscr{A}_{2y,i}\mathscr{G}_{2y,j}$	-0.012***	-0.015***	0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)
$\mathscr{A}_{3y,i}\mathscr{G}_{3y,j}$	-0.021***	-0.024***	-0.017***	-0.022***
	(0.004)	(0.005)	(0.005)	(0.005)
$\mathscr{A}_{4y,i}\mathscr{G}_{4y,j}$	-0.023***	-0.027***	-0.012**	-0.014**
	(0.005)	(0.005)	(0.005)	(0.006)
Fixed Effects	No	Yes	No	Yes
Observations	34,782	32,220	34,782	28,730

Note: Standard-errors in parentheses; * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

First factor of exporter interactive fixed effect $(\mathcal{G}_{1y,j})$



First factor of importer interactive fixed effect $(\mathcal{A}_{1y,i})$

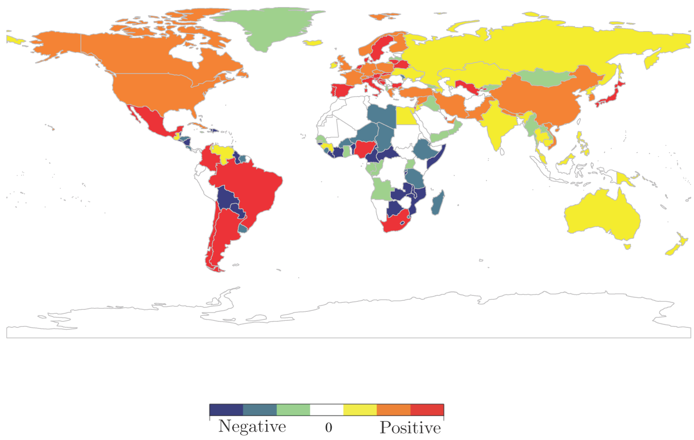
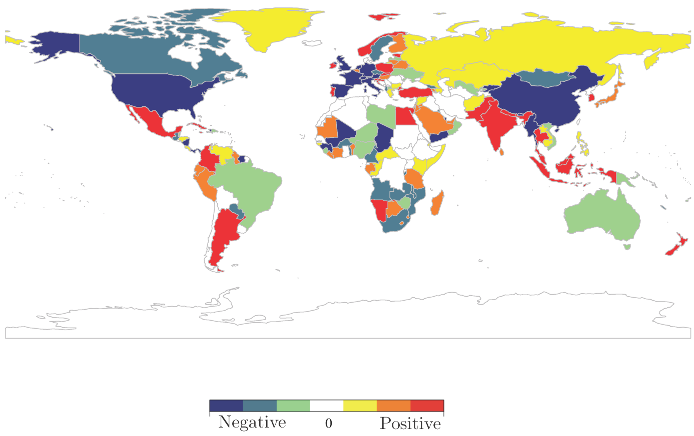


Figure 4.3: First Interactive Terms of the Outcome Equation on the World Map

Second factor of exporter interactive fixed effect ($\mathcal{G}_{2y,j}$)



Second factor of importer interactive fixed effect ($\mathcal{A}_{2y,i}$)

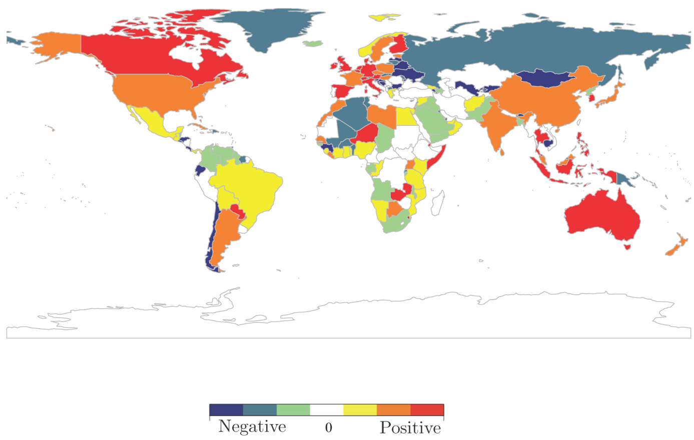


Figure 4.4: Second Interactive Terms of the Outcome Equation on the World Map

Table 4.9: Estimation Result: Selection Equation (4.1)

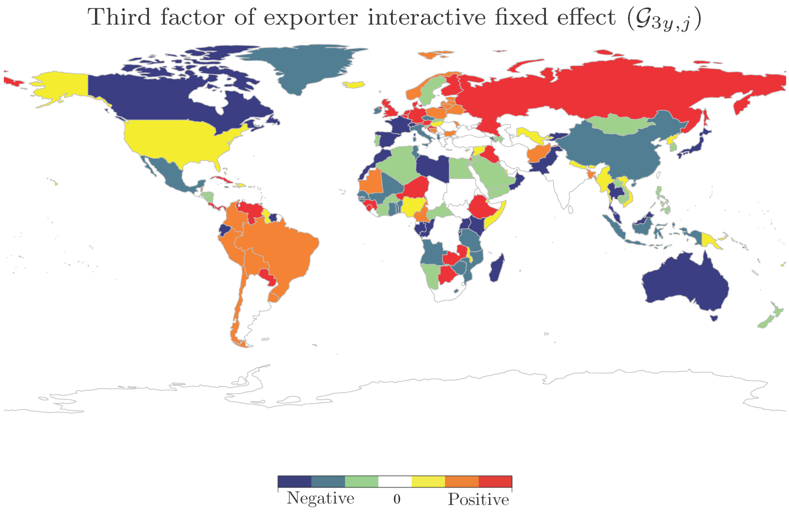
Variables	R=1	R=2	R=3	R=4	R=5	Takara (2017)
	The number of factors					
Distance	-0.825	-0.907	-0.958	-1.034	-1.212	-0.698
	(0.006)	(0.004)	(0.004)	(0.003)	(0.002)	(0.026)
Border	0.098	0.064	0.110	0.152	0.195	0.100
	(0.420)	(0.427)	(0.415)	(0.192)	(0.149)	(0.103)
Language	0.644	0.675	0.686	0.756	0.885	0.491
	(0.135)	(0.076)	(0.100)	(0.082)	(0.046)	(0.248)
Colony	0.655	0.848	0.911	1.141	1.167	0.635
	(0.173)	(0.170)	(0.425)	(0.308)	(0.082)	(0.100)
Religion	0.125	0.034	0.112	0.115	0.179	-0.112
	(0.242)	(0.241)	(0.230)	(0.200)	(0.091)	(0.079)

Note: Standard-errors are in parentheses.

Table 4.10: Estimation Result: Outcome Equation (4.2)

Variables	R=1	R=2	R=3	R=4	R=5	Takara (2017)
	The number of factors					
Distance	-1.574	-1.598	-1.497	-1.460	-1.437	-1.167
	(0.018)	(0.021)	(0.020)	(0.019)	(0.018)	(0.340)
Border	0.586	0.539	0.632	0.721	0.892	0.962
	(0.122)	(0.130)	(0.128)	(0.094)	(0.091)	(0.203)
Language	1.110	1.136	1.088	1.071	1.073	0.831
	(0.059)	(0.050)	(0.052)	(0.052)	(0.046)	(0.248)
Colony	1.674	1.701	1.720	1.793	1.859	0.976
	(0.085)	(0.095)	(0.121)	(0.109)	(0.085)	(0.316)
Religion	0.855	0.906	1.095	1.090	1.305	0.333
	(0.108)	(0.107)	(0.102)	(0.101)	(0.082)	(0.206)
σ	2.299	2.198	2.075	2.018	1.965	—
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	—
ρ	0.219	0.243	0.250	0.348	0.495	—
	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)	—

Note: Standard-errors are in parentheses.



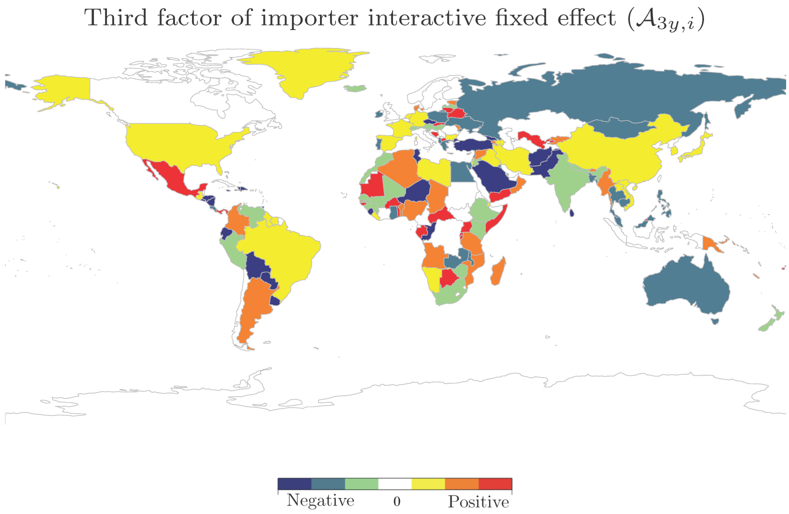
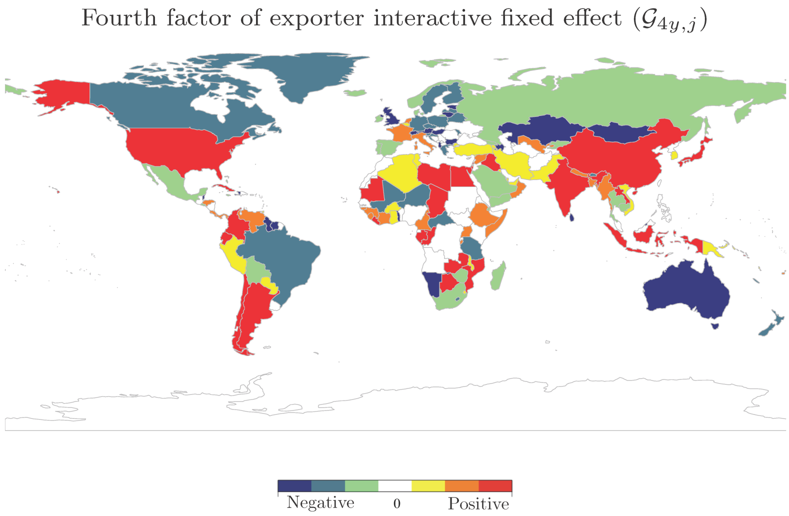


Figure 4.5: Third Interactive Terms of the Outcome Equation on the World Map



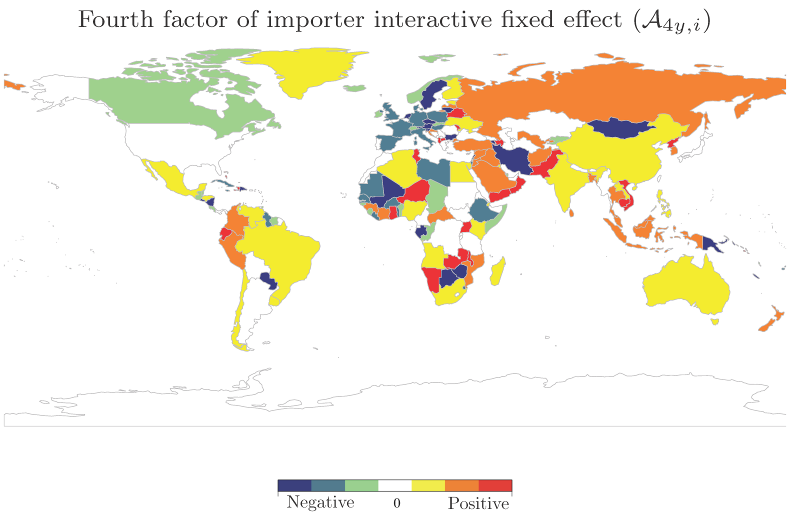


Figure 4.6: Forth Interactive Terms of the Outcome Equation on the World Map

Chapter 5

Conclusions

This dissertation mainly discusses the role of cultural factors in the economics, especially in the trade of cultural goods, using the large dyadic trade dataset. Through the dissertation, we demonstrate; (a) ways to construct cultural proximity variables; (b) impacts of cultural factors on cultural goods trade; (c) quantitative cultural relations extracted from cultural goods trade data; (d) related estimation procedures and bias correction methods.

In Chapter 2, we estimate the effects of cultural differences on the trade of cultural goods using the large dataset of traded music CDs in 188 countries. To estimate the effects, we construct novel cultural proxy variables referring to the ethnomusicology and political science studies. One cultural variable reflects the difference of the traditional musical backgrounds; the other dose the difference of the modern values each society has. We employ the modified gravity model of trade to control for the effect of sample selectivity and the economic conditions. This model contains two equation; the first one is to determine whether the country j exports to the country i or not (selection equation), and the second one is to determine how much the trading volume is (outcome equation). Each equation contains importer– and exporter– specific additive fixed effect terms. We also assume that there are two types of consumers in the market, to satisfy the exclusion restriction of the two stage estimation procedure. From the estimation results, we confirm that the cultural differences have significant effect on cultural goods trade; the difference of traditional music have significant effect in the selection equation and the difference of mass culture have significant effect on both equations. The estimated coefficients of other economic variables are also consistent with trade theory and results of previous studies.

In Chapter 3, we consider an analytical bias correction method for a sample selection model with two–way fixed effects in panel data. Our estimation results in Chapter 2 are bothered with incidental parameter problems due to the the presence of incidental parameters. The correction method is applicable to the panel and dyadic trade data and applied this method to our estimates in Chapter 2. We discuss the general case of the bias correction of the two–step estimation procedure and demonstrate an example of the case for the sample selection model with two–way fixed effects. We also conduct the Monte Carlo experiments and confirm the degree of the bias and bias corrections in some cases.

In Chapter 4, we investigate the effects of asymmetric cultural relations on the cultural goods based on the discussion in Chapter 2. The concept of asymmetric cultural relations in this section is an extended one of the cultural difference or proximity as mentioned in the previous section. We regard the cultural relations as unobserved heterogeneities and include them with our empirical model as multiple interactive fixed effects. We propose the estimation procedure of this model using expectation conditional maximization algorithm. The estimated values of interactive terms are extracted by the method of principal component analysis. To confirm what the values capture, we regress the cultural proximity indices on them and project the values on world maps. In conclusion, we find that our estimated values of interactive terms succeed in capturing cultural relations; one factor capture the relation that enhances the demand for culturally familiar goods and other does the relation that represents the demand for cross–cultural goods. These two opposite tendencies can be summarized as follows; while the difference of traditional musical backgrounds promotes the music trade, the similarity in the music trend also encourages the music trade. In addition, our coefficient estimates of observed explanatory variables in the gravity equation become more reliable as proxies of trade friction, since the effect of cultural relations is absorbed by interactive terms.

Our findings enhance the importance of cultural factors in the field of cultural economics. In conclusion, the cultural proximity acts as trade friction cost and has the negative effect against the cultural convergence or invasion in the context of music trade. The results of this dissertation extend the knowledge of the role of cultural factors in the cultural goods trade. However, we should note that there are still lots of topics of culture and economics to be investigated in future researches. Nevertheless, this dissertation results help us to investigate further research topics of the relation between cultural factors and economic issues. Based on these research results, we hope to contribute to the progress of the study in cultural economics.

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