Foreign Entry, Quality, and Cultural Distance: Product-Level Evidence from U.S. Movie Exports*

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Abstract

This paper investigates the effect of quality on foreign entry using data on international movie exports and direct and revealed measures of movie quality. Strict quality sorting is predicted by a model of firm heterogeneity. An alternative model is random entry, in which entry decisions are independent of the movie's quality. I develop a discrete choice model that allows for both of these extremes as special cases, and use graphical techniques and simulations to compare their predictions to the data. I then use regression analysis to estimate the effect of quality on the propensity to enter foreign markets. A one-standard-deviation increase in quality increases the probability of entry by 25-50%. Systematic differences in taste for different genre types are used to estimate a measure of cultural distance between countries. Movies in "culturally dependent" genres are less likely to enter foreign markets and their probability of entry is less sensitive to quality. The cultural distance measure enters a gravity equation of U.S. bilateral trade significantly.

JEL Classification Numbers: F23, L82

Keywords: heterogeneous quality, cultural goods trade, cultural affinity

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1 Introduction

The movie industry makes an interesting laboratory for studying quality and trade patterns. Rather than quality being reflected in unit prices, as is often assumed for manufactured goods, movies tend to be priced identically within a geographic market, regardless of demand. Hundreds of viewers express their opinions on the quality of movies on Web sites every week. Furthermore, financial data on box-office sales and production budget are readily available. I make use of these direct and indirect measures of quality to study the foreign entry decisions of individual movies and the degree to which foreign markets appear to agree on quality.[1] The study is conducted at the product level. When a movie is released in an international market, we know that it is the exact same product, dubbing or subtitling notwithstanding. It is rare for firms to make a single product, and most firm-level measures of quality likely reflect a mix of the product line.

Rather than adopting the standard Melitz (2003) type model of heterogeneous firms, characterized by constant-elasticity of substitution preferences and monopolistic competition, I model demand in a discrete choice framework. Like the Melitz model, however, the simplest version predicts a double hierarchy, whereby if a movie of a given quality is distributed in some market, d, it will go to all markets that are at least as attractive as d; and if a country of a given attractiveness imports a movie, m, it will import all movies that are at least as high quality as m. Eaton et al. (2011) investigate this type of hierarchy for French exporters and note that it fails to hold in the data. They introduce destination-firm-specific demand shocks to account for the discrepancy. Bernard et al. (2011) similarly argue strongly for inclusion of idiosyncratic shocks. I study the extent to which the movies data conforms to the hierarchy and compare the "pure sorting" hypothesis to that of random entry. I use a simulation technique to graphically contrast predictions from the two models, which are nested in the theoretical framework. I further

[1] Crozet et al. (2012) use expert ratings in their study of Champagne exports and quality.

investigate the role of quality in export decisions with regression analysis. The model predicts that a movie will be released in a given market if the expected revenue obtained would be sufficient to overcome the fixed cost of distribution. Revenue is increasing in quality, cultural affinity and market size and wealth. Probability regressions confirm important roles for quality and market attractiveness in the international pattern of movie releases.

This paper is related to the literature on trade in cultural goods, and the measurement of cultural distance. Attempts to measure differences in culture have often relied on analysis of questionnaires.[2] This paper develops a measure of *revealed* cultural distance by analyzing the pattern of trade in the motion picture industry. A movie is an example of a "cultural product", the trade of which not only spreads ideas and values, but reflects the current state of shared preferences. Producers face extra costs to serving additional markets, including adapting to market, advertising campaigns, and distribution. Because viewers may discount the quality of a foreign cultural product, the potential size of the importing market is determined not only by destination-specific factors, such as population and wealth, but also by the bilateral cultural affinity between the origin and destination countries. I exploit data on movie genre to back out a cultural component from destination fixed effects. The procedure relies on the fact that the movie quality for some genres—such as *comedy* and *drama*—is discounted more heavily by foreign cultures than for other genres, like *action* or *thriller*. The cultural distance measure captures the extent to which the propensity to import diverges between the two genre types.

I am not the first to look at trade patterns as a measure of cultural distance. Disdier et al. (2010) use a gravity framework to estimate the "extra" aggregate bilateral trade in sectors that UNESCO deems to be cultural industries. They interpret bilateral excess trade as cultural affinity and find that it has explanatory power in a gravity equation for all merchandise trade. I use product-level data and a heterogeneous quality framework.

[2]e.g. Hofstede (1980), and more recently Maystre et al. (2009)

This allows me to control for product quality in the empirical analysis. For example, the fact that a given country imported blockbusters like *Titanic* and *Harry Potter* is less likely to point to cultural affinity than if the country imported more obscure (less appealing) titles. My analysis also exploits variation in the extensive margin of trade—whether a title is released in a given country—rather than the intensive volume of bilateral trade.

There are existing industry-specific studies of the trade patterns of cultural goods. Hanson and Xiang (2011) develop a heterogeneous firms model of trade for the motion picture industry, and estimate using aggregate sales data by foreign market. Abramitzky and Sin (2012) use data on international book translations from UNESCO's *Index Translationum*, and the "natural experiment" of the fall of communism in Eastern Europe, to estimate the extent to which communism slowed the trade in book translations—and hence information flows. Ferreira and Waldfogel (2013) study the international trade in popular music and find that trade volumes are higher between countries that are geographically proximate and those that share a common language. Ferreira et al. (2012) develop a structural econometric model of the global movie market and investigate how consumer welfare is affected by investments in movie quality.

The remainder of the paper proceeds as follows. In section 2 I provide a theoretical model of the international trade in a unit-demand product of which varieties are heterogeneous in quality. I present an overview of the movies data in section 3, while in section 4 I present the results of three exercises. In section 4.1, I compare key statistics of the data to predictions from hierarchy and random entry models. In section 4.2, I estimate the average effect of quality on the propensity to enter foreign markets. In section 4.3, I estimate a measure of cultural distance and investigate its properties. Section 5 concludes.

2 Theory

The theory examined in this paper is based on a simple discrete choice model. The use of this framework is motivated by the application to the motion picture industry, in which consumers make the binary decision of whether or not to see a movie. Anderson et al. (1992) show that the Constant Elasticity of Substitution (CES) utility function can be used to describe the preferences of a representative consumer only if each consumer also chooses a volume of consumption. Since this is not the case for movies, I depart from the standard CES model. The discrete choice framework is applicable to many industries where quantity is not relevant. Other cultural (or creative) industries, such as books and music, exhibit the same characteristic.

The real-world institutional features of movie distribution are more complicated than depicted in the model. In particular, whereas I model decisions of movie entry as though they are independent from one another, each movie is in fact part of a portfolio belonging to a distribution company. There are six major studios in the United States, all of which are vertically integrated with distribution subsidiaries.[3] The third node in the vertical chain is the exhibitor, or movie theatre. Exhibitors are generally separate from studio-distributors—they are regulated as such in the United States—and receive a portion of box-office revenues. In addition, foreign distribution rights are licensed to foreign distributors in some countries.

Given the two (or three) firms involved in taking a movie from one reel to screens around the world, there is scope for behaviour not captured by the model in this essay. For example, a studio might negotiate that a foreign distributor or exhibitor will take on a lower-quality movie as a condition to obtaining the rights to an attractive blockbuster. Such tied selling is beyond the scope of the present essay. This consideration notwith-

[3]The six majors (and their parent companies) are Paramount (Viacom), Warner Brothers (Time Warner), Columbia (Sony), Walt Disney (Walt Disney), Universal (Comcast/General Electric), and 20th Century Fox (News Corporation).

standing, the forthcoming model presents a basic structure with which to analyze the effect of quality on entry decisions. In what follows I present increasingly refined versions of the model to guide the empirical work.

2.1 Hierarchal Sorting

There are in principle many sectors in each country, but we will focus on one differentiated product (e.g. movies) and leave the rest in the background. Individuals in destination country d purchase a variety, m, of the differentiated product if their indirect utility of doing so is greater than zero. As in Ferreira et al. (2012), indirect utility of individual i from country d consuming variety m is modelled as follows:

$$v_{idm} = \beta q_m + \rho y_d - \alpha p_{dm} + U_{idm}, \tag{1}$$

where q_m is the perceived quality of the variety, β is the marginal utility of quality, y_d is per capita income in destination d, ρ captures how tastes for the differentiated product vary with income, p_{dm} is the price of variety m in destination d, α is the marginal utility of income, and U_{idm} is the individual's idiosyncratic utility.

As in Hanson and Xiang (2011), heterogeneity across varieties is limited to the demand side. Variable costs of exhibition, given by c_d, vary by destination country but are common across varieties. Operating profits from exporting to country d, Π_{dm}, are given as the product of the price minus the variable cost and the number of people who purchase the variety. This latter quantity can be expressed as the product of the total population and the proportion of the public who purchase:

$$\Pi_{dm} = (p_{dm} - c_d) M_d \mathbb{P}[v_{idm} > 0], \tag{2}$$

where M_d is the population of country d and the proportion of the purchasing public is replaced by the probability that any of the (symmetric) individuals in the country will purchase.

Plugging 1 into 2,

$$\begin{aligned}\Pi_{dm} &= (p_{dm} - c_d)M_d\mathbb{P}[\beta q_m + \rho y_d - \alpha p_{dm} + U_{idm} > 0] \\ &= (p_{dm} - c_d)M_d\mathbb{P}[U_{idm} > \alpha p_{dm} - \beta q_m - \rho y_d] \\ &= (p_{dm} - c_d)M_d(1 - \mathbb{P}[U_{idm} < \alpha p_{dm} - \beta q_m - \rho y_d]) \qquad (3)\end{aligned}$$

If U_{idm} is distributed exponentially with parameter λ, then the above reduces to:

$$\Pi_{dm} = (p_{dm} - c_d)M_d e^{\lambda + \beta q_m + \rho y_d - \alpha p_{dm}} \qquad (4)$$

Given the decision to enter a market, distributors set the price to maximize operating profits. The first-order condition for maximizing equation 4 implies an optimal price of $p^*_{dm} = c_d + 1/\alpha \equiv p_d$. Thus, prices vary across destination markets but are homogeneous within each market.

Producers of a variety export to foreign market d if the operating profits from doing so are greater than the cost of entry, given by F_d. Variety m is therefore exported to market d if net profits are greater than zero: $\Pi_{dm} - F_d > 0$. Since revenues are increasing in quality, a hierarchal order is predicted, whereby if a given variety is exported to market d then all varieties with higher quality are also exported to market d. If a variety is not exported to market d, than neither are any varieties with lower quality. The cutoff quality level, q_d^*, for each market d can be found by setting profits equal to zero:

$$\begin{aligned}
\Pi_{dm} - F_d &= 0 \\
(p_d - c_d) M_d e^{\lambda + \beta q_m + \rho y_d - \alpha p_d} - F_d &= 0 \\
q_d^* &= \frac{1}{\beta}\left[\ln \frac{\alpha F_d}{M_d} + 1 + \alpha c_d - \rho y_d - \lambda\right],
\end{aligned} \tag{5}$$

where the last equality uses the fact that $p_d = c_d + 1/\alpha$. This is a very strong prediction but is not specific to the present model. Such "ability" sorting is present in any entry model with fixed costs of entry and where profits and revenues are increasing in ability.[4] In particular, the Melitz (2003) model and related papers exhibit this feature. Eaton et al. (2011) demonstrate that such a hierarchy is at odds with the facts for French exports. It is easy to find counterexamples in the movies data of this paper. Eaton et al. (2011) introduce destination-variety-specific demand shocks to the Melitz model to reconcile the theory with the facts. This "consumer tastes" term is also found to be important in Bernard et al. (2011) and Crozet et al. (2012), among others.

2.2 Destination-Variety-Specific Demand Shocks

We can integrate the idiosyncratic shocks parsimoniously within the the existing model. Let ψ_{dm} equal the average idiosyncratic consumer utility for variety m over all individuals in destination d and define u_{idm} to be the individual idiosyncratic utility from consumption in excess of the destination d average. Then U_{idm} can be decomposed as

$$U_{idm} = \psi_{dm} + u_{idm}. \tag{6}$$

[4]In general, increasing profits does not imply increasing revenues since there may be costs associated with quality. If higher marginal costs are required for higher quality, and if prices are a function of marginal cost, then revenues may fall with quality—through movement *along* the demand curve—even as profits increase due to a higher price per unit. The relevant condition is a comparison of the elasticity of consumer demand with respect to quality versus the elasticity of marginal cost with respect to quality.

Plugging this expression into 3 and assuming u_{idm} is exponentially distributed, we obtain:

$$\Pi_{dm} = (p_{dm} - c_d)M_d e^{\lambda+\beta q_m+\psi_{dm}+\rho y_d-\alpha p_{dm}}, \tag{7}$$

which breaks the monotonic relationship between quality and revenues, since, although a variety may have high quality, it may have a low destination-specific affinity, ψ_{dm}. Thus, high-quality varieties may not enter a market even when lower-quality varieties do so.

The destination-variety-specific shocks are not observed by the econometrician, but suppose they are distributed according to the distribution function $G(\psi)$. Then the probability that variety m is imported to destination d is given by the probability that operating profits exceed fixed costs:

$$\begin{aligned}
\mathbb{P}[\mathcal{E}_{dm} = 1] &= \mathbb{P}[(p_{dm} - c_d)M_d e^{\lambda+\beta q_m+\psi_{dm}+\rho y_d-\alpha p_{dm}} > F_d] \\
&= \mathbb{P}[\psi_{dm} > -\lambda - \beta q_m - \rho y_d + 1 + \alpha c_d + \ln \frac{\alpha F_d}{M_d}] \\
&= \mathbb{P}[\psi_{dm} < \lambda - 1 + \beta q_m + \rho y_d + \ln M_d - \alpha c_d - \ln \alpha F_d], \qquad (8)
\end{aligned}$$

where the last equation holds assuming $G(\cdot)$ is symmetric about zero. As the variance of ψ_{dm} collapses to zero, operating profits approach those described by (4) and we obtain the hierarchal prediction: the probability of entry equals zero or one, depending on whether or not quality exceeds the cutoff in equation 5. As the variance of ψ_{dm} approaches infinity, the idiosyncratic component dominates the determination of operating profits, and quality becomes irrelevant to the entry decision. The situation could then be modeled as random entry, with each variety equally likely to be released in any given market.

These observations suggest a test of the importance of quality versus idiosyncratic demand shocks. Under pure hierarchal sorting, a country that imports N varieties should import the N of highest quality. Under pure random entry, the N varieties would be drawn from a uniform distribution without replacement. This has implications for the relationship between the number of imported varieties and observable aggregate statistics: the minimum, mean, and maximum quality for each destination market. In section 4.1, I compare the observed country-level statistics to the pure-sorting predictions and a monte carlo simulation of random entry for U.S. movies. In section 4.2, I estimate entry equation 8 using the U.S. movies data. Entry is predicted to be more likely for higher-quality movies, and for destination markets with higher populations and per capita incomes. Higher fixed and variable costs are predicted to lower the probability of entry.

2.3 Measuring Cultural Distance

Destination-variety-specific demand shocks imply that a pure hierarchal sorting of foreign entry will not in general hold. Recall that these demand shocks are conceptually defined as country-level averages of individual idiosyncratic utility for each variety. In other words, the demand shocks reflect a central tendency of individuals' tastes within each country. Hofstede (2002) emphasizes that culture is not a fundamental that exists in its own right, but is a construct that reflects unobservable "mental programs". We can infer from observable behaviour—words or deeds—the presence of these mental programs and construct notions of culture accordingly. In the same article, Hofstede concedes that national culture is not easily measured, but that *differences* in culture can be obtained. This is the spirit in which I carry out the present exercise. Culture can mean different things in different contexts. The definition I will adopt is that *culture is the aggregation of a society's tastes for what is regarded as excellent in the arts.*[5] Differences in idiosyncratic demand shocks for cultural goods might thus be useful in measuring differences in culture between countries.

If we had perfect measures of the country-level variables present in equation 8, we might infer from the destination component of the residuals of that estimation a measure

[5]This definition is the author's adaptation of the first definition in Random House (2010).

of cultural affinity with the United States. Lacking such measures, destination fixed effects capture a mixture of effects relating to market size, wealth, trade costs, regulations, etc. It is not obvious how to extract a cultural component from this. Suppose the variety-space of the product in question could be partitioned into two subsets. For one subset, consumption value is dependent on cultural context, and for the other it is not. For the culturally dependent set of varieties, idiosyncratic consumer utility will tend to be low for individuals in countries that are culturally distant from the United States. For the case of movies, this subset could be movies in the genres *comedy* and *drama*, whereas the compliment subset is made up of the *action*, *adventure* and *thriller* genres.[6]

Equation 6 decomposes idiosyncratic consumer utility into country-level and individual-specific terms. We can further decompose this term by defining η_{dg} as the average demand shock in a country over all varieties in a genre-type, and writing the decomposition:

$$U_{idm} = \eta_{dg_m} + \hat{\psi}_{dm} + u_{idm}, \tag{9}$$

where $\hat{\psi}_{dm}$ is the destination-variety demand shock in excess of the genre shock. Operating profits become

$$\Pi_{dm} = (p_{dm} - c_d) M_d e^{\lambda + \beta q_m + \eta_{dg_m} + \hat{\psi}_{dm} + \rho y_d - \alpha p_{dm}}, \tag{10}$$

and the probability of entry becomes[7]

$$\mathbb{P}[\mathcal{E}_{dm} = 1] = \mathbb{P}[\hat{\psi}_{dm} < \lambda - 1 + \beta q_m + \rho y_d + \ln M_d - \alpha c_d - \ln \alpha F_d + \eta_{dg_m}]. \tag{11}$$

Consider estimation of this equation using the two different genre types: varieties in culturally dependent genres and varieties in culturally neutral genres. Label the destination fixed effects FX_d^C and FX_d^N for the two samples, respectively. Then, for $g \in \{C, N\}$,

[6] The precise partition used will be explained in the empirical section.

[7] Once again we use the fact that the optimal price is $p_{dm} = c_d + 1/\alpha$ for all m.

$FX_d^g = \eta_{dg} + \rho y_d + \ln M_d - \alpha c_d - \ln \alpha F_d$, and thus $FX_d^N - FX_d^C = \eta_{dN} - \eta_{dC}$. The variation in this measure across destinations reflects the difference in affinity that countries exhibit for the different samples. This measure equals zero if both sets of varieties carry equal affinity, but increases as the degree of affinity for culturally dependent varieties lags that for culturally neutral varieties. I define this difference as country d's "cultural distance" from the origin country. In effect, differencing the fixed effects from the two samples strips away all of the destination-specific influences that are common across the genre types and leaves only the difference in destination-genre affinity. The assumption required to interpret this measure as cultural distance is that for countries that are culturally close to the origin country, discounting of culturally dependent genres will be small; whereas culturally distant countries will discount culturally dependent genres more heavily than neutral genres. For the case of movies, everyone can appreciate a good action scene, but viewers in culturally distant countries will draw systematically lower demand shocks for movies in genres that are culturally laden, like dramas and comedies. I carry out this exercise on the sample of U.S. movies in section 4.3.

3 Data

The movies data for this study comes from the International Movie Database (IMDb), an international project that catalogues movie trivia on line. I extracted the full set of titles, release dates by country, countries of origin, and user-ratings. I am therefore able to tell, for any given movie, where it was produced, where it was released, and how users of imdb.com rated it on a score from one to ten.

The total number of titles covered in the database is 437,041, produced in 53 countries and released in 115 countries. I remove from the sample all movies that were not released theatrically outside of film festivals. A key movie-level attribute in this study is the perceived quality, or popular appeal. Because the population of IMDb contributors may not be representative of the universe of potential movie-goers, it is useful to have alternative measures of quality. To this end, I exploit a database of movie titles and ratings provided by the commercial site Netflix.com. Netflix allows customers to rent movies on line, then sends them a copy of the chosen DVDs by mail.[8] The Netflix ratings are based on customer feedback. The data set became available to the public when Netflix announced a contest open to the machine-learning community. The data consists of every rating by each individual for a sample of 17,000 movies. I use the average rating given to each movie. These ratings suffer from the same potential sampling problems as the IMDb ratings, but offer an independent measure nonetheless. I focus on viewer ratings rather than "expert" film critics' since the logic of selection is based on expected sales volumes. The quality I am interested in derives from consumer preferences and not conceptual art. Moreover, the Netflix service was only available in the United States during the sample period, and thus the quality ratings reflect home-country preferences. Intersecting the IMDb data set with the Netflix films reduces the sample considerably, to a total of 6,413 distinct titles. After restricting the sample to U.S.-produced movies released between 1995 and 2004, the sample size drops to 1,604.

I compliment the two ratings-based quality measures with two financial measures. The first is the U.S. domestic box-office revenue. This measure roughly tells us how many people actually went to see the movie in the United States. Since people often act on recommendation and word-of-mouth when choosing a movie, domestic revenues indicate how well-received the movie was at home. To the extent that distributors delay foreign entry, U.S. revenues may directly influence foreign-entry strategy. In any case, the measure is likely correlated with studios' expectations in foreign markets. This measure also coincides with that of Khandelwal (2010), who defines quality as market share, given equal prices.

The second financial measure of quality is the movie's production budget. Assuming

[8]The Netflix business model has since changed to focus on digital distribution of movies.

Table 1: Pairwise Correlations between Quality Proxies

	Netflix	IMDb	U.S. Revenue	Budget
IMDb	0.531			
	(0.000)			
U.S. Revenue	0.449	-0.012		
	(0.000)	(0.686)		
Budget	0.176	-0.044	0.606	
	(0.000)	(0.215)	(0.000)	
No. of Markets	0.289	0.174	0.647	0.517
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Significance levels (p-values) are shown in parantheses. U.S. Revenue refers to U.S. box-office revenues. Budget refers to the production budget. Both of these measures are entered in logarthmic form. No. of Markets refers to the number of markets in the sample in which the movie was released theatrically.

that a higher investment produces a better product, this measure should be correlated with quality. De Vany (2004) finds that (expensive) star power is a good predictor of movie success. Kugler and Verhoogen (2012) also find supporting evidence that more expensive inputs lead to higher quality in their sample of Columbian manufacturing firms. Both of these financial variables come from the Web site www.the-numbers.com. U.S. box-office data is available for 1,236 of the 1,604 movies in the sample. Production budget data is available for just 802 movies.

Table 1 gives the pairwise correlations between each of the quality proxies in addition to the number of foreign markets entered. The theory predicts that higher-quality movies will be released in more markets. Indeed, each of the quality proxies is significantly correlated with the number of markets. The U.S. revenue exhibits the strongest relationship while the IMDb rating exhibits the lowest correlation with market entry. Surprisingly, the IMDb rating is uncorrelated with U.S. revenues and production budget.

For the entry regressions, I use data on GDP, population, bilateral distance, and other typical gravity covariates described in the empirical section. All of this data was obtained from CEPII.

Information on movie genre is contained in a separate file in the International Movie Database. After merging the data, the sample size is reduced to 877 movies. Of these, 459 are coded as *comedy* or *drama*. The set of countries that imported a positive number of both sets of movies is reduced in size from 97 to 86.[9]

4 Empirical Results

The empirical enquiry proceeds in three steps. First, I compile country-level statistics describing the distribution of movie qualities in each market. I use a graphical simulation to contrast pure quality sorting against random entry, and investigate where the data fits between these two extremes. Second, I estimate the foreign entry equation to discern how important movie quality and destination characteristics are to the probability that a given U.S. movie will be released in a given destination country. Third, I repeat the estimation of the entry equation on two different genre types, and interpret the difference between the destination-genre fixed effects as a measure of cultural distance. I then compare this measure to other proxies of cultural distance and test its explanatory power in a gravity equation of bilateral trade.

4.1 Selection versus Random Entry

The simplest model of section 2 makes strong predictions about which movies are shown where. If all countries agreed on which are the best films, then we should see a hierarchal sorting in the release pattern. The best movie would go to the most destinations, and countries that are attractive enough to import more would select down the list in order of quality. Chen and Moore (2010) study the entry decisions of French foreign direct investors, and document a negative relationship between the number of firms investing

[9]The following countries had zero imports in at least one of the two subsets of movies: Bahamas, Bosnia-Herzegovina, Cuba, Faroe Islands, Ghana, Iran, South Korea, Macau, Nepal, Syria, Tanzania.

and the minimum productivity of these firms. They cite this as evidence of sorting, but their analysis omits a critical factor: purely random entry will also lead to a negative slope. The expected minimum value taken from N draws of a distribution is decreasing in N.

In order to distinguish quality sorting from random entry, I add two components to the analysis. The first is to look at statistics other than the minimum. Under randomness, the *mean* quality will not vary with the number of releases; whereas, under quality sorting, the mean quality would be decreasing. The maximum quality will be increasing under randomness for the same reason the minimum is decreasing (choosing an extremum from a larger number of draws). Under selection, the best movie is released in all countries and hence the maximum does not vary with the number of releases. The second addition to the analysis is to simulate random entry by drawing from the empirical distribution of movie quality. For each number of movies in the sample released (a country-level variable ranging from one to 105), I draw that many times from the empirical quality distribution. I take the relevant statistics (min, mean, and max) and then repeat ten thousand times, saving the 5th and 95th percentiles and the mean over the ten thousand repetitions. Figures 1–3 plot the results along with the actual data and the pure quality-sorting predictions for the year 2004. U.S. box-office revenue is the preferred quality proxy and results are given for this variable.[10]

Inspection of Figure 1 shows that the actual minimum quality values lie above those predicted by random entry, with the majority of data points lying above the 95th percentile. This is evidence in favour of selection on quality, since under selection, a country importing few movies will tend to release the better ones. Comparing the data to the pure quality-sorting predictions, however, shows that idiosyncratic demand shocks pull the minimum-quality values toward randomness.

[10]Figures for the other quality proxies are qualitatively similar, though the evidence in favour of the quality-sorting model is strongest for the box-office revenue measure.

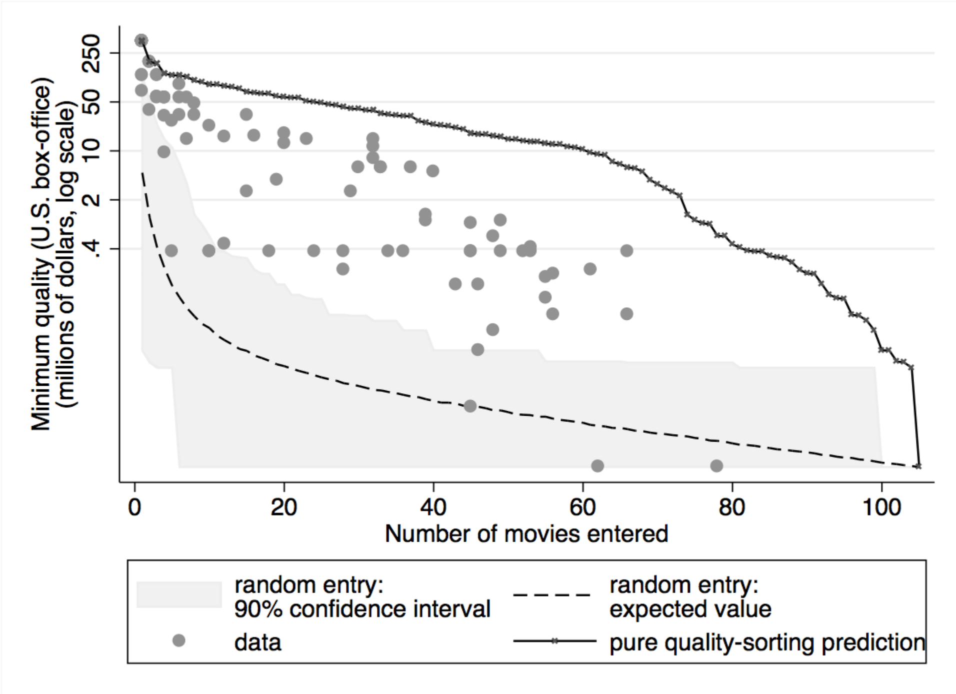

Figure 1: Minimum Quality vs. Number of Releases by Country in 2004

Figure 2 plots the mean quality of entering movies and provides stronger support for the quality-sorting model. The mean quality of entering movies decreases in the number of releases, indicating that countries importing more movies are on average adding lower-quality films. As the simulation confirms, random entry would predict no relationship (a horizontal slope) between mean quality and the number of releases. The data points are close to the values predicted by quality sorting, and lie well above the 95th percentile from the random-entry simulation.

Figure 3 illustrates the data and simulation for the maximum quality movie in each market. Under selection, we would expect every country to release the top-ranked movie. The simulation confirms that under random entry, the expected maximum quality increases in the number of releases. The data points are largely consistent with the quality-sorting model: the top-quality movie was released in all but seven of the 90 countries in the sample.

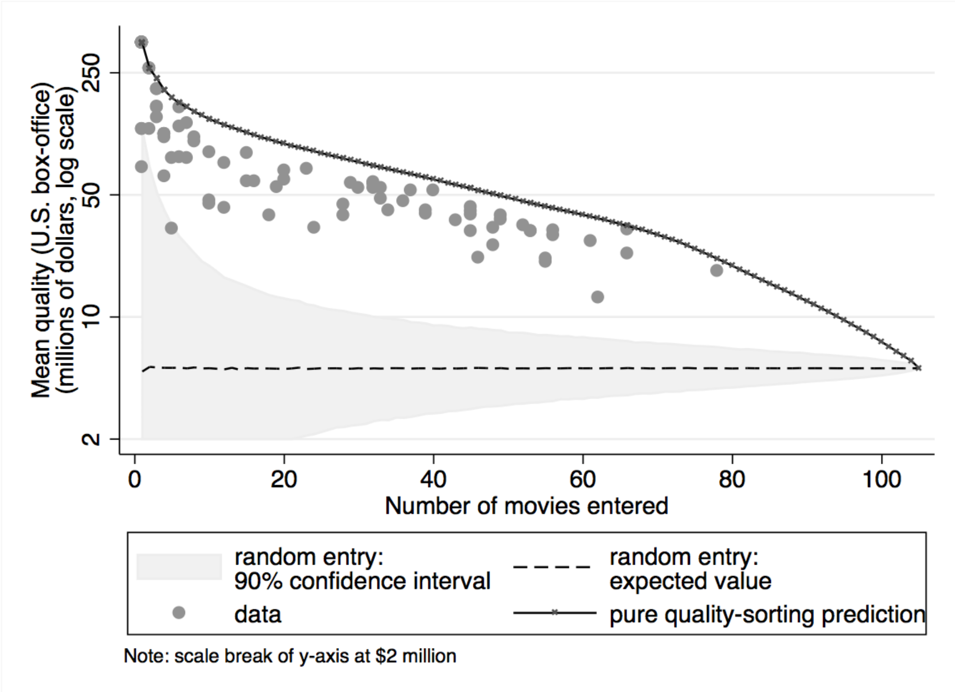

Figure 2: Mean Quality vs. Number of Releases by Country in 2004

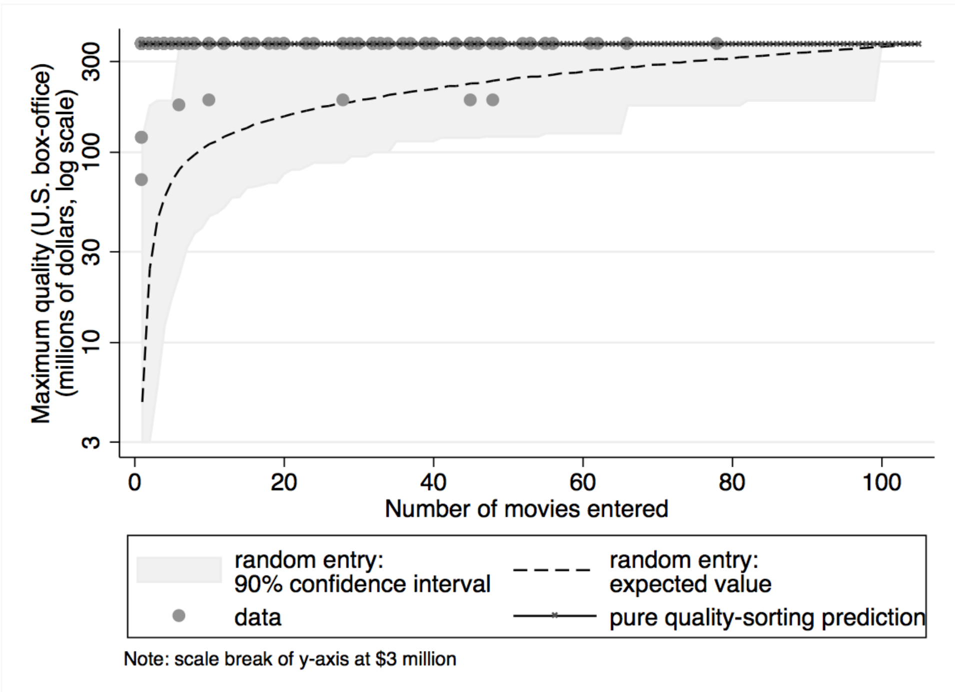

Figure 3: Maximum Quality vs. Number of Releases by Country in 2004

The evidence suggests that quality selection is taking place, but that movie-destination-specific demand shocks are also drivers of the distribution pattern. In the following section, I estimate the average effect of the quality proxies on the probability of a movie's import. In section 4.3, I attribute a component of the idiosyncratic demand shocks to country-genre preferences, and interpret differences in preferences as cultural distance.

4.2 Predicting Movie Imports: Quality and Geography

The model in section 2 predicts that the probability of entry is increasing in the size and wealth of the destination market and the quality of the movie, and decreasing in the magnitude of variable and fixed costs required to enter the market. Entry is stochastic from the point of view of the analyst since we do not observe the destination-movie-specific demand shocks.

The empirical proxies for movie quality and country characteristics are necessarily imperfect. We can express the theoretical variables in terms of the empirical proxies and an error term:

$$\begin{aligned}
q_m &= \tilde{q}_m + \epsilon_m \\
y_d &= \tilde{y}_d + \epsilon_d^y \\
M_d &= \tilde{M}_d + \epsilon_d^M \\
\alpha c_d + \ln \alpha F_d &= \gamma X_d + \epsilon_d^X,
\end{aligned}$$

where $\tilde{q}_m$ is either viewer ratings from Netflix or IMDb, log U.S. revenues, or log production budget; $\tilde{y}_d$ and $\tilde{M}_d$ are measured per capita income and population, respectively; and X_d is a vector of variables thought to be correlated with variable and fixed costs of entry. As pointed out by Hanson and Xiang (2011) for the case of movies, and Helpman et al. (2008) more generally, it is difficult to distinguish between measures that affect variable costs and fixed entry costs. I follow a large literature on gravity equations, including the two studies cited above, by setting X_d to include log geographic distance and a set of dummy variables indicating whether the destination country shares with the United States a common border, common official language, common colonial origins, a free trade agreement, or a strict currency union. Substituting into equation 8, and defining $\delta_m = \beta\epsilon_m$ and $\delta_d = \rho\epsilon_d^y + \epsilon_d^M - \epsilon_d^X$, we obtain

$$\mathbb{P}[\mathcal{E}_{dm} = 1] = \mathbb{P}[\psi_{dm} - \delta_m - \delta_d < \lambda - 1 + \beta\tilde{q}_m + \rho\tilde{y}_d + \ln\tilde{M}_d - \gamma X_d]. \tag{12}$$

Error terms of observations for the same movie will be correlated due to δ_m and error terms of observations for the same destination country will be correlated due to δ_d. This will lead to a downward bias of standard errors, which can be corrected by two-way clustering of standard errors along both movie and destination dimensions.[11] It is possible that omitted variables captured by δ_d are correlated with the destination-specific right-hand-side variables in (12). To allow for this, we can move δ_d out of the error term and replace all destination-specific terms by a destination fixed effect. This precludes estimation of coefficients on destination characteristics, but weakens the assumptions required for consistent estimation of β.

Table 2 reports results of estimating equation 12 on a sample of 1,236 U.S. movies and 97 destination countries, using log U.S. revenues as the quality proxy. The movies were released in the United States over the ten-year period between 1995 and 2004. The binary variable $Entry_{dm}$ is coded as one if destination d had imported movie m by the end of 2009. Since we are restricting attention to cinematic releases, the lag between the last U.S. release date and the end of 2009 should be sufficient to allay any concerns of censorship. Indeed, the last observed entry in the sample occurred in 2005.

[11] Two-way cluster-robust standard errors are developed in Thompson (2011) and Cameron et al. (2011). Stata code is available on Mitchell Peterson's Kellogg Web site.

Table 2: Probability of Foreign Release

	Probit		LPM	
Model:	(1)	(2)	(3)	(4)
Depvar:	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$
logUSrevenue$_m$	0.114***	0.107***	0.091***	0.089***
	(0.006)	(0.006)	(0.010)	(0.010)
logPopulation$_d$	0.067***		0.078***	
	(0.011)		(0.011)	
logGDPPC$_d$	0.127***		0.136***	
	(0.011)		(0.011)	
logDistance$_d$	0.014		-0.008	
	(0.036)		(0.034)	
Border$_d$	-0.076		-0.145	
	(0.063)		(0.090)	
English$_d$	-0.013		0.0001	
	(0.036)		(0.038)	
FTA$_d$	0.041		0.038	
	(0.032)		(0.031)	
CurrencyUnion$_d$	-0.037		-0.053	
	(0.071)		(0.046)	
Destination FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	117,420	119,892	117,420	119,892
R^2	0.33	0.47	0.27	0.40

Note: Statistical significance of 1% is indicated by ***. Pseudo-R^2 reported for Probit specifications. Probit coefficients are reported as average partial effects. Robust standard errors are adjusted for clusters in movies and destinations.

The left panel of Table 2 displays results for probit estimation; the right panel is for the linear probability specification. Columns 1 and 3 omit destination fixed effects and therefore allow for estimation of coeffients on destination-level determinants of entry. Data on gross domestic product is unavailable for Cuba and Faroe Islands so they are dropped from these regressions. Columns 2 and 4 include destination fixed effects and the focus is on the impact of quality on the entry.

The U.S. box-office revenue has been normalized by subtracting its mean and dividing by its standard deviation. The coefficient can thus be directly interpreted as the increase in the probability of entry associated with a one standard deviation increase in the movie's domestic revenues. The coefficients suggest that the probability of entering an "average" destination is between nine and eleven-and-a-half percentage points higher for a movie whose quality is one standard deviation higher than a movie with average quality. This compares to an overall probability of entering a foreign market of about 17%.

Population and per capita GDP are also associated with more entry, as predicted. Surprisingly, none of the gravity "linkage" variables enter significantly. This does not imply that entry costs are insignificant, just that these costs do not appear to be correlated with the typical gravity covariates.

The U.S. box-office revenue is just one measure of movie quality. Alternatively, we could use the ratings found in the International Movie Database or from Netflix, or consider the cost of production, assuming that a higher investment leads to a better product. Table 3 reports estimates for these three alternative quality measures. The variables have been standardized from their original scales.

All three alternative quality measures are highly statistically significant predictors of entry. A one-standard-deviation increase in log budget is associated with a seven-to-eight percentage point increase in the probability of entry. The counterpart numbers for Netflix and IMDb ratings are 4.5 and 2.5 percentage points, respectively. Results for the

Table 3: Probability of Foreign Release: Alternative Quality Proxies

	Probit			LPM		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Depvar:	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$
logBudget_m	0.069***			0.075***		
	(0.005)			(0.008)		
Netflix_m		0.047***			0.044***	
		(0.004)			(0.005)	
IMDB_m			0.024***			0.025***
			(0.004)			(0.005)
logPopulation_d	0.080***	0.058***	0.056***	0.093***	0.067***	0.068***
	(0.013)	(0.009)	(0.009)	(0.014)	(0.010)	(0.010)
logGDPPC_d	0.149***	0.109***	0.107***	0.163***	0.117***	0.117***
	(0.013)	(0.010)	(0.009)	(0.013)	(0.010)	(0.010)
logDistance_d	0.019	0.016	0.015	-0.003	-0.007	-0.007
	(0.043)	(0.032)	(0.031)	(0.040)	(0.029)	(0.029)
Border_d	-0.114	-0.057	-0.051	-0.201	-0.113	-0.114
	(0.080)	(0.054)	(0.039)	(0.120)	(0.071)	(0.071)
English_d	-0.023	-0.012	-0.012	-0.007	0.001	0.001
	(0.044)	(0.030)	(0.028)	(0.045)	(0.032)	(0.032)
FTA_d	0.071	0.039	0.040	0.076	0.032	0.032
	(0.040)	(0.027)	(0.029)	(0.041)	(0.024)	(0.024)
CurrencyUnion_d	-0.041	-0.031	-0.029	-0.060	-0.039	-0.040
	(0.084)	(0.064)	(0.055)	(0.054)	(0.037)	(0.037)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	76,190	152,380	152,380	76,190	152,380	152,380
R^2	0.29	0.24	0.21	0.29	0.20	0.19

Note: Statistical significance of 1% is indicated by ***. Pseudo-R^2 reported for Probit specifications. Probit coefficients are reported as average partial effects. Robust standard errors are adjusted for clusters in movies and destinations.

destination-specific characteristics are not qualitatively different from those reported in Table 2.

4.3 Movie Trade and Cultural Affinity

In this section I consider how countries' different propensities to import U.S. movies might be interpreted as cultural differences. To identify a cultural component from the destination fixed effects, I estimate the entry equation of two samples of movies. Each movie in the IMDb is assigned one or more genre. Typically, movies will be assigned more than one genre; for example, *drama-musical*, or *romance-comedy.* It is well known in the industry that *drama* and *comedy* movies do not travel as well overseas as *action*, *adventure*, or *thriller* films.[12] I code a movie as culturally dependent if *comedy* or *drama* is listed among its genres, but *action*, *adventure* and *thriller* are not. A film such as Jackie Chan's *Rush hour* (1998) is considered an *action-comedy-thriller-crime* movie, according the IMDb's genre data. I would therefore not code it as culturally dependent.

Table 4 reports estimates of the entry equation for a linear probability fixed effects model. The effect of U.S. box-office revenue is robust to the reduced sample size. Culturally dependent movies are less likely to enter an average destination, as predicted. A *comedy* or *drama* would have to be about one-third of a standard deviation higher in quality in order to have the same probability of entry as its culturally neutral counterpart. Moreover, the interaction term suggests these movies are about 25% less sensitive to quality. In column 4 I include destination-genre fixed effects. Differencing these fixed effects by destination will give the measure of cultural distance from the United States. I call this measure the country's "Hollywood distance" because it is estimated using U.S.

[12]Film distributor Hammad Zaidi (2010) writes that, "When it comes to comedies, romantic comedies, dramas, coming-of-age films, personal stories, family films...you have a better chance of winning the lottery than you do of enjoying healthy sales internationally...The reason that most genres don't work overseas is because their content is specifically designed to work within the country they were made. For example, in comedies, what's funny in Los Angeles may not be funny in Zimbabwe and in romantic comedies, what's romantic in Nashville may be offensive in China."

Table 4: Probability of Foreign Release: Genre Effects

Model:	(1)	(2)	(3)	(4)
Depvar:	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$	$Entry_{dm}$
logUSrevenue$_m$	0.097***	0.094***	0.112***	0.094***
	(0.010)	(0.010)	(0.014)	(0.010)
Comedy-Drama		-0.032***	-0.031***	
		(0.009)	(0.009)	
Comedy-Drama X logUSrevenue$_m$			-0.031***	
			(0.011)	
Destination FE	Yes	Yes	Yes	No
Dest-Genre FE	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	61,576	61,576	61,576	61,576
R^2	0.41	0.42	0.42	0.42

Note: Linear probability model. Statistical significance of 1% is indicated by ***.
Robust standard errors are adjusted for clusters in movies.

movies. Recall that it is not strictly a measure of the country's Hollywood (dis)affinity, however, because it is based on the difference in propensity to import genre-types. Any general affinity toward U.S. movies is thus wiped out. There is an extra degree of freedom in estimating a full set of fixed effects in addition to a constant. An arbitrary restriction must therefore be imposed. I choose to normalize so that the minimum value of Hollywood distance is zero.

A potential issue of using the linear probability model is that predicted probabilities could lie outside the $[0, 1]$ interval. For column 4 of Table 4, there are 1,910 observations with a predicted probability less than zero, all but 79 of which (i.e. 96%) are associated with no entry. The range of predicted probabilities is $[-0.25, 0.88]$; the percentage of out-of-bounds observations is 3.1%.[13]

Figure 4 provides a histogram of Hollywood distance. There is a large group of countries with a relatively low Hollywood distance, and the number of countries falls as

[13] As a robustness check, I also estimated a probit model with fixed effects, which potentially suffers from the incidental parameters problem. The resulting Hollywood distance has a correlation coefficient of 0.99 with the index reported using LPM estimation.

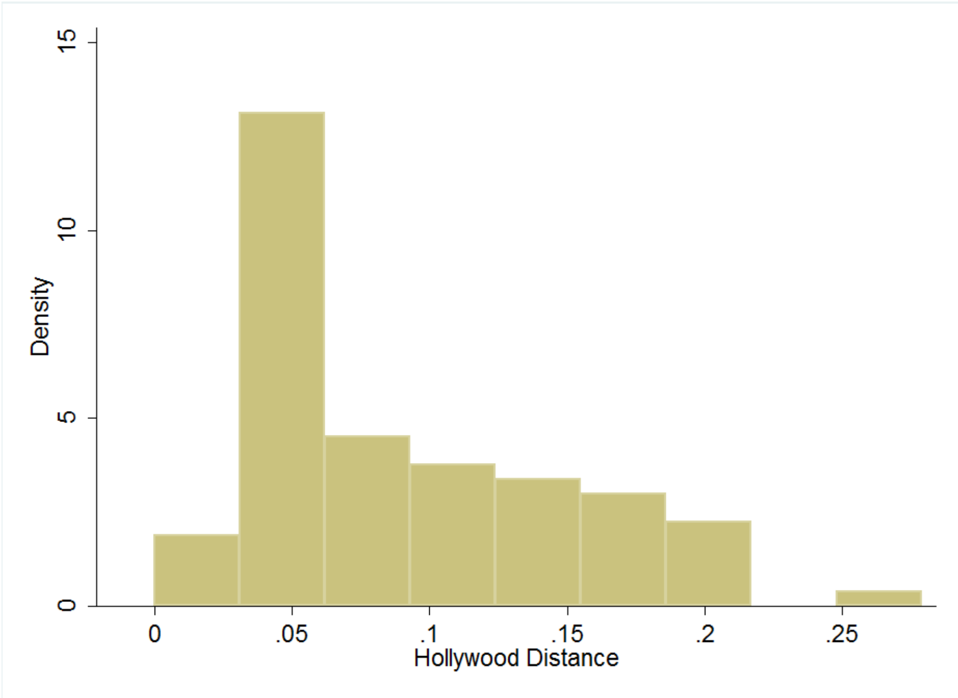

Figure 4: Histogram of Hollywood Distance

the distance increases. There is no particular interpretation one can give to the specific values of the measure. To interpret the economic significance of Hollywood distance, we can investigate how it compares to other measures of cultural distance, and how much it is associated with economic outcomes, like international trade. Figure 5 plots Hollywood distance versus geographic distance. Reassuringly, Canada has the lowest cultural distance, while Kuwait is by far the most “distant”. With the exception of Mexico, geographically proximate countries are also culturally close to the United States. The correlation coefficient for Hollywood distance and log geographic distance is 0.23 with a p-value of 0.036.

We can also compare Hollywood distance to other indices of cultural distance or similarity. The correlation coefficient between the variable and an index of language similarity among Indo-European languages, constructed in Dyen et al (1992), is 0.19, but is not statistically significant (p-value of 0.13). The correlation with a measure

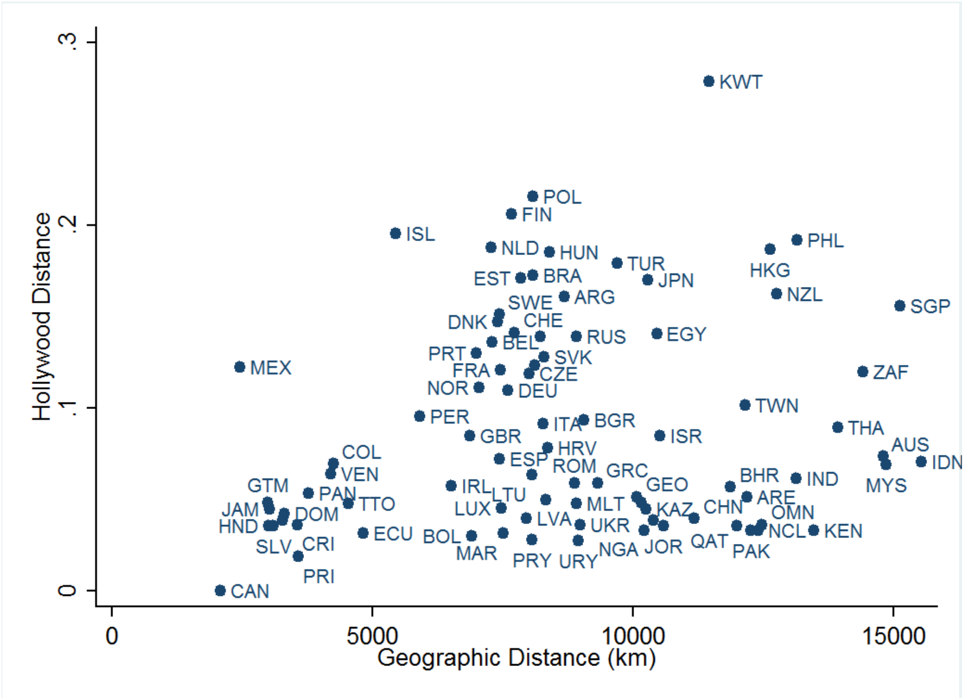

Figure 5: Hollywood Distance versus Geographic Distance

of genetic distance, measuring the degree of genetic diversity due to allele frequency differences among populations (Cavalli-Sforza et al., 1994), is -0.10 but is also statistically insignificant (p-value of 0.34). Hollywood distance is also insignicantly correlated with a measure of religion similarity, defined as the probability that an individual from one population will share the same religion as a randomly chosen individual from the other population (correlation coefficient of 0.03, p-value of 0.75).

While Hollywood distance is correlated with geographic distance, it does not appear to correlate with other measures of cultural distance, related to language, genetic drift, or religion. But does Hollywood distance capture an economically meaningful component of culture? To investigate further, I include it as a covariate in a standard gravity equation of U.S. international trade in goods. If Hollywood distance captures cultural distance between the United States and its trading partners, and if cultural distance is an impediment to trade in goods, then we expect Hollywood distance to be negatively related to the value of bilateral trade.

I obtained industry-level bilateral exports between the United States and each of the 82 countries in my movies sample for the years 2002 to 2004. The data is from The Center for International Data at UC Davis. I merge the export data with the CEPII gravity covariates and Hollywood distance. Disdier et al. (2010) match HS6 industry descriptions to a UNESCO definition of cultural goods. I use their list of HS cultural sectors to code each of the industries in the sample as "cultural" or "not cultural", and aggregate the industry trade volume data for each partner-year according to this variable. Table 5 displays the results of running different specifications of a gravity equation. The first column includes the traditional gravity variables of geographic distance, exporter GDP and importer GDP, in addition to Hollywood distance and a dummy variable for cultural goods trade. The elasticities of distance and the two GDP measures with respect to trade volumes are approximately equal to one in magnitude, in line with the existing gravity literature.[14] The coefficient on Hollywood distance is negative and statistically significant, and implies that a one-standard-deviation increase in Hollywood distance is associated with a 10% decrease in bilateral trade.

Column 2 reports results for the specification where other bilateral gravity variables are included. These variables all enter significantly except for colony, which indicates a common colonial relationship. The coefficient on Hollywood distance turns positive and loses statistical significance. In this specification, the new variable does not have explanatory power above and beyond existing gravity variables. In column 3, I add an interaction term between the cultural industry dummy and Hollywood distance, to identify whether a different relationship exists for the two types of trade. Surprisingly, the interaction is positive and significant, whereas the implied effect on non-cultural trade turns negative, but remains insignificant. In column 4, I run the same specification but omit trade flows involving Kuwait. Recall that Kuwait is a large outlier on the Hollywood

[14] See Disdier and Head (2008).

Table 5: U.S. Bilateral Trade, 2002-2004

Model:	(1)	(2)	(3)	(4)
Depvar:	ltrade	ltrade	ltrade	ltrade
Hollywood distance	-0.101**	0.0360	-0.0674	-0.122**
	(0.0446)	(0.0555)	(0.0504)	(0.0503)
Cultural dummy	-5.725***	-5.727***	-5.739***	-5.703***
	(0.0808)	(0.0752)	(0.0750)	(0.0733)
log Distance	-0.858***	-1.055***	-1.056***	-1.047***
	(0.0910)	(0.129)	(0.128)	(0.126)
log GDP_o	1.120***	1.078***	1.078***	1.070***
	(0.0273)	(0.0330)	(0.0333)	(0.0313)
log GDP_d	1.123***	1.080***	1.080***	1.077***
	(0.0272)	(0.0292)	(0.0295)	(0.0289)
Border		-0.703**	-0.703**	-0.670**
		(0.279)	(0.284)	(0.281)
English		0.505***	0.505***	0.498***
		(0.174)	(0.173)	(0.173)
Colony		0.284	0.284	0.287
		(0.215)	(0.215)	(0.212)
FTA		1.116***	1.117***	1.113***
		(0.133)	(0.132)	(0.130)
Currency Union		0.300*	0.301*	0.312**
		(0.162)	(0.156)	(0.153)
Comm. Legal Origin		0.569***	0.570***	0.575***
		(0.182)	(0.181)	(0.181)
Cult X Holly. dist			0.210**	0.353***
			(0.0924)	(0.0769)
N	963	963	963	952
adj. R^2	0.879	0.897	0.897	0.903

Note: Column (4) omits imports from and exports to Kuwait. Statistical significance of 1%, 5%, and 10% indicated by ***, **, and *, respectively. Robust standard errors in parentheses.

distance scale. Results indicate that Kuwait is influencing the previous estimates. The coefficent on Hollywood distance becomes significantly negative, doubling in absolute value to -0.122.

This result is consistent with interpreting Hollywood distance as an index of cultural distance, with larger values associated with either higher costs of trade or lower congruities in demand. Curiously, cultural goods are traded more intensively as Hollywood distance increases. One reason for this unexpected result is that the value reported in trade statistics is of the physical products moving across borders. It is possible that this trade could be determined more by comparative advantages in production than lower transaction costs due to closer cultural understanding.

5 Conclusion

In this paper I developed a simple model of international trade in a heterogeneous unit-demand product. Foreign revenues are rising in variety quality and destination-country size and wealth. Fixed costs of entry imply that only varieties that are appealing enough will be exported. Using U.S. box-office revenue as a measure of movie quality, I test how well U.S. movie exports adhere to this hierarchy. Graphical techniques suggest that selection is important, but leave room for destination-movie-specific demand shocks to play a role in foreign entry decisions. I use direct and revealed measures of movie quality to look for a systematic role for movie quality in export decisions. Estimates suggest that a one-standard-deviation increase in the (log) U.S. box-office revenue from the average leads to an eight-to-eleven percentage point increase in the probability of entry. This compares with an overall probability of 17% in the sample.

I exploit data on movie genre to estimate a measure of cultural distance ("Hollywood distance") between destination countries and the United States. This measure of cultural distance is correlated with geographic distance, but uncorrelated with prominant other indices of cultural distance. Hollywood distance is associated with lower bilateral trade volumes between the United States and its trading partners, but higher apparent trade volumes for cultural industries.

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