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Globalization and Heterogeneity: Evidence from Hollywood

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Abstract: Linder (1961) conjectured that taste differences could impede trade flows. We extend Krugman (1980) to allow for producers that face taste heterogeneity with volatile demand. Consumers are characterized by different taste over product attributes and idiosyncratic risk. Firms face a portfolio type of problem where they trade off supplying the largest consumer groups against higher exposure to group-specific risk. We develop an empirical strategy to estimate consumer taste from observed market shares across multiple distinct markets of the same product, as well as the key parameters that pin down the firm's portfolio choice problem. We apply our framework to estimate the impact of the rise of China on the global movies market and characterize the heterogeneous welfare effects across countries.

JEL classification: F11, F14

Key words: taste heterogeneity, volatility, gains from trade

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1 Introduction

"For now, the China market remains at once too great an opportunity to disregard and too unpredictable to rely on."

Rance Pow, president of Artisan Gateway

International trade allows firms to reach a large customer base across multiple countries. However, for many products customers across countries have different tastes over product attributes and design.[1] It is also well-known that exporting is a risky endeavor driven by large volatility in demand.[2] The combination of risk and heterogeneous tastes poses a challenge to firms who sell products which are difficult or impossible to customize: these firms can either cater to the largest group of consumers with their product design and be exposed to idiosyncratic swings in that group's demand, or embrace a design that caters to a more diversified customer base, but at the cost of foregoing revenue in the most important markets. While practitioners have recognized this trade-off, in the literature the implications of international trade are typically evaluated using representative agent models that abstract from taste heterogeneity (Arkolakis, Costinot and Rodríguez-Clare, 2012). Furthermore, the implications of volatile demand - in particular how it intersects with taste heterogeneity across markets - are even less explored in the trade literature.[3]

In this paper, we examine welfare consequences of globalization when firms develop products for heterogeneous consumers across countries and when furthermore demand is volatile across countries. We incorporate this logic into both a stylized and quantitative trade model and characterize the equilibrium distribution of supply and welfare. We apply our methodology to the movie market[4] where most product characteristics are easily observable and price competition is less important than for other products. We focus on a large change in the composition of that market driven by the rise of China at the beginning of the century and its impact on the product

[1] See Coşar et al. (2018) and Auer (2017) for some evidence.

[2] For recent evidence on this compare Eaton, Kortum and Kramarz (2011), Munch and Nguyen (2014), Esposito (2022) and di Giovanni, Levchenko and Mejean (2014).

[3] As we will discuss below, recent exceptions that explore either taste heterogeneity are given by (Auer, 2017; Coşar et al., 2018) and recent exception that explore the relationship between trade and volatile demand is given by Allen and Atkin (2022) and Esposito (2022).

[4] While we focus on movies because data are easily available and mostly uniformly priced, our results have implications for other sectors, where customization is very costly.

composition in this market. We find that after the increase in the Chinese movie import quota in 2012 the distribution of movies becomes flatter with a share of movies moving closer to the taste of Asian audiences. This change in product design lead to a large drop in welfare for regions, whereas Asia gained from the policy change.

We hand collect data about international movie box office and movie characteristics from different sources. Our data accounts for a large share of the US movie market and about half of the revenue generated with movies globally. About half of the revenue by the Hollywood movies in our sample is generated abroad. As in other sectors, China's importance as an outlet for Hollywood movie has increased dramatically since the early 2000s.

We start by investigating the consequences of the change in the composition in demand using the discrete increase in China's importance for the movie market in 2012. We run a difference-in-difference estimation of the correlation of market shares between the US and Hong Kong and the US and Western Europe. While the market shares show a common pattern before 2012, we find a bi-furcation of market shares after the Chinese liberalization: the covariance increases between the US and Western Europe, and decreases between the US and Hong Kong. At the movie level, we find the post-2012 to be stronger for types of movies which are likely to be greenlighted by Chinese censors, i.e. unrated movies, action movies, but not, for example, for Comedy movies or movies involving nudity.

Table 1 shows that the US and Hong Kong, which we use as an unrestricted market with Chinese taste, shared four out five movies in the list of the best-performing movies before China increased its import quota for foreign movies. In the period after the Chinese policy change, however, their top five lists have only one movie in common. We find that this divergence in movie success continues to hold in a large sample of movies.

We also find that Hollywood studios decreased their investment into R-rated movies, Comedies and re-directed funds towards Sci-Fi movies, and co-productions with Chinese production companies. Our results are robust to restricting the sample to movies released in China. A change in the type of movies produced by Chinese production companies around 2012 is unlikely to account for our results, because we also observe a change relative to Western Europe, where the movie market was more stable. Because falling DVD sales and increasing popularity of streaming services were multi-year trends, these changes are also unlikely to explain the discontinuous change in market share correlation around 2012.

We then develop a stylized theoretical model that can rationalize the key developments in the movie market. The model combines two separate elements. On the one hand, we allow for

Table. 1. Top 5 Movies by Market Share

Rank	Year	US	Hong Kong
2008-2012			
1	2009	Avatar	Avatar
2	2012	The Avengers	Toy Story 3
3	2008	The Dark Knight	Transformers: Dark of the Moon
4	2012	The Dark Knight Rises	The Avengers
5	2010	Toy Story 3	The Dark Knight
2013-2017			
Rank	Year	US	Hong Kong
1	2015	Star Wars: Episode VII - The Force Awakens	Iron Man 3
2	2017	Star Wars: Episode VIII - The Last Jedi	Captain America: Civil War
3	2015	Jurassic World	Avengers: Age of Ultron
4	2016	Rogue One: A Star Wars Story	Transformers: Age of Extinction
5	2017	Beauty and the Beast	Jurassic World

The top panel lists the top 5 movies by market share in the US and Hong Kong from 2008 until 2012, i.e. before China increased the quota for foreign movies from 20 to 34 in 2012. The bottom panel also shows top 5 movies by market share, but for the period after the quota increase 2013 until 2017. Colored cells indicate movies which are both in the US and Hong Kong Top 5 in each period.

consumers to have have heterogeneous (homothetic) preferences over differentiated products. To do so, we incorporate an address based description of consumption as in Anderson et al. (1992) and characterize distinct consumer groups with bliss points - their address - in an arbitrary taste space. On the other hand, on the supply side, firms face a market that is composed of heterogeneous consumers and each consumer group has volatile preferences. Firms enter this market by paying a fixed cost to supply a product at different points of this taste space. Different proximity to different bliss points in that space determines both the total revenue of the product, but also the overall risk, with products that more heavily rely on one single group of consumers are more exposed to that group's idiosyncratic risk. We follow the finance literature Campbell (2017) and characterize the firm's supply choice in terms of a portfolio choice.[5]

[5]This approach towards incorporating both first and second moment considerations into trade models has recently been adopted by Allen and Atkin (2022) and Esposito (2022). Our approach differs significantly to both of these papers. Allen and Atkin (2022) focus on the impact of market integration and risk considerations on crop choice in a developing country context and Esposito (2022) introduces volatile demand into a monopolistic competition model. Instead we focus on how product-level volatility arises endogenously due to differences in taste across markets.

The equilibrium distribution of products across the taste space is then determined by the trade-off between return and risk, where market composition determines both jointly. The supply response determines the product composition. Heterogeneity in preferences implies heterogeneous welfare across consumer groups. We characterize the equilibrium response to changes in the population distribution across consumer groups and the resulting welfare consequences.

We then turn towards applying our model quantitatively to analyze the movies market. In a first step we extend the model to an arbitrary number of locations across a discretized but unrestricted taste space both on the supply and demand side. We then turn towards estimating the model on our data. To estimate the demand parameter we proceed in two steps. We first employ a contraction mapping following Berry and Waldfogel (2010) to back out the average quality shifters across all countries. In a second step we then obtain the bilateral taste shifters for a movie across all countries. By construction the global quality shifters are orthogonal to the bilateral taste shifters. In a final step, we then estimate two dimensional taste space that fits and rationalizes the observed bilateral taste shifters. The estimation is seemingly challenging because of its high dimensionality, but it shares properties with a sequential trilateration problem - a convex optimization problem with strong convergence properties. In a final step, we estimate the key parameter pinning down the firm's supply choice, by estimating the risk aversion parameter which is pinned down by the indifference curve between expected returns and volatility at the product level.

We use the quantitative model to estimate the distributional welfare effects of the rise of China. We find that after the increase in the Chinese movie import quota in 2012 the a share of movies moved closer to the taste of Asian audiences. This change in product design led to a significant drop in simulated welfare for all regions, but Asia. The simulated model incorporating both first and second moment effects of the market composition on the equilibrium is needed to rationalize the observed welfare movements. Our results provide a quantitative argument in the debate about China's influence on US industries, in particular the movie industry (Tager (2020), Li (2021)).

This paper contributes to two distinct literatures. First, it contributes to a long-standing literature that, beginning with Linder (1961), examines the impact of taste heterogeneity on international trade flows. More recently, the literature has focused on non-homothetic preferences and income heterogeneity across countries (Foellmi, Hepenstrick and Zweimüller, 2017; Fieler, 2011; Fajgelbaum, Grossman and Helpman, 2011). As mentioned before Auer (2017) develops a trade model similar to ours and shows that the endogenous supply response compensates for taste differences. We contribute by providing a theoretical rationale where taste heterogeneity affects product composition via both a first and second moment effect. We also propose an intuitive methodology to estimate, analyze and visualize taste heterogeneity as a low-dimensional taste space. We illustrate the significance of the first and second moment channel for welfare effects for the international box office.

Second, the paper contributes to the literature on 'preference externalities' with a particular focus on creative content markets. The idea of preference externalities has been widely examined in (Waldfogel, 2003; George and Waldfogel, 2003; Ferreira and Waldfogel, 2013; Ferreira, Petrin and Waldfogel, 2012; Berry and Waldfogel, 2010). Closest to our current paper, Ferreira, Petrin and Waldfogel (2012) also examines the international box office and finds that half of the gains from trade in movies come higher quality, which is possible due to the larger market size, while the other half comes from the larger choice of movies available to consumers. We augment the analysis by isolating the distributional welfare effect across countries with distinct preferences and incorporate the volatility channel into the analysis.[6]

The structure of the paper is as follows. Section 2 provides background on the international box office and introduces the data. Section 3 then proceeds to provide reduced-form evidence on the presence of both the preference externality and volatility channel in the revenue data. Section 4 introduces the trade model incorporating consumer heterogeneity. Section 5 describes how to estimate the taste space from market share data, and conducts the counterfactual welfare analysis quantifying the effect of China's rise in the international movie market on the welfare across different countries. Section 6 concludes.

2 Background and Data

In this section, we describe the change in the Chinese movie import quota which created a large discontinuous change in the composition of the audience of Hollywood movies. We also introduce the hand-collected dataset that allows us to document the consequences of this regulatory change.

[6] An additional distinction is that while Ferreira, Petrin and Waldfogel (2016) study the preference externality impact of the increasing importance of China in the movie market, we allow movies to have different taste locations but focus only on Hollywood movies, whereas they study movies coming from different countries, but restrict differences in a movie's taste location to its country of origin. Furthermore, different from Ferreira, Petrin and Waldfogel (2012) we focus Hollywood movies as a product that differs from movies from other countries and study how a change in the composition of audiences affected the quality and taste distance of movies. They focus on the quality channel and the impact of having different varieties of movies available.

2.1 Background: Hollywood and China

China has traditionally restricted the entry of foreign movies by quotas. Until 1994 no foreign movies were shown in China. Between 1994 and 2001 regulators selected 10 foreign productions per year which could be shown on Chinese movie screens. After 2001 the quota was further increased to 20 movies per year, where it remained until Februay 2012. Starting from 2021, the quota was again increased to 34 foregin movies and the share of boxoffice revenue foreign studios received was also increased from previously 13% to 25%. The additional 14 spots were reserved for 3-D or IMAX movies. The combination of the increase in the quota and the larger share of revenue constitutes a large, discontinuous increase in demand for Hollywood studios from China.[7]

2.2 Data

We have hand-collected data from two sources: Our main data come from BoxOfficeMojo,[8] which has information about boxoffice revenues for a lot of countries for each movie, country-specific release dates, and various movie characteristics. We add data from the International Movie Database (IMDB) which contains information about whether a movie is a sequel, a remake or a spin-off. The IMDB data also has information about the movie cast as well as production locations. IMDB and BoxOfficeMojo have a common identifier for movies, which allows us to combine the information from the two datasets accurately.

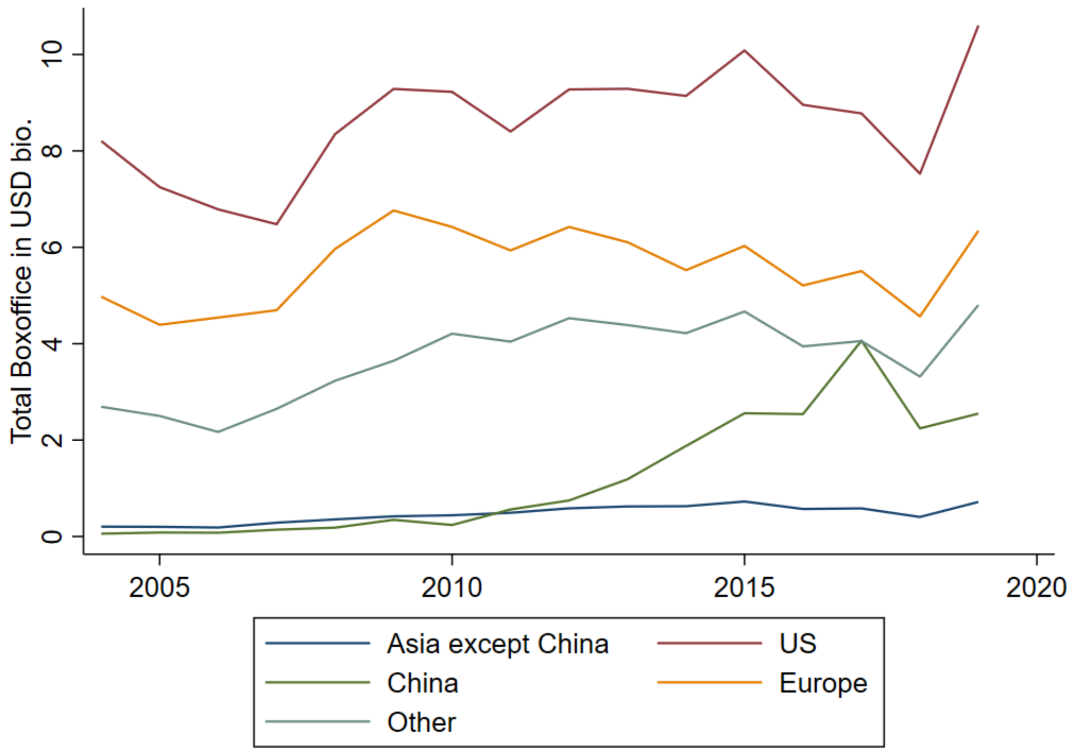
Sample. Our sample starts in 2004 when the international boxoffice revenue becomes reliable. We end our sample in 2019 to avoid the complications involved by including data from the pandemic. We exclude movies with missing information about the production budget and no information about boxoffice revenue outside the US. The final dataset contains 1946 movies including boxoffice revenue data from up to 53 countries. The movies in our final sample account for 80% of total boxoffice revenue in the US and about 50% of global boxoffice revenue on average over the sample period (Appendix Figure A.3). Table A.1 shows summary statistics of our main variables. On average, movies in our sample generate almost half of their boxoffice revenue abroad and the they are very profitable: the median return in our sample is almost 100%.[9] Our sample contains almost exlusively US productions, where some of these movies are co-produced

[7]We are not the first to use this regulatory change as a source of arguably exogenous variation. Hermosilla, Gutierrez-Navratil and Prieto-Rodriguez (2018), for example, study whether Hollywood studios catered more to Chinese audiences' preference for actors with fair skin after 2012.

[8]retrieved in April 2020

[9]First, our production costs are likely to underestimate the true cost and, second, our data filters are likely to select more profitable movies.

Figure 1. Evolution of the International Movies Market



Notes: Total annual boxoffice by group of country. Other countries include African, Middle Eastern, and South American countries and Japan, Australia and New Zealand.

with studios from other countries. In sum, our sample consists mainly of Hollywood productions which rely heavily on foreign audiences to generate revenue.

Evolution of the International Movies Market. Our dataset allows us to to track the relative importance of different audiences for Hollywood boxoffice revenues. We sort countries into regions and plot total annual boxoffice revenue over time in Figure 1. While the relative importance of different regions varies little over time, the stunning increase of the importance of the Chinese market after 2012 stands out.

3 Hollywood and China: Stylized Facts

In this section, we document two stylized facts using the boxoffice data and exploiting the change in the composition of foreign audience after China's liberalization of movie imports in 2012.

3.1 Demand Externality

The policy change in 2012 increased demand for foreign movies from China, but did the liberalization also change the type of movies produced by Hollywood studios? Anecdotal evidence reported by Tager (2020) and Li (2021) suggests that Hollywood indeed adapted to the new situation, mainly by avoiding issues sensitive to Chinese censors. Although we cannot disentangle the two motives, we also expect that Hollywood studios have changed movies towards the taste of Chinese *audiences* and not only the Chinese censors.

We quantitatively test whether the appeal of Hollywood movies to Western and Eastern audiences changed after 2012, by comparing how Hollywood movies fared with local audiences in the West and the East before and after 2012. Similar to Ferreira, Petrin and Waldfogel (2016), we focus on Hong Kong to study how well Chinese audiences liked a particular movie. While Hong Kong's population is mostly Chinese, Hong Kong never restricted the number of foreign movies and thus constitutes a better comparison group to Western markets than mainland China.

We use our country-level box office data introduced in the previous section to construct location-specific market shares for Hong Kong and the US. To control for changes in the way Hollywood studios exported movies abroad unrelated to China, we also include Western Europe as a control group. In our baseline regression, we restrict our sample to movies released in China, but results are similar (Appendix Table A.5) when extending the sample to all movies released in Hong Kong and Western Europe. We also limit the sample to movies released between 2008 and 2016 to keep a closer window around the policy change. To test for a change in taste differences, we regress the market share of each movie in the US on the market share of the same movie in Hong Kong and in Western Europe. We use the regulatory change in 2012 for the difference in difference regression:

$$\begin{aligned} MarketShare_{m,t,US} = \alpha_c + \gamma_t + \beta_1 MarketShare_{m,t,c} + \beta_2 MarketShare_{m,t,c} \times Post_t \\ + \beta_3 MarketShare_{m,t,c} \times HK_c + \beta_4 MarketShare_{m,t,c} \times HK_c \times Post_t \end{aligned}$$

with $Post_t$ indicating years after 2012, and HK_c indicating observations of Hong Kong.

Stylized Fact 1: Market Polarization between East and West.

The difference in difference estimates in Table A.3 indicate a polarization of markets after 2012. We find a statistically significant increase in the comovement of market shares between the US and Western Europe, and an decrease in the comovement of market shares between the

US and Hong Kong in the Post period across all columns. Column (1) shows OLS estimates whereas Columns (2) and (3) also include time and region fixed effects. Column (3) also includes several movie characteristics as control variables. The decrease in the comovement of market shares between Hong Kong and the US becomes larger and statistically significant when adding controls to the regression in column (3), relative to column (2). This indicates that the divergence between Hong Kong and the US likely comes from unobserved movie characteristics.

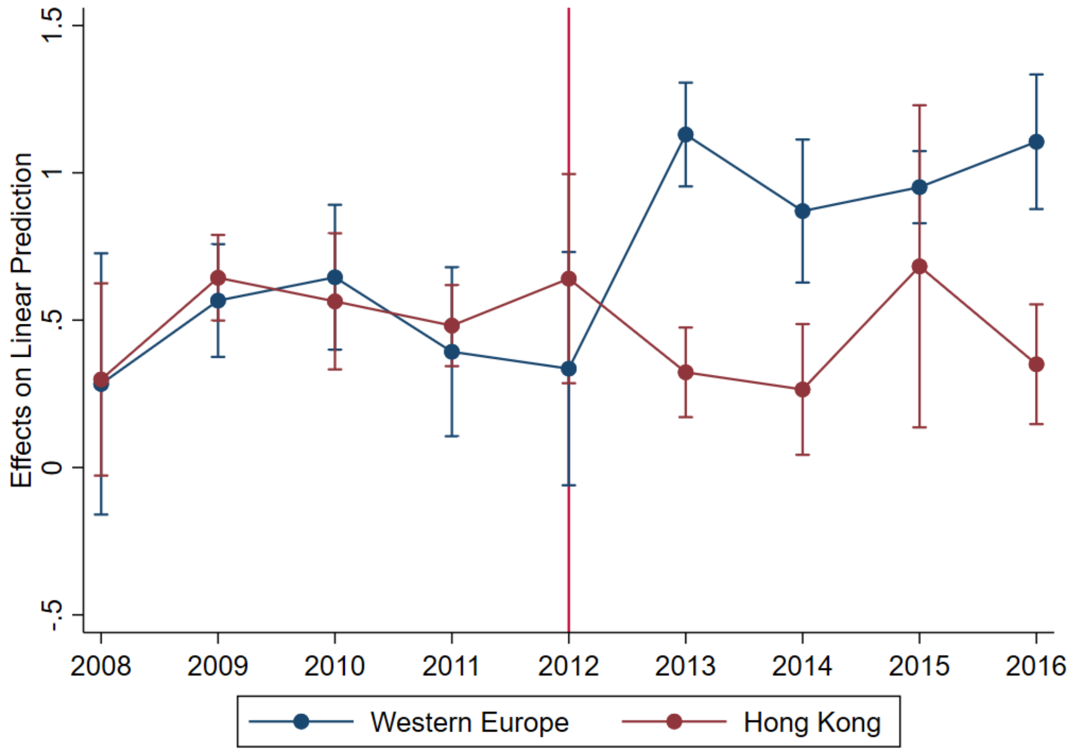
As for the economic magnitude, the estimates in Column 3 of Table A.3 correspond to a 90% increase relative to the pre-2012 period for Western Europe and a 45% decrease in the comovement of market shares between Hong Kong and the US. The regression results indicate that Hollywood studios changed movies leading to a bi-furcation in the comovement of market shares. Figure 2 illustrates this bi-furcation graphically by showing separate regression coefficents for each year representing the comovement of US and Hong Kong and US and Western European market shares respectively. There is a clear change between the pre-2012 period where the comovement is closely aligned and the post-2012 period where the coefficients differ significantly for all but one year.

In Online Appendix C, we explore the source of the bi-furcation in more detail: we find that the correlation does not change for R-rated movies, but for movies with a less restrictive rating, such as G, PG, or PG-13. Because Chinese censors almost never approve R-rated movies to be shown in China this provides support for our interpretation. Hollywood studios have left R-rated movies unchanged after China's policy change, but changed movies that can potentially be approved by Chinese censors. We also find no change in the correlation for comedy movies, crime movies, and movies showing nudity, which are movies that are more difficult to translate (comedy movies) or less likely to pass censors (crime, nudity).

Alternative Explanations. Between 2008 and 2016 Hollywood also faced a strong decline in DVD sales and increasing competition from streaming services. While we think that Hollywood studios probably also have changed the type of movies produced in reaction to these challenges, both the decline in DVD sales and the increasing popularity in streaming services do not exhibit a discontinuity similar to the Chinese import liberalization before and after 2012.

Finally, a change in the type of movies produced in China around 2012 might have caused the lower correlation between the US and Hong Kong (where Chinese Movies are also shown). But, if our result was only driven by changes in the Chinese movie production, we should not observe a change in the correlation between the US and Western Europe, where the type of movie produced has not changed dramatically around 2012.

Figure 2. US and Hong Kong Box vs US and Western European Box Office Revenues



Notes: Covariance of market shares between the US and Western Europe (blue) and the US and Hong Kong (red) obtained from a regression of US market shares on Western European and Hong Kong market shares with 95% confidence intervals. The sample is limited to movies released in China and produced, at least in part, in the US.

3.2 Sequels, Remakes, and Spin-offs

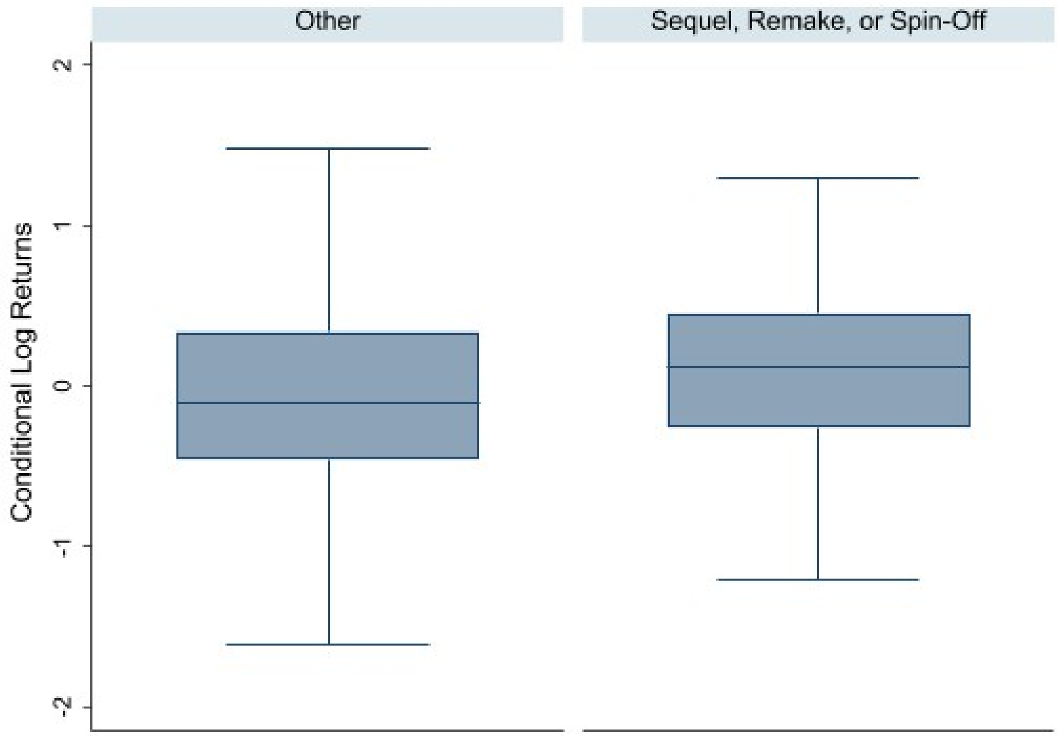
In this subsection, we document two related stylized facts about sequels, remakes, and spin-offs. While there are numerous complaints about the increase in non-original content,[10] our data allows us to quantify the increase precisely. We use the information on the IMDB movie connections page, which lists predecessors and successor movies as well as other connections to movies, to classify movies in our sample. Sequels continue the story of the predecessor movies, remakes are a new version of an older production, and spin-offs are side-stories of previous movies developed into a full movie. A limitation of our data is that we cannot distinguish between a sequel movie which has been planned as such, and sequels planned and produced only after the success of the initial movie.

Stylized Fact 2(a): Sequels, Remakes, and Spin-offs have lower return variance.

For the first stylized fact we compute movie returns as $\frac{\text{Boxoffice}-\text{Production Budget}}{\text{Production Budget}}$. The production

[10]See, for example, The Atlantic 2016 and Cosmopolitan 2021.

Figure 3. Distribution of Residual Returns



Notes: Distribution of log returns of non-original movies and all other movies. The log returns are residuals after conditioning on log production budget, runtime, indicator variables for the country of production, the genre, the release year, and whether the movie is rated-R or not. Raw returns are computed as total revenue minus production budget divided by the production budget.

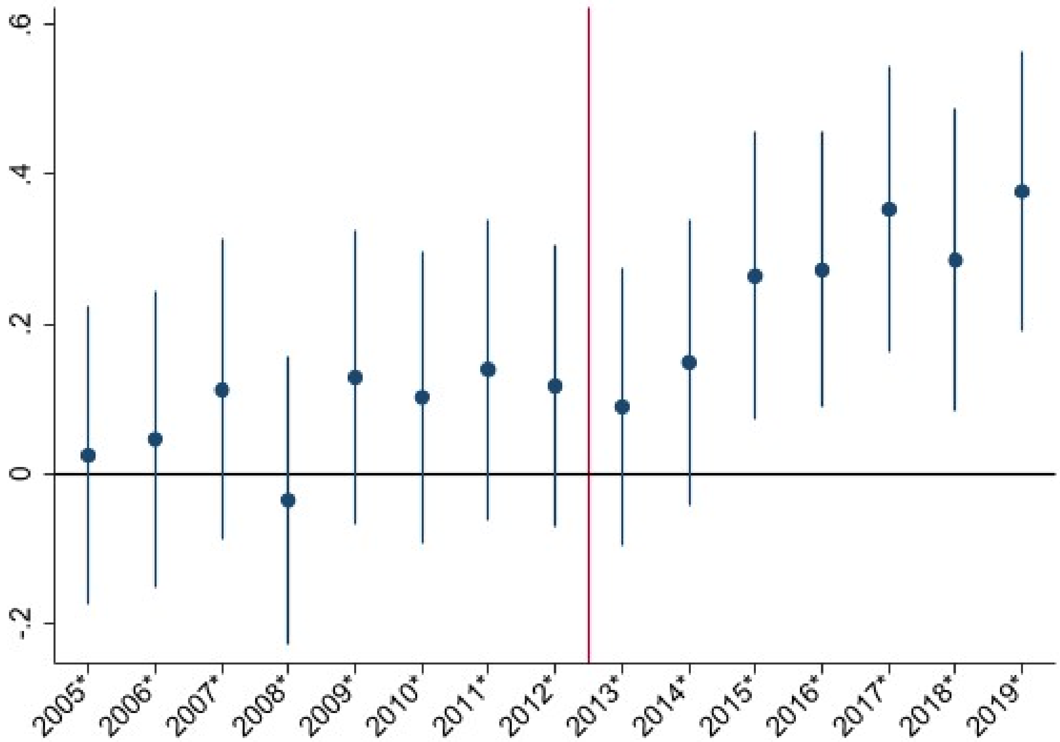
budget is often only estimated and does not include advertisement and distribution costs but unfortunately data for these additional costs are not readily available. We then purge the returns of different factors by running a regression of log of returns as the dependent variable and log budget, the genre of a movie, the production country, and run-time as indenpendent variables. Figure 3 shows the distribution of the residual movie returns both for sequels, remakes, and spin-offs as well as for all other movies. Non-original movie productions have a compressed residual return distribution relative to all other movies, and they also offer a higher average residual return.[11] As suggested by news articles (see above) sequels, remakes, and spin-offs are a popular choice with Hollywood studios because they offer safer, and on average higher returns.

Stylized Fact 2(b): Sequels, Remakes, and Spin-offs are more frequently chosen after 2012.

We now investigate the effect of the 2012 Chinese movie import quota liberalization had on Hollywood studios' decision to produce a non-original movie. Figure 4 shows the budget-

[11]The average *residual* movie return is zero by definition.

Figure 4. Share of Sequels, Remakes, and Spin-offs



Notes: Coefficients indicating the share of sequels, remakes, and spin-offs each year relative to the baseline year 2004. Observations are weighted by production budget.

weighted share of sequels, remakes, and spin-offs produced each year, relative to the first year in our sample, 2004. Before 2012, the share of non-original movies produced is never statistically different from the baseline year. After 2012, however it is statistically different for the last five years in our sample. The share of non-original movies increases around 30 percentage points relative to 2004 towards the end of our sample. It seems that the increase in the importance of Chinese audiences after 2012 has also led to higher risk, which Hollywood studios have tried to address by producing more movies with non-original content.

The change in the comovement of market shares and the increase in the share of production budget allocated to sequels, remakes, and spin-offs after 2012 points to a potentially important change in how Hollywood studios produced movies. In the following, we build a structural model of product design, heterogeneous taste and uncertainty. We will then study the increased importance of China through the lens of the model.

4 Theory: Heterogeneous Demand and Volatility

The aim of this section is to extend Krugman (1980) by incorporating two dimension. First of all, we allow for consumers to have have heterogeneous (homothetic) preferences over differentiated products. To do so, we incorporate an address based description of consumption as in Anderson et al. (1992) and characterize distinct consumer groups with bliss points - their address - in an arbitrary taste space.

On the supply side, firms then face a market that is composed of heterogeneous consumers. Firms enter this market by paying a fixed cost to supply a product at different points of this taste space. Different proximity to different bliss points in that space determines the total revenue of the firm and thus the total number of firms that supply across the 'taste space'.

To enrich the supply side of the model we also incorporate volatile demand. Firms then have to trade-off targeting specific consumer groups versus being more exposed to that group's idiosyncratic risk. This channel is novel to the literature.[12]

4.1 Setup

There is one global market, populated by a mass of L consumers. Consumers belong to a finite set of distinct consumer groups, $i \in \mathcal{I}$. Each consumer has preferences over a homogenous outside good and over a finite set of differentiated varieties. Each distinct consumer group is characterized by a bliss point $v_i \in \mathcal{S}$, where $\mathcal{S}$ is a closed bounded set of a finite dimensional Euclidean space, which we call the *taste space*. Each firm is also characterized by a position in the taste space $a_j \in \mathcal{S}$ that represents its product characteristics. Utility derived from consuming a differentiated variety is decreasing in the distance between the bliss point and the product position, $\mathcal{D}(v_i, a_j)$. This distance in the taste space reflects how well the product matches the specific preferences of each consumer group.

4.2 Demand and Welfare

Each consumer is endowed with income $\theta_i = \theta$. The fraction of the population allocated to each consumer group is given by $\pi_i \in [0, 1]$. We posit a random utility model (RUM), and independent

[12] While demand risk and its impact on trade has been recently explored by Esposito (2022) our model traces out how the heterogeneous taste endogenously creates risk for different products in the taste space which creates a unique trade-off on the supply side and channel that determines the product composition in the market and the welfare distribution across markets.

of the bliss point, each consumer is also endowed with a product-firm specific preference shock ε_{ij}. The utility of a consumer i with fixed bliss point v_i is given by,

$$U_i = (o_i)^{1-\alpha} \left(\sum_{j \in J} q_{i,j} \times \delta_j \times \mathcal{D}(v_i, a_j) \times \varepsilon_{ij} \right)^{\alpha}$$

where δ_j is a mean quality shifter that is subject to an investment choice by the firm, α is the expenditure share on the set of differentiated varieties, q_{ij} is the quantity of product j consumed by consumer i. The consumer's decision is subject to a budget constraint given by,

$$o_i p_O + \sum q_{i,j} p_j \leq \theta_i$$

Consider the different terms of the utility function. First, some products might be universally better for all consumers, that is firms have the option to *vertically differentiate* their products by choosing a higher δ_j. Second, there is *horizontal* differentiation with some products being more closely located to the bliss point of one consumer groups rather than another, as indicated by the presence of the distance term, $\mathcal{D}(v_i, a_j)$.

Finally, consider the multiplicative preference shock, ε_{ij}. The preference shock is consumer-firm specific and orthogonal to either the horizontal or vertical differentiation of a product. A common interpretation (Anderson et al., 1992) is that the idiosyncratic taste shock mirrors unoberserved heterogeneity of consumers within each group. Notice that following Anderson et al. (1992) there exists an isomorphism between the RUM model presented here and the a representative agent featuring a constant elasticity of substitution between products. As in Krugman (1980) the preference structure therefore introduces market power into the model. Throughout the analysis, we assume that the preference shock is Frechet distributed, i.e.

$$G_x(\varepsilon_{ij}) = \exp\left[-\varepsilon_{ij}^{-\sigma}\right]$$

We now towards solving for a firm's demand and a consumer's welfare. We begin by noting that consumer i consumes both the outside good and a composite of the set of differentiated varieties, $\sum_{j \in J} q_{i,j} \times \delta_j \times \mathcal{D}(v_i, a_j) \times \varepsilon_{ij}$. The upper-utility function between the composite and the outside good is Cobb-Douglas and implies fixed expenditure shares, i.e.

$$M_i = (1-\alpha)/p_{M,i} \text{ and } O_i = \alpha/p_O$$

where $p_{M,i}$ is the price of the composite for consumer i and p_O is the price of the outside good.

Since varieties are perfect substitutes for each other, the consumer chooses the variety that yields the highest indirect utility, taking the preference shock into account. The resulting demand is given by the following proposition,

Proposition 1 (Demand) *The demand of a firm at taste location a_j and price p_j across all consumers is given by,*

$$D_j\left(a_j, p_j\right) = L(1-\alpha)\theta_i p_j^{-(1+\sigma)} \int_{v \in V} f_v(v) \frac{\delta_j^\sigma \times p_j^{-\sigma} \times \mathcal{D}\left(a_j, v\right)^\sigma}{P(v)^{-\sigma}} dv$$

where $P(v)$ denotes the price index of consumers at the bliss point v and is given by,

$$P(v) \equiv \left(\sum_{n \in J} \delta_n^\sigma p_n^{-\sigma} \mathcal{D}\left(a_n, v\right)^\sigma\right)^{-1/\sigma}$$

The proof of the proposition is provided in the appendix and extends the derivation in Auer (2017) to allow for Frechet distributed preference shocks and vertical product differentiation. Similar to Auer (2017), the proof relies on previous research showing that random utility models with extreme value distributed preference shocks can give rise to love for variety and monopolistic competition (Anderson et al., 1992; Gabaix et al., 2010).

While preferences are comparable to Dixit and Stiglitz (1977); Krugman (1980), the current framework exhibits distinct distributional effects, where the position of supply in the taste space determines relative welfare effects across consumer groups. These welfare effects can furthermore be characterized by the expected utility as given by the following corollary. Detailed derivations can be found in Appendix A.1.

Corollary 1 (Consumer Welfare) *Denote welfare as the expected (ex-ante) utility derived from the above optimization problem, which can be written for consumer i at bliss point v_i featuring income θ_i as follows expected welfare of consumer i*

$$E\left(U_i\left(v, \theta_i\right)\right) = (1-\alpha)^{1-\alpha} \alpha^\alpha \Gamma\left(1 - \frac{\sigma}{\alpha}\right) (P(v))^{-\alpha} \theta_i$$

where $P(v)$ is the ideal price index of the consumer as defined above.

Corollary 1 conveniently allows us, given knowledge about the location of consumers and varieties, as well as their quality, to evaluate the welfare that each consumer group derives from participating in the global market. Similarly, we can construct consumer welfare for different market conditions, such as changes in the demand or supply structure of the market.

4.3 Supply

In what follows we characterize a studio which is considering investing in a movie either in the home or in the uncertain foreign market. Consider a stylized setting where there is a home market, H , and a foreign market, F. The home market offers predictable and certain returns, while the foreign market is subject to stochastic revenue shocks which are normally distributed, i.e.

$$\tilde{x} \sim N\left(\mu, \sigma^2\right)$$

We follow the finance literature (Campbell, 2017) and assume risk-averse preferences by the studios and characterize the resulting portfolio problem. For simplicity and tractability, we assume that the studio has constant absolute risk aversion (CARA) preferences,

$$\max_{\theta} V\left(\theta\right) = \mathrm{E}\left[-\exp\left(-A\left(W\left(\theta\right)\right)\right)\right]$$

where the parameter A pins down the degree of absolute risk aversion which in turn determines the studio's trade-off between expected returns and volatility. Applying the property of the expectation of log normal distributed random variables that the log of the expectation is equal to the expected of the log plus half the variance, we obtain,

$$\max_{\theta} V\left(\theta\right) = \mathrm{E}\left(A\left(W\left(\theta\right)\right)\right) - \frac{1}{2} Var\left(A\left(W\left(\theta\right)\right)\right)$$

The following proposition summarizes the optimal investment share in the foreign market given the risk aversion parameter, A, and the demand uncertainty the studio faces. Detailed derivations can be found in Appendix A.2.

Proposition 2 (Portfolio Choice) *Consider a setting where studios choose to produce a movie that targets the certain home market or the volatile foreign market. Denote by θ_F the share of investment in the foreign market which is given by,*

$$\theta_F = \frac{\Delta\Pi_0\left(a_F, a_H\right) + \left(1 - \pi_H\right) \times L \times \left(\Delta\pi\left(a_F, a_H, v_F\right)\right) \times \mu}{A^2\left(1 - \pi_H\right)^2 \times L^2 \times \left(\Delta\pi\left(a_F, a_H, v_F\right)\right)^2 \times \sigma^2}$$

where $\Pi(a_j)$ *is the revenue of a product at location* a_j*. Where,* $\Delta\pi(a_F, a_H, v_F) \equiv \pi(a_F, v_F) - \pi(a_H, v_F) > 0$ *refers to the differences in market shares between* F *and* H *for a product at point* F*, and where,* $\Delta\Pi_0(a_F, a_H) \equiv \Pi_0(a_F) - \Pi_0(a_H)$ *refers to the difference in expected profits for a product targeting* F *compared to a product targeting* H*. Notice that for for* $\mu = 0$*, we obtain the simpler formula,*

$$\theta_F = \frac{\Delta\Pi_0(a_F, a_H)}{A^2(1-\pi_H)^2 \times L^2 \times (\Delta\pi(a_F, a_H, v_F))^2 \times \sigma^2}$$

The proposition characterizes the equilibrium distribution of product characteristics across the taste space. It summarizes the two competing forces embedded into the framework. On the one hand, firms or studios target a set of heterogeneous consumers in the global market, and are specifically seeking to tailor their product to the taste of the largest mass of consumers. This mechanism is sometimes referred to as preference externality (Waldfogel, 2003). In our setting this effect is partially offset an insurance mechanism. Targeting the largest market also implies being more exposed to the idiosyncratic risk of that market. Therefore, θ_F increases in the relative size of the foreign market, but decreases with its volatility.

4.4 Equilibrium

This subsection solves for the closed economy equilibrium. In our empirical application, we will rely on the closed-economy equilibrium only and abstract from the additional implications of trade and transportation costs. The following proposition solves for the industry equilibrium, that is given the free entry condition, we solve for the number of firms entering production at each point a_j. Free entry implies that revenues have to be equalized across the 'taste space' and that furthermore revenue needs to compensate for the fixed cost of entry. The proposition below characterizes the equilibrium both for the stylized case in Auer (2017) for two distinct consumer and product location $i, j \in [H, L]$ in which case the endogenous supply intensity $[n_H, n_L]$ can be solved for by equalizing the revenue across these two location, i.e. $\Pi_L = \Pi_H$. Furthermore, the proposition also gives the same condition for the case where the number of consumer and product locations are larger than 2.

Proposition 3 (Equilibrium) *Denote by* n^A *the autarky equilibrium number of firms and by* n_H^A *the autarky equilibrium fracition of entrepreneurs producing at location* a_H*. There exists a* *unique number of entrants* $N = \frac{L}{\sigma f}$ *and the interior equilibrium is given by*

$$n_H = \frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_F,v_F))-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_H,v_F))}\right)$$
$$-\frac{(1-\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)$$

where, $\gamma = \frac{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_F,v_F))-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_H,v_F))}$ *is an adjustment factor that emphasizes the difference between the volatility adjusted expected returns compared to the non-volatility baseline.*

Notice that in the case where volatility does not play a role the equilibrium mirrors the autarky equilibrium in Auer (2017) and is given by,

$$n_H = \left(\omega_H\frac{\tilde{\mathcal{D}}(a_L,v_L)^{-\sigma}}{\tilde{\mathcal{D}}(a_L,v_L)^{-\sigma}-\tilde{\mathcal{D}}(a_H,v_L)^{-\sigma}}-(1-\omega_H)\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)$$

Furthermore, notice that given information on the location of products and customers, as well as their population and income weights, the proposition above allows us to uniquely solve for the equilibrium of the model.

4.5 Comparative Statics

The model above can be used to derive empirical predictions for how market composition affects supply, expenditure shares, and welfare. In the proposition below we derive empirical predictions for the impact of a change in the market composition on expenditure shares. This prediction motivates our empirical analysis on observed expenditure shares. Detailed derivations are available in Appendix A.3.

Proposition 4 (Comparative Statics) *Consider a small change to the fraction of the population that resides in the H location, i.e.* $d\ln\omega_H \neq 0$. *Taking a first order approximation, we characterize the changes in the difference in expenditure share ("Market Polarization"), i.e.*

$$d\ln\Delta\pi(a_F,a_H,v_F) = \varepsilon_2\times\varepsilon_1\times d\ln\pi_H$$

where ε_2 *characterizes the elasticity of expenditure shares differences with regard to changes in the equilibrium supply of goods in the H location, i.e.* $d\ln n_H$ *and where* $\varepsilon_1 \equiv \frac{d\ln n_H}{d\ln\pi_H}$, *characterizes* *the elasticity of the equilibrium supply of goods with regard to changes in the fraction of the population that resides in the H location. The following is shown in the appendix,*

$$\varepsilon_1 \approx \frac{\frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_F,v_F))-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}(1-\tilde{\sigma}^2(a_H,v_F))}+\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)}{n_H}$$

$$\varepsilon_2 = \left(\frac{\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}n_H\frac{\tilde{\mathcal{D}}\left(a_H,v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}}-\frac{\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}n_H\frac{\tilde{\mathcal{D}}\left(a_H,v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)$$

Notice that this proposition implies a positive impact of market composition on the difference between expenditure shares. That is to say, as markets become more polarized and imbalanced, the industry supply will shift to match that and observed expenditure shares will also become more polarized. This testable empirical prediction motivates our study of the international box office market and the impact China had on its composition. Furthermore, notice that the positive impact is attenuated by the risk aversion of the studio, as mirrored by the presence of the attenuation term γ. This is to say that net effect depends on the trade-off increasing market opportunities and exposure to larger idiosyncratic risk.

5 Quantifying the welfare effects of volatility and taste heterogeneity

In this section, we apply our methodology to analyze the welfare effects of China's rise on the international box office. Utilizing a unique and comprehensive dataset on the performance of movies across a large set of international markets, we apply our methodology first to estimate the taste space as well as the parameters that determine the firms supply choice, and second to examine the rise of China and its distributional welfare impact. Before doing so, we first extend the stylized model of the previous section to a setting where firms supply products across a discretized, but arbitrary taste space.

5.1 Extending the baseline model

Setup. Before applying our model quantitatively, we extend the model from the simple two location setting to a generalized setting with an arbitrary taste space. In this setting, there is a finite, but arbitrary number of locations across the taste space. As before, there is one global market, populated by a mass of L consumers. Consumers belong to a finite set of distinct consumer groups, $i \in \mathcal{I}$, with preferences being characterized by bliss points $v_i \in \mathcal{S}$, where $\mathcal{S}$ is a finite dimensional space which we call *taste space*. Each product is characterized by a position in the taste space $a_j \in \mathcal{S}$ that represents its product characteristics. Demand is characterized as in Proposition 1.

Supply. We model supply as a variation of the portfolio choice model introduced in Proposition 2. However, instead of a simple choice between two locations, studios consider investing across a finite, but arbitrary number of locations across the taste space. As above, producing a movie in a taste location a_j provides a stochastic return that is given by,

$$\Pi\left(a_j\right) = \sum_i \omega_i \times L \times \pi\left(a_j, v_i\right) \times \left(1 + \tilde{x}_i\right)$$

where - as before - ω_i denotes the population shares, $\pi\left(a_j, v_i\right)$, denotes the expenditure shares of consumers in location i on a product in taste location a_j, and $\tilde{x}_i$ is a stochastic demand shock that captures residual uncertainty the demand of consumer group i. We assume that this demand shock is normally distributed with a group-specific variance, i.e.

$$\tilde{x}_i \sim N\left(0, \sigma_i^2\right)$$

and as before studios are assumed to have CARA preferences, which implies that the expected profits from releasing a movie in location a_j are given by,

$$\mathbf{E}\left[\Pi\left(a_j\right)\right] = \Pi_0\left(a_j, \theta_1, \ldots, \theta_n\right) - \frac{A^2}{2}\sigma^2\left(a_j\right)$$

For tractability we assume that studios choose what movie to produce subject to a multiplicative preference shock that is Frechet distributed with a common shape parameter γ. This additional stochasticity on the supply side allows us to derive convenient closed-form expression for the investment share across the discretized taste space. The shock can be interpreted to capture unobserved heterogeneity in the production cost across the taste space. The studio's problem is then to choose the location that maximizes expected profits, i.e.

$$\max_{i} \left(\mathbf{E} \left[\Pi \left(a_i \right) \right] \times \epsilon_i \right)$$

The proposition below summarizes the resulting supply choice and equilibrium.

Proposition 5 (Supply and Equilibrium) *Consider a setting where studios choose to produce across a finite number of locations in the taste space. Denote by θ_i the share of firms that choose to produce in location i. The share of studios that choose to produce in that location is given by,*

$$\theta_j = \frac{\left(B_j \left(a_j, \theta_1, \ldots, \theta_n \right) \right)^{\gamma}}{\sum_{h \in \mathcal{G}} \left(B_j \left(a_j, \theta_1, \ldots, \theta_n \right) \right)^{\gamma}} \tag{1}$$

where

$$B_j = \Pi_0 \left(a_j, \theta_1, \ldots, \theta_n \right) - \frac{A^2}{2} \sigma^2 \left(a_j, \boldsymbol{\theta_1}, \ldots, \boldsymbol{\theta_n} \right)$$

where the equilibrium is represented by the set of investment shares $[\theta_1, \ldots, \theta_N]$ that solves the fixed point that is generated by the optimal supply choice in Equation 1.

5.2 Estimation of structural parameters

In this subsection we describe the estimation of the key parameters of the model. We first describe how we estimate the demand system, i.e. the distribution of bliss points across a low-dimensional taste space that characterizes the distribution of consumer demand. We then estimate the risk aversion parameter that pins down the mean-variance trade-off on the supply side.

5.2.1 Demand parameters: Estimating the taste space

Market definition. We rely on market shares to estimate the appeal of different movies to domestic and foreign audiences, but in reality movies are released continuously over time. We assume that movies compete only against other movies released in the same quarter of the year. About 50% of movies are released at least one quarter later than in the US. We therefore use the local release date to compute market shares.

The estimation proceeds in three steps: In a first step we exploit the multiplicative separability between the horizontal taste heterogeneity and the vertical differentiation to back out the quality shifters for each movie. This is being done employing a standard technique from empirical IO. In a second step, we then proceed to first obtain the implied residual heterogeneous market share shifters and then to fit them by constructing a low-dimensional taste space that best fits the data given a chosen distance metric. In a third step we construct welfare measures. We do so in two distinct ways, one empirically motivated, the other simulating the industry equilibrium that is consistent with the estimated taste space.

Separating global from local product appeal. Assuming the same ticket price for all movies, the market share of a movie j across all locations v, i.e. countries, is given by demand in Proposition 1. Taking logs, and following Berry (1994), we apply a contraction mapping procedure, where for an initial guess for $\{\delta_j^0\}$ we can construct the mean market shares across all markets, $\sigma(\cdot)$, and update δ_j accordingly, i.e.

$$\theta \ln\left(\delta_t^{h+1}\right) - \theta \ln\left(\delta_t^{h}\right) = \ln\left(s_t\right) - \ln\left(\tilde{\sigma}_j\left(\delta_{ht}\right)\right)$$

we iterate this system of equations until convergence and thereby obtain the full set of quality shifters that rationalize the mean market shares of products across all markets.

Estimating the taste space. In a second step, given $\{\delta_j\}$ we use a contraction mapping to back out $\{\mathcal{D}\left(a_j, v_i\right)\}$. Given an initial guess $\left\{\mathcal{D}\left(a_j, v_i\right)^{(0)}\right\}$, we solve iterative until convergence for the updated guess,

$$\tilde{\mathcal{D}}\left(a_j, v_i\right)^{(1)} = s_{ij} \times \frac{\sum_k \tilde{\delta}_k \times \tilde{\mathcal{D}}\left(a_j, v_i\right)^{(0)}}{\tilde{\delta}_j} \ldots \forall j$$

From the previous step we obtain the full set of δ_j and $\mathcal{D}\left(a_j, v_i\right)$. As a next step we estimate movie taste locations a_j and country taste locations v_i. We assume that the taste distance term, $\mathcal{D}\left(a_j, v_i\right)$, has the following form:

$$\mathcal{D}\left(a_j, v_i\right) = \left(\sum_l \left(v_{i,l} - a_{j,l}\right)^2\right)^{\frac{1}{2}} \tag{2}$$

We solve the following non-linear optimization problem,

$$\min_{\{v_i, a_j\}} \eta' \eta$$

where the error term is given by

$$\eta_{ij} = \mathcal{D}\left(a_j, v_i\right) - \hat{\mathcal{D}}\left(a_j, v_i\right)$$

The problem is challenging since it is high-dimensional. However, as we argue below, the problem shares properties with the problem of trilateration - a well-behaved convex optimization problem (Dattorro, 2005).

Identification. The problem described is high-dimensional. For any given distance norm, let D be the number of spatial dimensions, N the number of products and J be the number of distinct consumer groups. The estimation then offers a maximum number[13] of $N \times J$ moments to estimate the $N \times D$ parameters that pin down the location of all the products and $N \times J$ parameters that pin down the location of all countries. A necessary condition for identification is that $N \times J > N \times (D + J)$, but since this is a non-linear problem this is barely sufficient and the large number of parameters might raise the question whether identification is at all feasible. However, while the overall optimization problem seems daunting, it shares similarities with a trilateration problem which itself is a well-behaved convex optimization problem. Conditional on normalizing the rotation and scale of the taste space - by fixing the location of any number of two countries, the problem can be tackled as a sequential trilateration problem, where conditional on the location of two countries and the observed 'distances' to any one movie pins down two feasible locations that rationalize the observed data. Choosing one, normalizes the rotation of the space. Additional distances allow us to iteratively determine the location of all other movies and countries sequentially. Estimating the problem jointly is akin to minimizing the joint measurement error across all observed distances. Acknowledging the potential for multiple local minima that arise due to the joint estimation process, in practice we employ a multi-start routine.

Understanding δ_j vs ϵ_{ij}. How does the separation between a movies' global appeal, i.e. δ_j, and a movies' local appeal, i.e. ϵ_{ij} matter? Figure A.2 decomposes the overall variance of market shares into three different components coming from δ_j, ϵ_{ij} or $s_{i,j}$. While the share of the variation coming δ_j has declined over the entire sample period, the share of the variance coming from the taste distance declined until about 2013, before increasing strongly in the post-2012 period. This change in the importance of the taste difference, mirrors our reduced form results in Section 3.1. Our model results indicate that the diverging covariance in market shares (US and Western Europe vs. US and Hong-Kong in Figure 2 are mostly coming from increased taste differences.

The difference between δ_j and ϵ_{ij} becomes apparent in Table A.4, which shows the five closest

[13] That is if the products are being released and observed in all markets. In practice, release is often selective and zeros will be prevalent in our datasets.

Table. 2. Regressions of estimated movie characteristics on observables

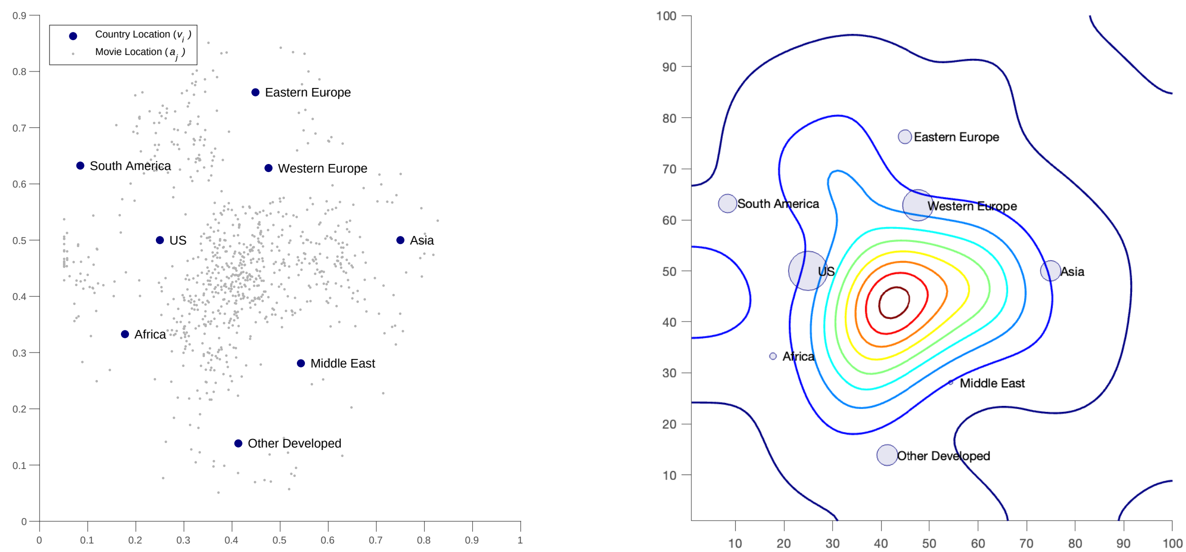
	(1) $m_{j,1}$ (W-E)	(2) $m_{j,2}$ (S-N)	(3) $log(\delta_j)$	(4) $m_{j,1}$ (W-E)	(5) $m_{j,2}$ (S-N)
$log(\delta_j)$	0.13^{***}	0.08^{**}			
Log Production Budget			0.51^{***}	0.04	0.02
Runtime			0.13^{***}	0.09^{*}	−0.02
Rated R			−0.03	−0.00	0.10^{**}
Sequel			0.16^{***}	0.01	−0.05
Remake			−0.00	0.03	−0.00
Spinoff			0.02	−0.03	−0.05
Co-Production					
China			−0.02	0.04	0.12^{***}
France			0.01	0.08^{***}	−0.03
Germany			−0.00	0.02	-0.08^{*}
UK			0.03	0.04	0.07^{*}
Genre					
Action			-0.08^{**}	0.05	-0.09^{*}
Adventure			−0.02	0.06	0.12^{**}
Animation			0.14^{***}	0.05	0.03
Comedy			−0.01	-0.08^{*}	-0.11^{**}
Crime			-0.07^{**}	−0.04	−0.02
Drama			-0.10^{***}	0.03	-0.12^{***}
Family			-0.11^{**}	0.03	−0.00
Fantasy			0.01	−0.00	0.05
Horror			0.01	0.04	0.02
Romance			−0.01	-0.07^{*}	0.04
Sci_Fi			0.06^{**}	−0.02	−0.01
Thriller			0.01	0.11^{**}	0.01
R^2	0.02	0.01	0.44	0.09	0.06
Observations	818	818	818	818	818

Notes: Regressions relating the taste space coordinates $m_{j,1}$ and $m_{j,2}$ to δ_j in columns (1) and (2) and the estimated movie characteristics to observables in columns (3) to (5). Movies with lower $m_{j,1}$ position means are closer to Western markets, movies with lower $m_{j,2}$ are closer to Southern markets. The coefficients are standardized to allow comparisons across columns. Significance levels are based on robust standard errors.

movies to the US and Asian location in the taste space. The 2017 movie Kung Fu Yoga was relatively unsuccesful globally, i.e. a low δ_j, whereas the 2004 movie Kung Fu Hustle had high global appeal. Both movies, however, are part of the top five closest movie to Asia's taste location because they were succesful in Asia relative to their global appeal.

In Table 2 we first regress the estimated taste space coordinates on δ_j. The coefficient in column (1) of Table 2 is positive and statistically significant. On average, movies in the East

Figure 5. Estimated Taste Space



(a) Estimated Taste Space **(b)** Quality-Weighted Contour

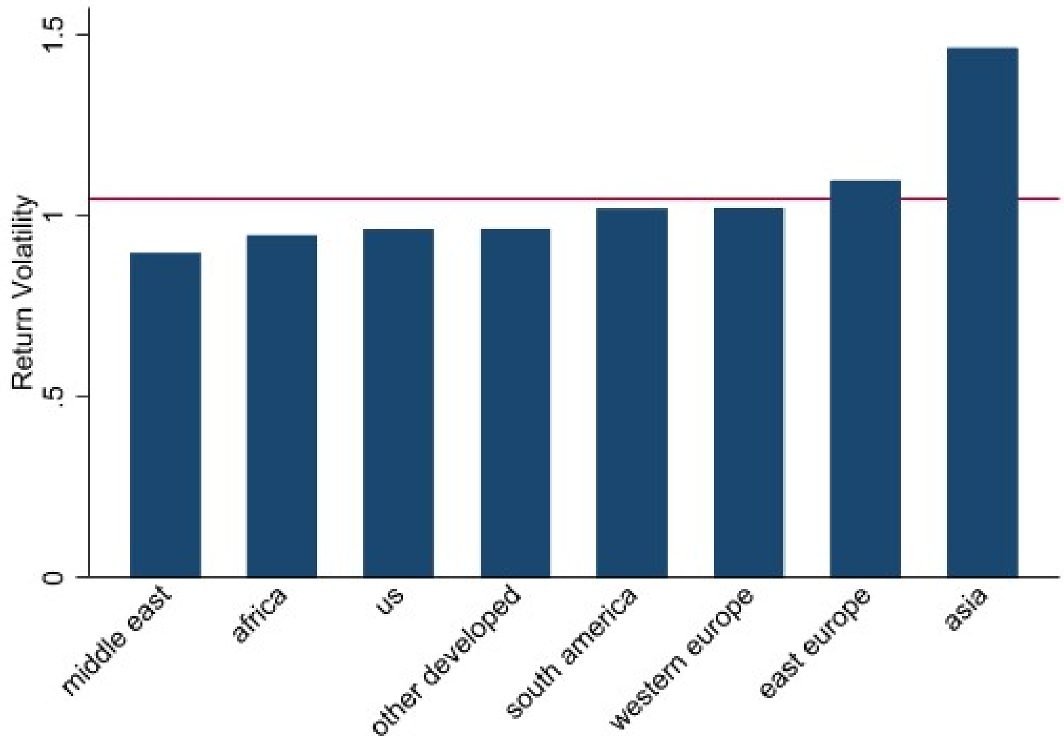
Notes: Bars indicate return volatility for each region calculated as the standard deviation across the log of region-specific returns. We add one to the region-specific returns as there are a lot of negative values. The red line is the average across all regions.

of the taste space have a higher global appeal. It is likely that only the highest δ_j selection of Hollywood movies are being shown in Asian markets. There is a weaker relationship between the global appeal of a movie and the North-South dimension of the taste space, as the coefficient in column (2) of Table 2 is about half the size of the W-E coefficient.

Are there specific movie characteristics contributing to a higher global appeal as opposed to a specific location in the taste space? Column (3) of Table 2 suggests that movies with higher global appeal tend to have higher production budgets, tend to be longer and, are often sequels. Action, Crime, Drama, and Family movies are less likely to be high δ_j movies, whereas Animation and Science fiction movies are often movies with high global appeal.

The taste space maps into observable movie characteristics. Column (4) of Table 2 describes the West-East dimension of the taste space. Romantic movies and Comedy are located more towards the West. This makes sense, because Comedy movies are more difficult to translate and Chinese censors have been known to block movies with sexual content. Turning to the North-South taste space dimension, we find that movies in the North are more likely to be rated-R, Adventure movies, but less likely to be Comedies or Dramas.

Figure 6. Return Volatility by Region



Notes: Bars indicate return volatility for each region calculated as the standard deviation across the log of region-specific returns. We add one to the region-specific returns as there are a lot of negative values. The red line is the average across all regions.

5.2.2 Supply parameters: Portfolio choice

The supply side estimation requires additional parameters which we estimate using our data and the δ_j obtained in the demand side estimation.

Region-Specific Return Volatility. As studios in our model face a trade-off between expected returns and the riskiness of these returns we start by estimating the return risk associated with each region in our data. Ideally, we would base our estimates on measures of ex-ante risk, but unfortunately we do not have a measure of ex-ante risk available. We compute region-specific movie returns as $\frac{\text{Regional Boxoffice Revenue} - \text{Production Budget}}{\text{Production Budget}}$. Because the region-specific return distribution is highly skewed, but also contains negative numbers we transform returns by adding one and then taking the log. Figure 6 shows the ex-post return volatility for each region. Asia stands out compared to other regions with a dramatically higher risk.

Studio Risk Aversion. To estimate the risk aversion of Hollywood studios we regress movie returns on region-specific volatility weighted by the share of revenue generated in that specific

Table. 3. Risk Aversion Estimation

	(1)	(2)	(3)
Revenue Share Weighted Variance	0.44**	0.36**	0.42*
	(0.21)	(0.17)	(0.23)
Log Production Budget	−0.39***	−0.16***	−0.54***
	(0.03)	(0.04)	(0.04)
Controls			✓
Weighted by budget		✓	
R^2	0.21	0.03	0.38
Observations	816	816	801

Notes: The table shows the regression coefficients of log movie returns on region-specific return variance weighted by the share of boxoffice revenue generated by the movie in that region. Control variables: log production budget, run-time, and indicator variables for the production country, the movie genre, sequel, remake, spin-off, and whether the movie is rated-R. Robust standard errors in parentheses

region.

$$log\,(Return)_j = \rho_0 + \rho_1 \sum_r w_{r,j}\widehat{\sigma}_r^2 + \rho_2 log(\text{budget})_j + \epsilon_j$$

with $\widehat{\sigma}_r$ the estimated region-specific return volatility, and $w_{r,j} = \frac{\text{Regional Boxoffice Revenue}_r}{\text{Boxoffice Revenue}}$ the weight of region r in the total boxoffice revenue.

Since Asia has the highest region-specific volatility movies generating a higher share of their total boxoffice revenue in Asia are considered riskier. Table 3 presents the results: all coefficients of the revenue share weighted variance are positive, i.e. movies with higher returns are generating more revenue in riskier markets ex-post, and are relatively stable across specifications between 0.36 and 0.44.

Elasticity of δ_j with respect to Budget. For our supply side estimation we also estimate the elasticity of global movie appeal, δ_j, with respect to production budget. In Table 4 we present estimates of a regression with $log(\delta_j)$ as the dependent variable and log production budget as the main independent variable. We find elasticity estimates between 0.57 and 0.78 depending on the specification.

Table. 4. Elasticity of δ wrt Production Budget

	(1)	(2)	(3)
	$log(\delta_j)$	$log(\delta_j)$	$log(\delta_j)$
Log Production Budget	0.61***	0.83***	0.65***
	(0.03)	(0.04)	(0.06)
Controls			✓
Weighted by budget		✓	✓
R^2	0.37	0.37	0.46
Observations	818	818	818

Notes: The table shows the regressions with log of estimated global movie appeal δ_j as dependent variable and log production budget as independent variable. Control variables: run-time, and indicator variables for the production country, the movie genre, the release year, sequel, remake, spin-off, and whether the movie is rated-R. Robust standard errors in parentheses.

5.2.3 Constructing Welfare

We construct welfare in two distinct ways. The first welfare measure takes the estimated quality parameter and taste location of each product $\{\delta_j, a_j\}$, as well as the country location $\{v_i\}$ to construct the price index directly and therefore the welfare measure directly, in accordance with Corollary 1. Secondly, given the bliss points for each country, we simulate the industry equilibrium and recover the densities $\{n_j\}$ along a grid that covers the whole taste space.

5.3 The welfare impacts of China's rise in the movies market

We now turn to the 2012 policy change in China, introduced in Section 2.1 and study the consequences of this shift through the lens of our model and the estimated taste space. Faced with increased demand from Asia, there are three potential scenarios of how Hollywood studios could react: first, shift movies towards the center of the taste space to please the average consumer. Second, produce some low δ_j movies very close to the Asian taste location, but keep most high δ_j productions close to the Western taste locations. Third, create a second cluster of movies close to Asia, splitting the allocation of global appeal between movies mainly catering to Western audiences and other movies catering to Asian audiences.

We start by comparing the movie taste locations before the policy change in Figure 7 against the taste locations after 2012 in Figure 8. Both figures include contour plots of the sum of δ_js for each location. Before 2012 there is just one large cluster of movies in the taste space between Western Europe, the US and Africa. This changes in the period after 2012, when a second cluster close to Asia appears. In addition the Western cluster shifts slightly towards the South.

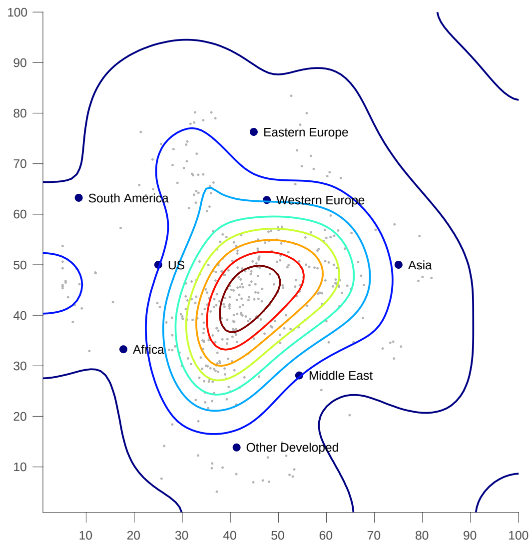


Figure 7. Before 2012

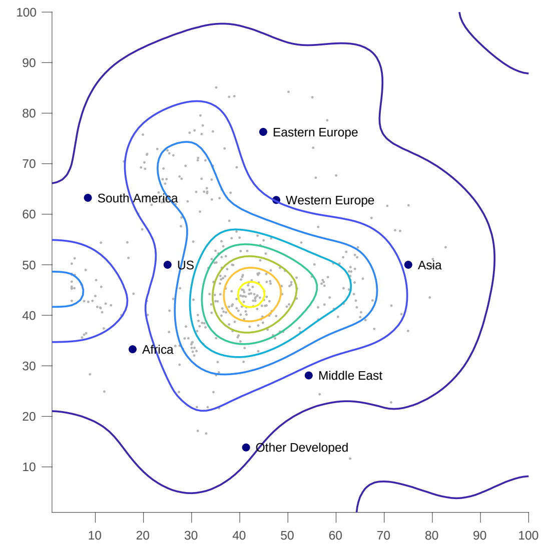


Figure 8. After 2012

Notes: The table shows the regressions with log of estimated global movie appeal δ_j as dependent variable and log production budget as independent variable. Robust standard errors in parentheses.

Our estimation results suggest that Hollywood studios have opted for the separation of movies clusters in the taste space, i.e. the third scenario, shifting a substantial amount of high δ_j movies towards Asia.

The change of movie locations in the taste space reduced the taste distance of movies to Asia and increased the distance to the US. Appendix Figure A.1 shows how the distribution of movie-region distances shifted after 2012.

The impact of the change in taste locations also affects the welfare ranking of regions. The second and third columns of Table 5 indicate that Western Europe, the US and Other Developed Countries are worse off post-2012, whereas all other regions gained from the consequences of the policy change in 2012, most notably Asia.

Understanding Var (δ_j) and Var (ϵ_{ij}) before/after 2012. Next, we will decompose the change in Figures 7 and 8 into changes in the taste space and changes in the global appeal of movies. Figure A.2 shows the total variance of observed market shares increased after 2012. When Hollywood studios start producing more movies specifically targeted to Asian audiences those movies have a lower appeal to Western audiences, resulting in a higher total variance of market shares. The decomposition in Figure A.2 points to an increase in the variance of $\epsilon_{i,j}$ as the main driver. Studios locating movies at different points in the taste space after 2012 are the main reason for this change in total variance.

Country	Total ($\mathcal{W}$)	Before ($\mathcal{W}$)	After ($\mathcal{W}$)	Before (Simulated)	After (Simulated)
Western Europe	1.00	1.00	1.00	1.00	1.00
US	0.98	0.89	1.07	1.36	1.09
Middle East	0.92	0.91	0.89	0.90	0.77
Africa	0.77	0.70	0.83	0.92	0.78
Asia	0.75	0.72	0.76	0.75	0.90
Eastern Europe	0.70	0.67	0.75	0.92	0.84
Other Developed	0.69	0.70	0.65	1.18	0.83
South America	0.60	0.52	0.68	0.88	0.83

Table. 5. Welfare Ranking relative to highest country-specific welfare.

Columns (1) in Table A.2 indicates that there is no change in the average δ_j, i.e. Hollywood studios did not increase the global appeal of their movies after 2012. Holding global appeal constant columns (2) and (3) indicate that movies moved both to the West and North in the post-2012 period.

Is the estimated taste space stable? Columns (4)-(6) of Table A.2 show that there are very few changes in how the taste-space related to observable movie characteristics in the post-2012 compared to the pre-2012 period. The coefficient of the Chinese co-production is not meaningful, because there were almost no Chinese co-production in the pre-2012 period. Finally, there are small changes with Horror movies having a higher global appeal post-2012, and Thriller movies moving towards the South in the post 2012 period.

6 Conclusion

Typically, the canonical models abstract from taste heterogeneity across country. However, at least for some markets and product groups this is a prevalent feature. Taste heterogeneity implies distributional welfare consequences and - in the presence of substantial customization cost - poses a difficult challenge to firms. Do firms target the largest market or do they diversify by targeting a broader and more diversified customer base. This paper is the first paper that proposes a model capturing this challenge and analyzes the trade-off between first and second moment impact of taste heterogeneity.

We apply our model quantitatively to the international box office market and demonstrate that the rise of China shifted the market composition, led to changes in product composition on the supply-side and finally led to distributional welfare effects across countries. The model quantitatively rationalizes the effect of the rise of China had on the international box office.

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Tables and Figures

Table. A.1. Summary Statistics: International Movie Releases

	Mean	P25	Median	P75	N
Production budget	53	16	35	70	1946
Total boxoffice	161	32	80	191	1946
Runtime (mins.)	110	96	107	120	1946
Foreign boxoffice/total	0.46				1932
US production	0.95				1946
Sequel	0.19				1946
Remake	0.09				1946
Rated R	0.40				1898

Notes: Summary statistics of our baseline sample. Data are from BoxOfficeMojo.com and IMDB.com. Sample period from 2004 until 2019. Production budget and total boxoffice are in million USD, runtime in minutes, all other variables are fractions.

Table. A.2. Regressions of estimated movie characteristics on a post-2012 dummy and observables

	(1)	(2)	(3)	(4)	(5)	(6)
	$log(\delta_j)$	$m_{j,1}$ (W-E)	$m_{j,2}$ (S-N)	$log(\delta_j)$	$m_{j,1}$ (W-E)	$m_{j,2}$ (S-N)
Post	0.02	-0.10^{***}	0.10^{**}	-0.37	-0.61^{**}	-0.45
Post x $log(\delta_j)$		0.08	-0.01			
Post x Log Production Budget				0.35	0.13	0.45
Post x Runtime				-0.07	0.32	0.20
Post x Rated R				-0.02	-0.03	0.04
Post x Sequel				-0.03	-0.04	-0.02
Post x Remake				-0.06	0.06	-0.07
Post x Spinoff				0.12^{**}	-0.03	0.04
Co-Production						
Post x China				-0.16^{***}	-0.21	0.16^{**}
Post x France				-0.00	0.01	-0.01
Post x Germany				-0.01	-0.02	0.07
Post x UK				-0.05	0.08	-0.11^{*}
Genre						
Post x Action				0.05	0.03	-0.03
Post x Adventure				-0.06	-0.08	-0.02
Post x Animation				0.04	-0.01	-0.11
Post x Comedy				-0.06	0.09	-0.05
Post x Crime				0.06	-0.01	0.04
Post x Drama				0.09	-0.02	0.11
Post x Family				0.02	0.10	0.09
Post x Fantasy				-0.04	-0.02	-0.02
Post x Horror				0.14^{***}	-0.00	0.07
Post x Romance				0.07	-0.05	-0.04
Post x Sci_Fi				0.02	0.01	-0.01
Post x Thriller				-0.00	-0.03	-0.14^{*}
R^2	0.00	0.03	0.02	0.46	0.14	0.10
Observations	818	818	818	818	818	818

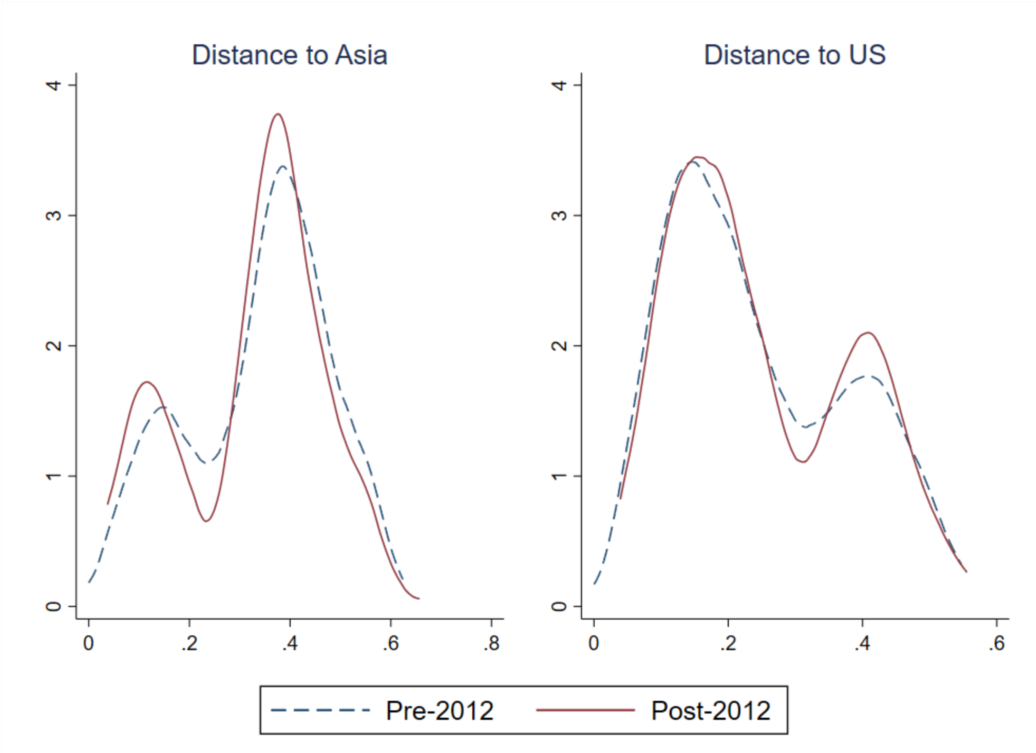
Notes: Regressions of $m_{j,1}$, $m_{j,2}$, and δ_j on a *Post* 2012 dummy in columns (1) to (3). Columns (4) to (6) regress $m_{j,1}$, $m_{j,2}$, and δ_j on observable movie characteristics allowing for different slopes before and after 2012. To save space, only the *Post* interactions are reported. The coefficients are standardized to allow comparisons across columns. Significance levels are based on robust standard errors.

Table. A.3. Difference in difference regression

	(1) OLS	(2) TWFE	(3) TWFE
Market Share	0.64***	0.58***	0.52***
	(0.07)	(0.06)	(0.08)
Market Share x Post	0.30**	0.37***	0.49***
	(0.12)	(0.12)	(0.10)
Market Share x Hong Kong	0.06	0.08	0.08
	(0.07)	(0.06)	(0.06)
Market Share x Hong Kong x Post	−0.46***	−0.49***	−0.68***
	(0.13)	(0.13)	(0.10)
$\beta_1 - \beta_2 = 0$	7.67***	10.2***	26***
$(\beta_1 + \beta_3) - (\beta_2 + \beta_4) = 0$	1.08	1.55	3.13*
Controls			✓
Weighted by budget	✓	✓	✓
R^2	0.75	0.78	0.89
Observations	430	430	430

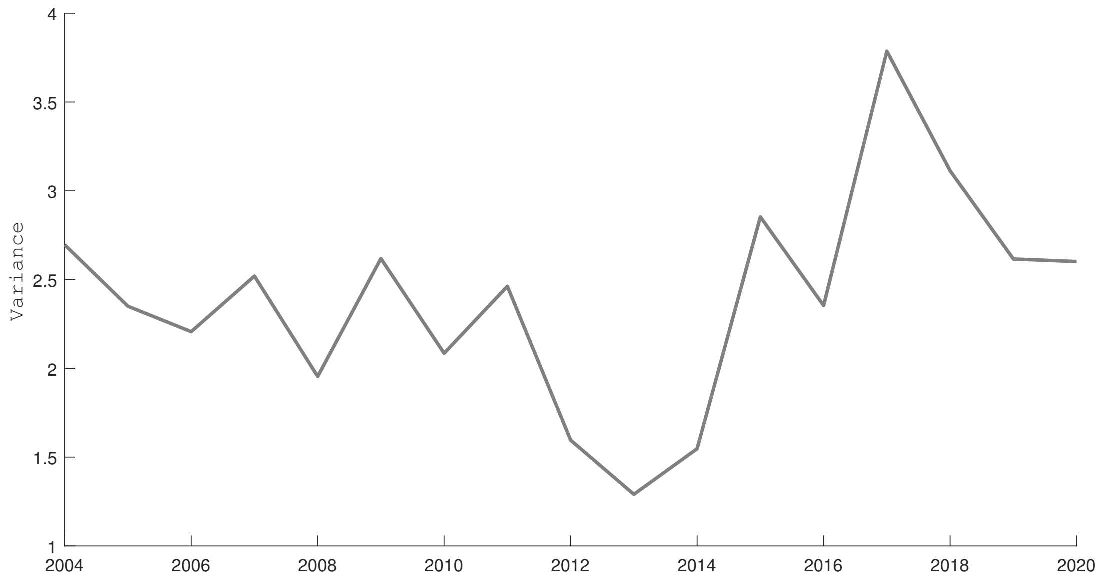
Notes: Difference in difference regressions with US market shares as dependent variable. *POST* indicates years after China increased the import quota for foreign movies from 20 to 34 movies in 2012. Western European countries are the control group. Control variables include the log production budget, the log runtime, indicator variables for the genre, indicators for whether the movie is a sequel, a remake, a spinoff, or, whether it is R-rated by the MPAA, and indicators for production countries. The sample includes all movies released in China, in Western Europe, and in Hong Kong and runs from 2008 until 2016. Standard erorrs clustered at the movie level in parentheses.

Figure A.1. Taste Distance to US and Asia Before and After 2012

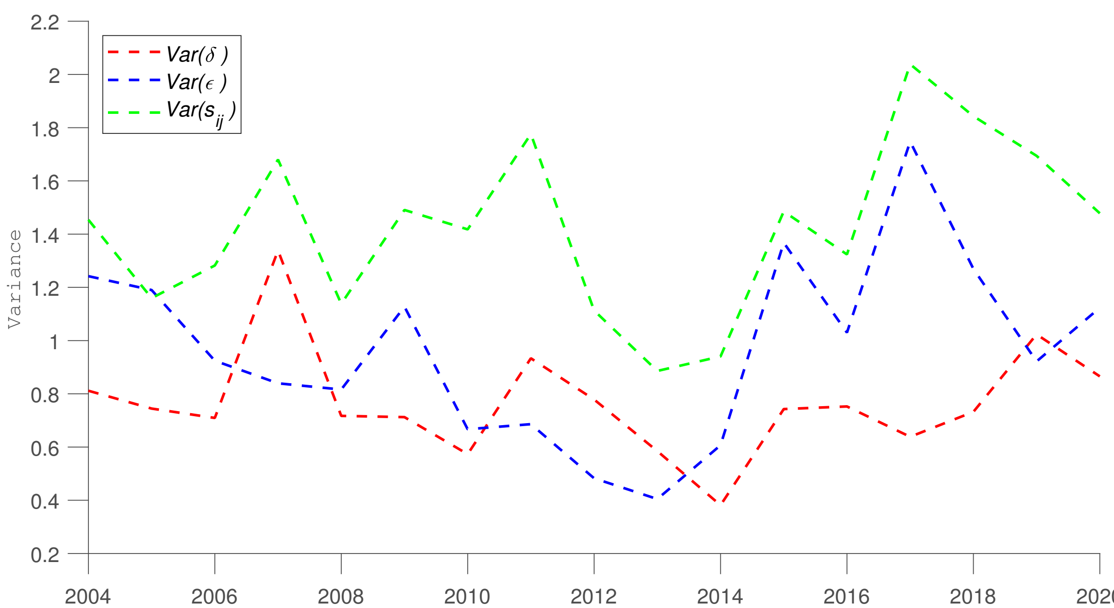


Notes: Densities of the distance between a movie taste location and Asia in the left hand side panel and to the US taste location in the right hand side panel. The distance is computed as: $(c_i(i,1) - m_j(j,1))^2 + (c_i(i,2) - m_j(j,2))^2)^{\frac{1}{2}}$ The blue dashed line includes only movies released before 2012, whereas the solid red line are movies released after 2012.

Figure A.2. Variance Decomposition
(a) Total Variance



(b) Variance Decomposition



Notes: The figure depicts the variance contribution of the quality shifter (δ_j), the bilateral taste shifter (ϵ_{ij}, as well as the overall variance of market shares across the sample.

Table. A.4. Five movies closest to the US and Asian taste location

Closest to US	Closest to Asia
Along Came Polly	EuroTrip
Crazy Rich Asians	Lust, Caution
Miracles from Heaven	Kung Fu Hustle
My Bloody Valentine	Kung Fu Yoga
Walk the Line	Spies in Disguise

Notes: List of movies closest to US and Asian taste location.

A Appendix: Derivations

This appendix presents derivations for the results in Section 2. Additional derivations are presented in Online Appendix B.

A.1 Section 4.2: Demand and Welfare

Sales are given by,

$$
\begin{aligned}
&D_j\left(a_j, p_j, v_i=\tilde{v}\right) \\
=&\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X} g_x\left(x_{i,j}\right)\Pr\left(\frac{\delta_j\times\mathcal{D}\left(a_j,\tilde{v}\right)\times x_{ij}}{p_j}=\max_{n\in J}\frac{\delta_n\times\mathcal{D}\left(a_n,\tilde{v}\right)\times x_{in}}{p_n}\right)dx_{ij} \\
=&\Pr\left(\ln\left(x_{i,n}\right)<\ln\left(p_n\right)-\ln\left(p_j\right)+\ln\delta_j-\ln\delta_n+\ln\mathcal{D}\left(a_j,\tilde{v}\right)-\ln\mathcal{D}\left(a_n,\tilde{v}\right)+\ln\left(x_{i,j}\right)\right)dx_{i,j}
\end{aligned}
$$

If x are distributed Frechet with scale parameter 0 and shape parameter $1/\sigma$, the following holds,

$$
\begin{aligned}
G_x\left(x\right)&=\exp\left[-x^{-\sigma}\right]=e^{-x^{-\sigma}} \\
g_x\left(x\right)&=\sigma x^{-\sigma-1}\exp\left[x^{-\sigma}\right]
\end{aligned}
$$

and thus,

$$
\begin{aligned}
P_{ij}&=\Pr\left(\ln\left(x_{i,n}\right)<\ln\left(p_n\right)-\ln\left(p_j\right)+\ln\delta_j-\ln\delta_n+\ln\mathcal{D}\left(a_j,\tilde{v}\right)-\ln\mathcal{D}\left(a_n,\tilde{v}\right)+\ln\left(x_{i,j}\right)\right) \\
&=\Pr\left(x_{i,n}<x_{ij}\times p_n/p_j\times\delta_j/\delta_n\times\mathcal{D}\left(a_j,\tilde{v}\right)/\mathcal{D}\left(a_n,\tilde{v}\right)\right) \\
&=\exp\left[-\left[\frac{x_{ij}p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]
\end{aligned}
$$

so that,

$$
\begin{aligned}
P_{ni}\mid\varepsilon_{ni}&=\prod_{n\neq j}\Pr\left(\ln\left(x_{i,n}\right)<\ln\left(p_n\right)-\ln\left(p_j\right)+\ln\delta_j-\ln\delta_n+\ln\mathcal{D}\left(a_j,\tilde{v}\right)-\ln\mathcal{D}\left(a_n,\tilde{v}\right)+\ln\left(x_{i,j}\right)\right) \\
&=\prod_{n\neq j}\exp\left[-\left[\frac{x_{ij}p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right] \\
&=\exp\left[-\sum_{n\neq j}\left[\frac{x_{ij}p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right] \\
&=\exp\left[-\left(p_j\right)^{\sigma}\left(\delta_j\right)^{-\sigma}\mathcal{D}\left(a_j,\tilde{v}\right)^{-\sigma}x_{ij}\sum_{n\neq j}\left[\frac{p_n}{\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]
\end{aligned}
$$

Plugging back in,

$$
\begin{aligned}
D_j\left(a_j,p_j,v_i=\tilde{v}\right)&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}g_x\left(x_{i,j}\right)\Pr\left(\frac{\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)x_{ij}}{p_j}=\max_{n\in J}\frac{\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)x_{in}}{p_n}\right)dx_{ij} \\
&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}\left(\prod_{n\neq j}\exp\left[-\left[\frac{x_{ij}p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]\right)g_x\left(x_{i,j}\right)dx_{ij}
\end{aligned}
$$

substituting for the density of the frechet function,

$$
\begin{aligned}
D_j\left(a_j,p_j,v_i=\tilde{v}\right)&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}\left(\prod_{n\neq j}\exp\left[-\left[\frac{x_{ij}p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]\right)\sigma x_{ij}^{-\sigma-1}e^{x_{ij}^{-\sigma}}dx_{ij} \\
&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}\left(\prod_{n\neq j}\exp\left[-x_{ij}^{-\sigma}\left[\frac{p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]\right)\sigma x_{ij}^{-\sigma-1}e^{x_{ij}^{-\sigma}}dx_{ij} \\
&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}\left(\prod_{n}\exp\left[-x_{ij}^{-\sigma}\left[\frac{p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]\right)\sigma x_{ij}^{-\sigma-1}dx_{ij} \\
&=\frac{(1-\alpha)\theta_i}{p_j}\int_{x_{i,j}\in X}\left(\exp\left[-x_{ij}^{-\sigma}\sum_{n}\left[\frac{p_n\delta_j\mathcal{D}\left(a_j,\tilde{v}\right)}{p_j\delta_n\mathcal{D}\left(a_n,\tilde{v}\right)}\right]^{-\sigma}\right]\right)\sigma x_{ij}^{-\sigma-1}dx_{ij}
\end{aligned}
$$

Define $t = x^{-\sigma}$ such that $-\sigma x^{-\sigma-1} dx = dt$, we obtain,

$$
\begin{aligned}
D_j\left(a_j, p_j, v_i = \tilde{v}\right) &= \frac{(1-\alpha)\theta_i}{p_j} \int_{x_{i,j} \in X} \left(\exp\left[-t \sum_n \left[\frac{p_n \delta_j \mathcal{D}\left(a_j, \tilde{v}\right)}{p_j \delta_n \mathcal{D}\left(a_n, \tilde{v}\right)} \right]^{-\sigma} \right] \right) (-dt) \\
&= \frac{(1-\alpha)\theta_i}{p_j} \left. \frac{\exp\left(-t \sum_n \left[\frac{p_n \delta_j \mathcal{D}\left(a_j, \tilde{v}\right)}{p_j \delta_n \mathcal{D}\left(a_n, \tilde{v}\right)} \right]^{-\sigma} \right)}{-\sum_n \left[\frac{p_n \delta_j \mathcal{D}\left(a_j, \tilde{v}\right)}{p_j \delta_n \mathcal{D}\left(a_n, \tilde{v}\right)} \right]^{-\sigma}} \right|_0^{\infty} \\
&= \frac{(1-\alpha)\theta_i}{p_j} \frac{1}{\sum_n \left[\frac{p_n \delta_j \mathcal{D}\left(a_j, \tilde{v}\right)}{p_j \delta_n \mathcal{D}\left(a_n, \tilde{v}\right)} \right]^{-\sigma}} \\
&= \frac{(1-\alpha)\theta_i}{p_j} \frac{\delta_j^{\sigma} p_j^{-\sigma} \mathcal{D}\left(a_j, \tilde{v}\right)^{\sigma}}{\sum_j \delta_j^{\sigma} p_j^{-\sigma} \mathcal{D}\left(a_j, \tilde{v}\right)^{\sigma}}
\end{aligned}
$$

A.2 Section 4.4: Proposition 3 (Equilibrium with volatility)

Free entry implies that (expected) returns from entry are equalized across space,

$$\mathbf{E}\left[\Pi\left(a_H\right)\right]=\mathbf{E}\left[\Pi\left(a_F\right)\right]$$

The home market offers predictable returns, while the foreign market is subject to stochastic revenue shocks which are normally distributed, i.e.

$$\tilde{x}\sim N\left(\mu,\sigma^2\right)$$

As above, we have that,

$$\Pi\left(a_H\right)=\omega_H L\times\pi\left(a_H,v_H\right)+\left(1-\omega_H\right)L\times\pi\left(a_H,v_F\right)\times\left(1+\tilde{x}\right)$$

$$\Pi\left(a_F\right)=\omega_H L\times\pi\left(a_F,v_H\right)+\left(1-\omega_H\right)L\times\pi\left(a_F,v_F\right)\times\left(1+\tilde{x}\right)$$

where we can furthermore distinguish between the stochastic and determinate returns. Define the determinate returns,

$$\Pi_0\left(a_F\right)\equiv\omega_H L\times\pi\left(a_F,v_H\right)+\left(1-\omega_H\right)L\times\pi\left(a_F,v_F\right)$$

Given the CARA assumption for studio preferences and the normal dsitribution of the stochastic returns we have the returns to releasing a film in location a_j being given by,

$$\mathbf{E}\left[\Pi\left(a_H\right)\right]=\mu\left(a_H\right)-\frac{A^2}{2}\sigma^2\left(a_H\right)$$

where $\mu\left(a_H\right)$ is the expected return and $\sigma^2\left(a_H\right)$ refers to the variance of the return.

$$\max_{\theta}V\left(\theta\right)=\mathrm{E}\left(A\left(W\left(\theta\right)\right)\right)-\frac{1}{2}Var\left(A\left(W\left(\theta\right)\right)\right)$$

Free entry implies (expected) returns from entry are equalized across space,

$$\mathbf{E}\left[\Pi\left(a_H\right)\right]=\mathbf{E}\left[\Pi\left(a_F\right)\right]$$

$$\mathbf{E}\left[\Pi\left(a_H\right)\right]\equiv\mu\left(a_H\right)-\frac{\gamma}{2}\sigma^2\left(a_H\right)$$

$$\begin{aligned}\mu\left(a_H\right)&\equiv\Pi\left(a_H\right)\\&=\omega_H L\frac{\tilde{\mathcal{D}}\left(a_H,v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}}+\left(1-\omega_H\right)L\frac{\tilde{\mathcal{D}}\left(a_H,v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\\&=\omega_H L\times\pi\left(a_H,v_H\right)+\left(1-\omega_H\right)L\times\pi\left(a_F,v_F\right)\end{aligned}$$

since only the foreign market demand is stochastic this implies,

$$\sigma^2\left(a_H\right)=\left(1-\omega_H\right)^2L^2\times\pi\left(a_H,v_F\right)^2\times\sigma^2$$

$$\sigma^2\left(a_F\right)=\left(1-\omega_H\right)^2L^2\times\pi\left(a_F,v_F\right)^2\times\sigma^2$$

notice that, since expenditure shares

$$\sigma^2\left(a_H\right)<\sigma^2\left(a_F\right)$$

which implies,

$$\omega_H L\frac{\tilde{\mathcal{D}}\left(a_H,v_H\right)^{-\sigma}}{P\left(v_H\right)^{-\sigma}}+\left(1-\omega_H\right)L\frac{\tilde{\mathcal{D}}\left(a_H,v_F\right)^{-\sigma}}{P\left(v_F\right)^{-\sigma}}-\frac{A^2}{2}\sigma^2\left(a_H\right)=\omega_H L\frac{\tilde{\mathcal{D}}\left(a_F,v_H\right)^{-\sigma}}{P\left(v_H\right)^{-\sigma}}+\left(1-\omega_H\right)L\frac{\tilde{\mathcal{D}}\left(a_F,v_F\right)^{-\sigma}}{P\left(v_F\right)^{-\sigma}}-\frac{A^2}{2}\sigma^2\left(a_F\right)$$

substituting,

$$\begin{aligned}&\omega_H L\frac{\tilde{\mathcal{D}}\left(a_H,v_H\right)^{-\sigma}}{P\left(v_H\right)^{-\sigma}}+\left(1-\omega_H\right)L\frac{\tilde{\mathcal{D}}\left(a_H,v_F\right)^{-\sigma}}{P\left(v_F\right)^{-\sigma}}-\frac{A^2}{2}\left(\left(1-\omega_H\right)^2L^2\times\pi\left(a_H,v_F\right)^2\times\sigma^2\right)\\&=\omega_H L\frac{\tilde{\mathcal{D}}\left(a_F,v_H\right)^{-\sigma}}{P\left(v_H\right)^{-\sigma}}+\left(1-\omega_H\right)L\frac{\tilde{\mathcal{D}}\left(a_F,v_F\right)^{-\sigma}}{P\left(v_F\right)^{-\sigma}}-\frac{A^2}{2}\left(1-\omega_H\right)^2L^2\times\pi\left(a_F,v_F\right)^2\times\sigma^2\end{aligned}$$

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} \left(1 - \frac{A^2}{2}\left((1-\omega_H) L \times \pi(a_H, v_F) \times \sigma^2\right)\right)$$
$$= \omega_H L \frac{\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} \left(1 - \frac{A^2}{2}\left((1-\omega_H) L \times \pi(a_F, v_F) \times \sigma^2\right)\right)$$

Define, $\tilde{\sigma}^2(a_H, v_F) \equiv \frac{A^2}{2}\left((1-\omega_H) L \times \pi(a_H, v_F) \times \sigma^2\right)$ and $\tilde{\sigma}^2(a_F, v_F) \equiv \frac{A^2}{2}\left((1-\omega_H) L \times \pi(a_F, v_F) \times \sigma^2\right)$

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} \left(1 - \tilde{\sigma}^2(a_H, v_F)\right)$$
$$= \omega_H L \frac{\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} \left(1 - \tilde{\sigma}^2(a_F, v_F)\right)$$

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)\right]} +$$
$$(1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_H, v_F)\right) - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_F, v_F)\right)}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]} = 0$$

since, $f\sigma = \frac{L}{N^A}$

$$\omega_H N f\sigma \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)\right]} +$$
$$(1-\omega_H) N f\sigma \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_H, v_F)\right) - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_F, v_F)\right)}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]} = 0$$

$$\omega_H \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)} +$$
$$(1-\omega_H) \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_H, v_F)\right) - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_F, v_F)\right)}{\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)} = 0$$

$$\frac{\omega_H}{1-\omega_H} \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}} + \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_H, v_F)\right) - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_F, v_F)\right)}{\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)} = 0$$

$$\frac{\omega_H}{1-\omega_H} \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}} = \frac{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_F, v_F)\right) - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}\left(1 - \tilde{\sigma}^2(a_H, v_F)\right)}{\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)}$$

$$\frac{1-\omega_H}{\omega_H} \frac{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}} = \frac{\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_F, v_F)) - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_H, v_F))}$$

$$(1-\omega_H)\left(\frac{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}\right) = (\omega_H)\left(\frac{\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_F, v_F)) - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_H, v_F))}\right)$$

$$n_H\left(\omega_H \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_F, v_F)) - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_H, v_F))} + (1-\omega_H)\left(\frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}\right)\right)$$
$$= (\omega_H)\left(\frac{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_F, v_F)) - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}(1 - \tilde{\sigma}^2(a_H, v_F))}\right) - (1-\omega_H)\left(\frac{\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}\right)$$

$$n_H \left(1+\omega_H \frac{\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}-\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_F, v_F\right)\right)-\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_H, v_F\right)\right)}-\omega_H\right)$$

$$=\left(\omega_H\right)\left(\frac{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_F, v_F\right)\right)-\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_H, v_F\right)\right)}\right)-\left(1-\omega_H\right)\left(\frac{\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{-\sigma}-\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}\right)$$

Define, $\gamma=\frac{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{-\sigma}-\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_F, v_F\right)\right)-\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_H, v_F\right)\right)}$

$$n_H=\frac{1}{\left(1-\omega_H+\omega_H \gamma\right)}\left[\left(\omega_H\right)\left(\frac{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_F, v_F\right)\right)-\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_H, v_F\right)\right)}\right)-\left(1-\omega_H\right)\left(\frac{\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{-\sigma}-\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}\right)\right]$$

$$\begin{aligned} n_H= & \frac{\left(\omega_H\right)}{\left(1-\omega_H+\omega_H \gamma\right)}\left(\frac{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_F, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_F, v_F\right)\right)-\tilde{\mathcal{D}}\left(a_H, v_F\right)^{-\sigma}\left(1-\tilde{\sigma}^2\left(a_H, v_F\right)\right)}\right) \\ & -\frac{\left(1-\omega_H\right)}{\left(1-\omega_H+\omega_H \gamma\right)}\left(\frac{\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{-\sigma}-\tilde{\mathcal{D}}\left(a_L, v_H\right)^{-\sigma}}\right)\end{aligned}$$

A.3 Section 4.5: Proposition 4 (Comparative Statics)

In this subsection we derive the effect of population changes on observed market share differences. That is we are interested in the following relationship,

$$d\ln\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_F)^{\sigma}}{P(v_F)^{-\sigma}}\right)=\varepsilon_2\times d\ln n_H=\varepsilon_2\times\frac{d\ln n_H}{d\ln\omega_H}\times d\ln\omega_H=\varepsilon_2\times\varepsilon_1\times d\ln\omega_H$$

$$\implies d\ln\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_F)^{\sigma}}{P(v_F)^{-\sigma}}\right)=\varepsilon_2\times\varepsilon_1\times d\ln\omega_H$$

We begin by deriving $\varepsilon_1=\frac{d\ln n_H}{d\ln\omega_H}$. Start with the equilibrium expression for firm entry at the home location.

$$n_H=\frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_F,v_F)\right)-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_H,v_F)\right)}\right)$$
$$-\frac{(1-\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)$$

Re-arranging,

$$n_H=\frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_F,v_F)\right)-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_H,v_F)\right)}+\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)$$
$$-\frac{1}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)$$

Totally differentiating with regard to changes in the population size of the home market, $d\omega_H\neq 0$, and assuming that $\partial\frac{1}{(1-\omega_H+\omega_H\gamma)}/\partial\omega_H\approx 0$, we have,

$$\frac{dn_H}{n_H}=\underbrace{\frac{1}{n_H}\frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_F,v_F)\right)-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_H,v_F)\right)}+\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)}_{\equiv\varepsilon_1}\frac{d\omega_H}{\omega_H}$$

$$\varepsilon_1\approx\frac{\frac{(\omega_H)}{(1-\omega_H+\omega_H\gamma)}\left(\frac{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_F,v_F)\right)-\tilde{\mathcal{D}}(a_H,v_F)^{-\sigma}\left(1-\tilde{\sigma}^2(a_H,v_F)\right)}+\frac{\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H,v_H)^{-\sigma}-\tilde{\mathcal{D}}(a_L,v_H)^{-\sigma}}\right)}{n_H}$$

How to derive ε_2?

$$d\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)=\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}\frac{dP(v_H)^{-\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\frac{dP(v_L)^{-\sigma}}{P(v_L)^{-\sigma}}$$

$$\frac{d\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}=\frac{\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}\frac{dP(v_H)^{-\sigma}}{P(v_H)^{-\sigma}}-\frac{\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}\frac{dP(v_L)^{-\sigma}}{P(v_L)^{-\sigma}}$$

$$d\ln\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)=\frac{\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}d\ln P(v_H)^{-\sigma}-\frac{\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}d\ln P(v_L)^{-\sigma}$$

$$d\ln\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)=\frac{\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}\frac{d\ln P(v_H)^{-\sigma}}{d\ln n_H}d\ln n_H-\frac{\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}(a_j,v_H)^{\sigma}}{P(v_H)^{-\sigma}}-\frac{\tilde{\mathcal{D}}(a_j,v_L)^{\sigma}}{P(v_L)^{-\sigma}}\right)}\frac{d\ln P(v_L)^{-\sigma}}{d\ln n_H}d\ln n_H$$

How to derive $\frac{d\ln P(v_H)^{-\sigma}}{d\ln n_H}$?

$$P(v)\equiv\left(\sum_{s\in S}n_s\delta_s^{\sigma}p_s^{-\sigma}\mathcal{D}(a_s,v)^{\sigma}\right)^{-1/\sigma}$$

$$P\left(v_H\right)^{-\sigma} = \sum_j n_j \tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma} = n_L \tilde{\mathcal{D}}\left(a_L, v_H\right)^{\sigma} + n_H \tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}$$

$$dP\left(v_H\right)^{-\sigma} = \tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma} dn_H$$

$$\frac{dP\left(v_H\right)^{-\sigma}}{P\left(v_H\right)^{-\sigma}} = \frac{n_H \tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}}{n_L \tilde{\mathcal{D}}\left(a_L, v_H\right)^{\sigma} + n_H \tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}} \frac{dn_H}{n_H}$$

$$d \ln P\left(v_H\right)^{-\sigma} = n_H \frac{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} d \ln n_H$$

Combining everything,

$$d \ln\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right) = \frac{\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)} n_H \frac{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} d \ln n_H - \frac{\frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)} n_H \frac{\tilde{\mathcal{D}}\left(a_H, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}} d \ln n_H$$

$$d \ln\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right) = \underbrace{\left(\frac{\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)} n_H \frac{\tilde{\mathcal{D}}\left(a_H, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}}{\left(\frac{\tilde{\mathcal{D}}\left(a_j, v_H\right)^{\sigma}}{P\left(v_H\right)^{-\sigma}} - \frac{\tilde{\mathcal{D}}\left(a_j, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)} n_H \frac{\tilde{\mathcal{D}}\left(a_H, v_L\right)^{\sigma}}{P\left(v_L\right)^{-\sigma}}\right)}_{\varepsilon_2} d \ln n_H$$

A.4 Section 5.1: Proposition 5 (Supply and Equilibrium)

Expected profits are given by,

$$\mathbf{E}\left[\Pi\left(a_j\right)\right]=\Pi_0\left(a_j,\theta_1,\ldots,\theta_n\right)-\frac{A^2}{2}\sigma^2\left(a_j\right)$$

where $\mu\left(a_H\right)$ is the expected return and $\sigma^2\left(a_H\right)$ refers to the variance of the return.

$$\Pi\left(a_j\right)=\sum_i \omega_i\times L\times\pi\left(a_j,v_i\right)\times\left(1+\tilde{x}_i\right)$$

where demand is assumed to be stochastic,

$$\tilde{x}_i\sim N\left(0,\sigma_i^2\right)$$

where we can furthermore distinguish between the stochastic and determinate returns. Define the determinate returns,

$$\Pi_0\left(a_j,\theta_1,\ldots,\theta_n\right)\equiv\sum_i \omega_i\times L\times\pi\left(a_j,v_i;\theta_1,\ldots,\theta_n\right)$$

$$\tilde{\sigma}_j^2\left(a_j,\theta_{\mathbf{1}},\ldots,\theta_{\mathbf{n}}\right)=L^2\sum_i\omega_i^2\pi\left(a_j,v_i;\theta_1,\ldots,\theta_n\right)^2\sigma_i^2$$

Studio's problem,

$$\mathbf{E}\left[\Pi\left(a_j\right)\right]\times\varepsilon_j$$

where ε_j is frechet distributed, The density for each unobserved component of utility is, $\left[\theta_1,\ldots,\theta_N\right]$

$$f\left(\varepsilon_{nj}\right)=\alpha\varepsilon_{nj}^{-\alpha-1}e^{-\varepsilon_{nj}^{-\alpha}}$$

and the cumulative distribution is

$$F\left(\varepsilon_{nj}\right)=e^{-\varepsilon_{nj}^{-\alpha}}$$

then choice probabilities are given by,

$$\begin{aligned}\theta_i&=\frac{\left(\mathbf{E}\left[\Pi\left(a_i\right)\right]\right)^\gamma}{\sum_j\left(\mathbf{E}\left[\Pi\left(a_j\right)\right]\right)^\gamma}\\&=\frac{\left(\Pi_0\left(a_j,\theta_1,\ldots,\theta_n\right)-\frac{A^2}{2}\sigma^2\left(a_j\right)\right)^\gamma}{\sum_j\left(\Pi_0\left(a_j,\theta_1,\ldots,\theta_n\right)-\frac{A^2}{2}\sigma^2\left(a_j\right)\right)^\gamma}\end{aligned}$$

then the expected return for a studio is given by,

$$\mathbf{E}\left[\max_i\left(\mathbf{E}\left[\Pi\left(a_i\right)\right]\times\epsilon_i\right)\right]=\left(\sum_j\left(\mathbf{E}\left[\Pi\left(a_i\right)\right]\right)^\gamma\right)^{\frac{1}{\gamma}}\Gamma\left(1-\frac{1}{\gamma}\right)$$

$$\theta_j=\frac{\left(B_j\left(a_j,\theta_1,\ldots,\theta_n\right)\right)^\gamma}{\sum_{h\in\mathcal{G}}\left(B_j\left(a_j,\theta_1,\ldots,\theta_n\right)\right)^\gamma}$$

$$B_j=\Pi_0\left(a_j,\theta_1,\ldots,\theta_n\right)-\frac{A^2}{2}\sigma^2\left(a_j,\theta_{\mathbf{1}},\ldots,\theta_{\mathbf{n}}\right)$$

Part

Online Appendix

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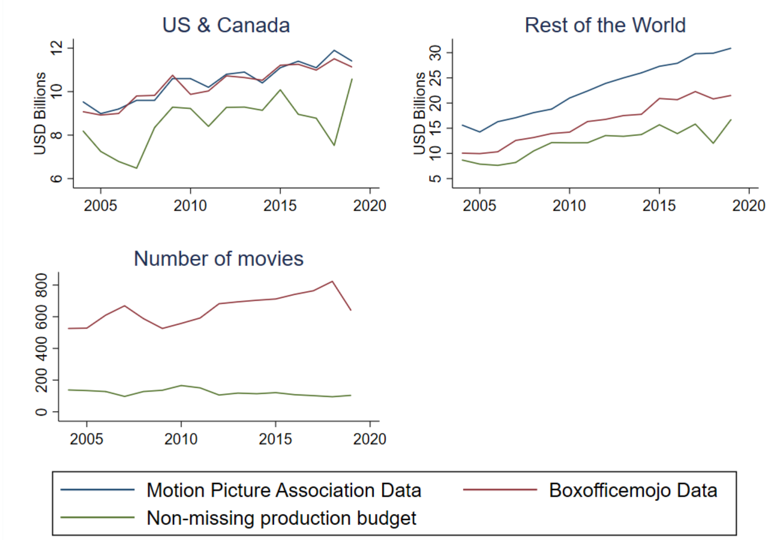
B Additional Tables and Figures

Figure A.3. Coverage of Boxofficemojo Data



Notes: Coverage of total boxoffice data from Boxofficemojo.com for US/Canada and the Global market. Aggregate data are from Motion Picture Association reports, retrieved from im+m business partners.

Table. A.5. Difference in difference regression

	(1) OLS	(2) TWFE	(3) TWFE
Market Share	0.57***	0.56***	0.50***
	(0.05)	(0.05)	(0.05)
Market Share x Post	0.35***	0.35***	0.45***
	(0.11)	(0.10)	(0.07)
Market Share x Hong Kong	−0.14***	−0.13***	−0.10***
	(0.04)	(0.04)	(0.04)
Market Share x Hong Kong x Post	−0.24**	−0.24**	−0.43***
	(0.11)	(0.11)	(0.08)
$\beta\_1 - \beta\_2 = 0$	10.27***	11.76***	47.2***
$(\beta\_1 + \beta\_3) - (\beta\_2 + \beta\_4) = 0$	3.38*	1.85	.08
Controls			✓
Weighted by budget	✓	✓	✓
R^2	0.52	0.54	0.61
Observations	1522	1522	1510

Notes: Difference in difference regressions with US market shares as dependent variable. *POST* indicates years after China increased the import quota for foreign movies from 20 to 34 movies in 2012. Western European countries are the control group. Control variables include the log production budget, the log runtime, indicator variables for the genre, indicators for whether the movie is a sequel, a remake, a spinoff, or, whether it is R-rated by the MPAA, and indicators for production countries. The sample includes all movies released, in Western Europe, and in Hong Kong and runs from 2008 until 2016. Standard erorrs clustered at the movie level in parentheses

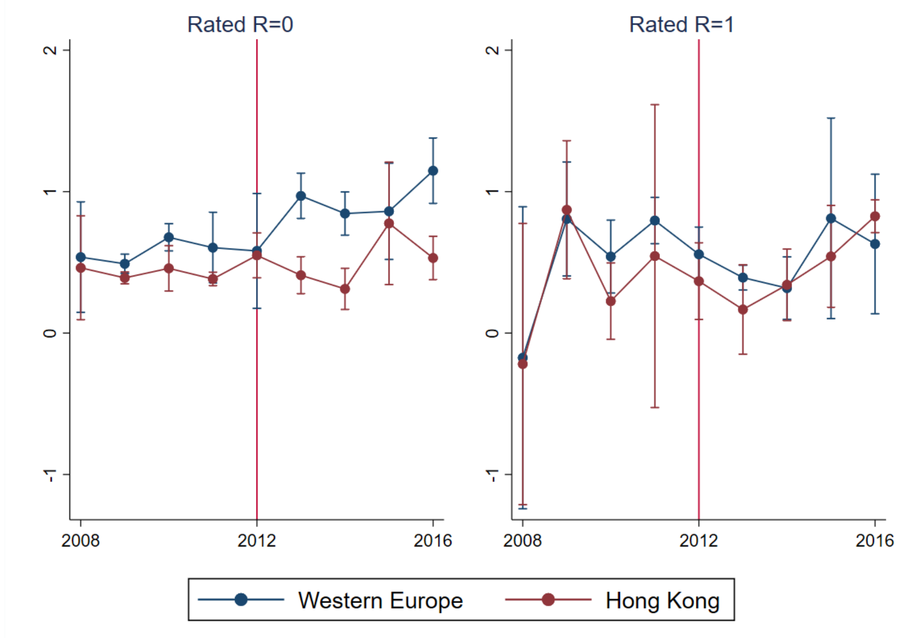
C Additional Reduced Form Results

We also split our sample into different categories. In Figure A.4 we find that the correlation does not change for R-ratd movies, but only for movies with a less restrictive rating (G, PG, PG-13). This supports our interpretation because Chinese censors almost never approve R-rated movies to be shown in China. Hollywood studios therefore are likely to have adapted movies without an R rating, but left R-rated movies unchanged after China's policy change. Figures A.5 and A.6 show similar results for movies of different genres. There is no change for comedy movies, which are more difficult translate into a different cultural context, but the change is evident for action movies. Similarly, there is no change for crime movies and movies involving nudity.

How does this divergence show up at the movie level? Figures A.8 and A.7 show the difference in the rank of movies' market shares in 2010 and 2013. A positive difference indicates that a movie was more successful in Hong Kong or Western Europe relative to the US, and vice versa. While the bars tend to point into the same direction in Appendix FigureA.7 there are visible differences in Figure A.8 after the policy change.

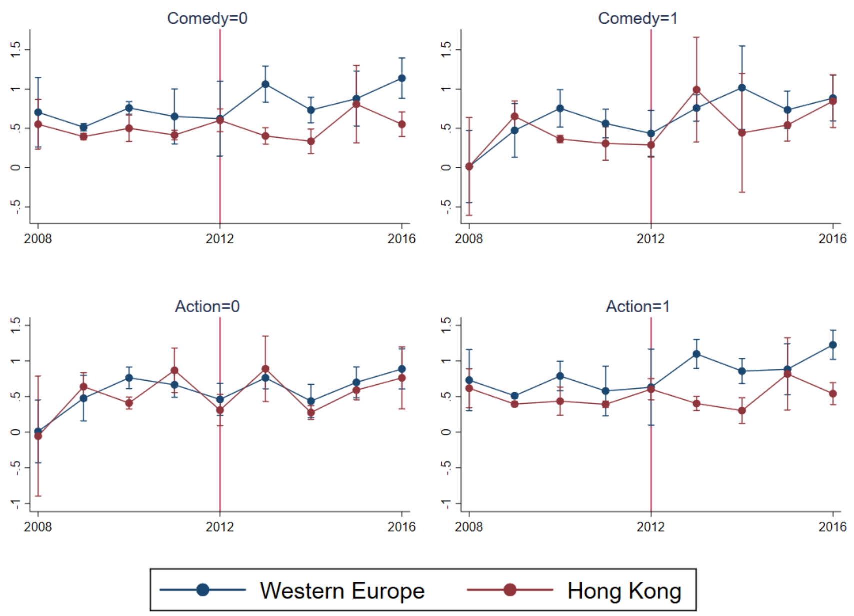
Most notably is the large difference for the movie "Pacific Rim", a PG-13 rated Action/Sci-Fi movie released in 2013. The movie was a commercial flop in the US and Western Europe, but successful in China.

Figure A.4. US and Hong Kong Box vs US and Western European Box Office Revenues



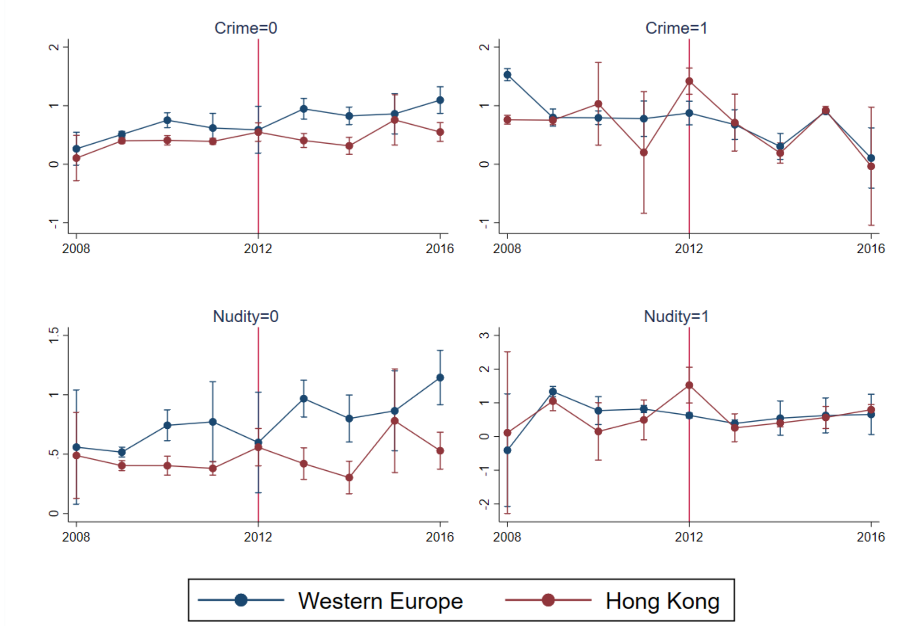
Notes: Covariance of market shares between the US and Western Europe (blue) and the US and Hong Kong (red) as in Figure 2 for subsamples of movies without R-rating (LHS Panel) and movies with R-Rating (RHS Panel).

Figure A.5. US and Hong Kong Box vs US and Western European Box Office Revenues



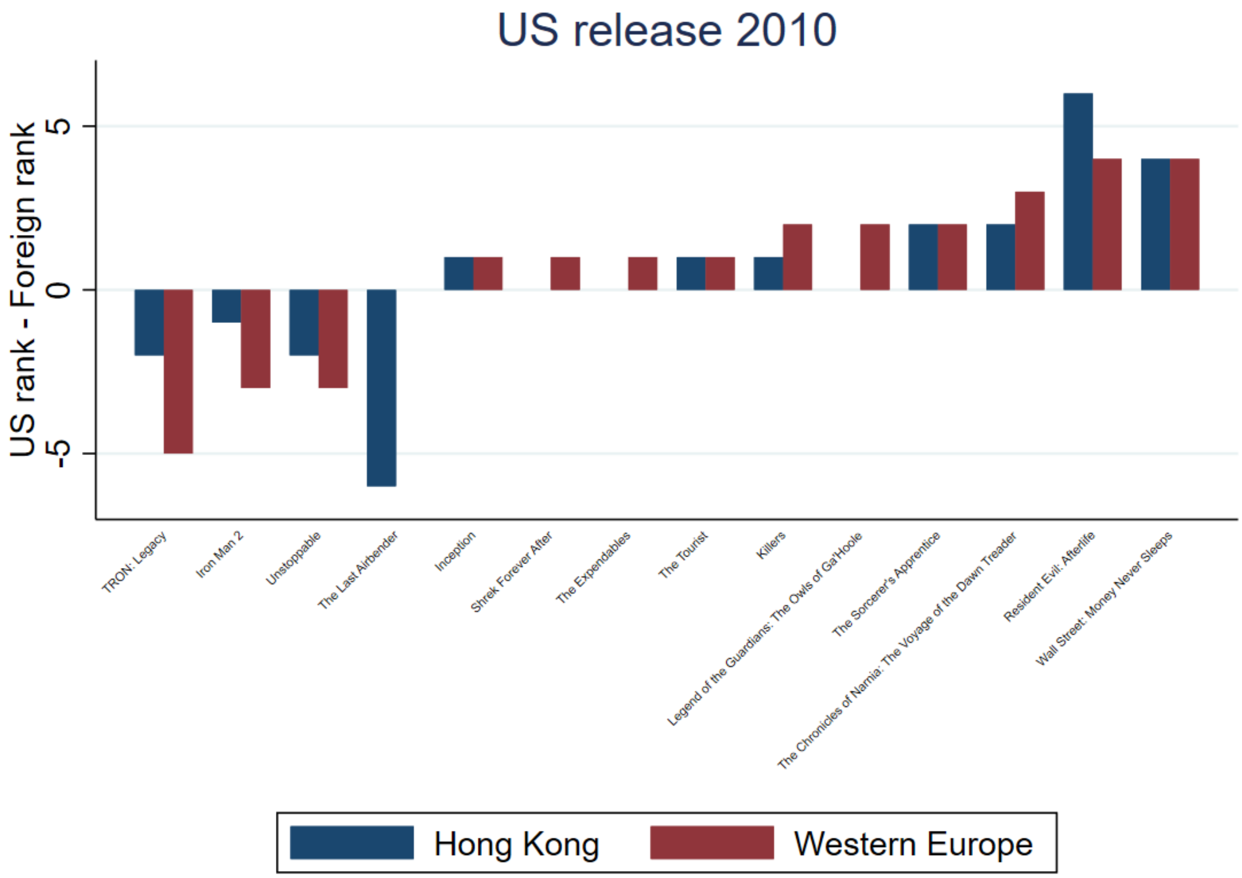
Notes: Covariance of market shares between the US and Western Europe (blue) and the US and Hong Kong (red) as in Figure 2 for subsamples of comedy movies and all other genres, and action movies and all other genres.

Figure A.6. US and Hong Kong Box vs US and Western European Box Office Revenues



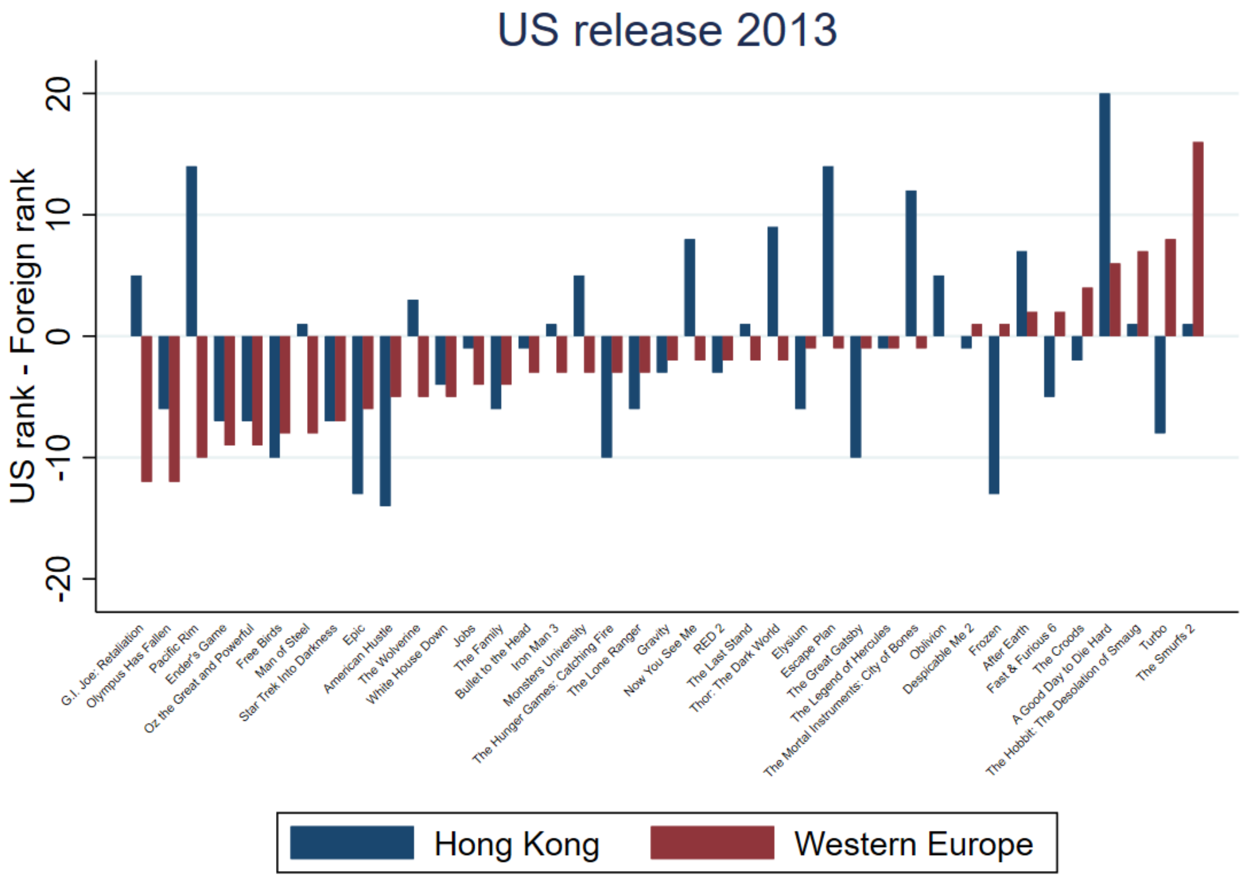
Notes: Covariance of market shares between the US and Western Europe (blue) and the US and Hong Kong (red) as in Figure 2 for subsamples of crime movies and all other movies and movies with nudity and all other movies.

Figure A.7. US and Hong Kong Box vs US and Western European Box Office Revenues



Notes: Covariance of market shares between the US and Western Europe (red) and the US and Hong Kong (blue) obtained from a regression of US market shares on Western European and Hong Kong market shares with 90% confidence intervals. The sample is limited to movies released in China and produced, at least in part, in the US. Data are from boxofficemojo.com.

Figure A.8. US and Hong Kong Box vs US and Western European Box Office Revenues



Notes: Difference in rank of market shares between the US and Western Europe (red) and the US and Hong Kong (blue) obtained from a regression of US market shares on Western European and Hong Kong market shares with 90% confidence intervals. The sample is limited to movies released in China and produced, at least in part, in the US. Data are from boxofficemojo.com.

D Additional Derivations

This appendix presents additional derivations.

D.1 Equilibrium without volatility

Consider the simplified case, where, $v_i \in \{\tilde{v}_H, \tilde{v}_F\}$, and the location of supply is similarly restricted, $a_j \in \{v_H, v_F\}$. Demand is given as in Proposition 1, and pricing is marginal cost pricing such that,

$$p_j = \frac{1+\sigma}{\sigma} c_j = \frac{1+\sigma}{\sigma} a_j^{\gamma}$$

Revenue is given by,

$$\Pi(a_j) = \omega_H L \frac{\tilde{\mathcal{D}}(a_j, v_H)^{\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_j, v_F)^{\sigma}}{P(v_F)^{-\sigma}}$$

Price index is given by,

$$P(v_H) = \left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)\right]^{-1/\sigma} \text{ and}$$
$$P(v_F) = \left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]^{-1/\sigma}$$

Free entry implies revenue must be equal everywhere,

$$\Pi(a_H) = \Pi(a_L)$$

which implies,

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} = \omega_H L \frac{\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{P(v_F)^{-\sigma}}$$

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{P(v_H)^{-\sigma}} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{P(v_F)^{-\sigma}} = 0$$

$$\omega_H L \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)\right]} + (1-\omega_H) L \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]} = 0$$

since, $f\sigma = \frac{L}{N^A}$

$$\omega_H N f\sigma \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right)\right]} + (1-\omega_H) N f\sigma \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\left[N\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]} = 0$$

$$\omega_H \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\left[n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}\right]} + (1-\omega_H) \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\left[\left(n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}\right)\right]} = 0$$

$$\frac{\omega_H}{1-\omega_H} \frac{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}} = \frac{\tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}$$

$$\frac{1-\omega_H}{\omega_H} \frac{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}} = \frac{n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}}$$

$$(1-\omega_H)\left(\frac{n_H \tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_F, v_H)^{-\sigma}}\right) = (\omega_H)\left(\frac{n_H \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma} + (1-n_H)\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma}}{\tilde{\mathcal{D}}(a_F, v_F)^{-\sigma} - \tilde{\mathcal{D}}(a_H, v_F)^{-\sigma}}\right)$$

re-arranging and simplifying, we obtain,

$$n_H = \left(\omega_H \frac{\tilde{\mathcal{D}}(a_L, v_L)^{-\sigma}}{\tilde{\mathcal{D}}(a_L, v_L)^{-\sigma} - \tilde{\mathcal{D}}(a_H, v_L)^{-\sigma}} - (1-\omega_H) \frac{\tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}{\tilde{\mathcal{D}}(a_H, v_H)^{-\sigma} - \tilde{\mathcal{D}}(a_L, v_H)^{-\sigma}}\right)$$

which defines the equilibrium supply of products at the H and F location.