Learning via Sequential Market Entry: Evidence from International Releases of U.S. Movies

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Abstract

This paper investigates the sequential entry of U.S. movies into foreign markets. In the model, sequential entry allows distributors to learn about their movies' quality from performance in successive markets, which are imperfectly correlated. Empirically, facts about the spatial-temporal pattern of entry are documented. A theory-derived Bayesian learning term is found to significantly enter an entry regression; the point estimate suggests that a one-standard-deviation increase in the update to expected box-office revenues, based on the last round of entry, is associated with a 25% increase in the probability of entry to a typical potential destination in the current round.

Keywords: heterogeneous quality, sequential entry, cultural goods trade

JEL Codes: F14, L82.

1. Introduction

Recent models of international trade have emphasized firm heterogeneity with respect to productivity or quality within each country. Taking the quality interpretation, the models imply that firms with higher quality products earn higher revenues within each market. Given assumed fixed costs of entering foreign markets, only firms with products of high enough quality will find it profitable to enter. In other words, each country is characterized by a cut-off level of quality, below which entry is not profitable. These models faces at least two challenges empirically.[1] First, disaggregated data show that many exporters move small volumes, make losses, and exit the export market. Small

[1] This literature originates in Melitz (2003) and Bernard et al. (2003). Refinements such as Eaton et al. (2011), which allow for idiosyncratic shocks to demand and/or cost, and thus a relaxation of the strict cut-off, are also subject to the challenges discussed here.

sales volumes don't appear to be consistent with significant fixed export costs. Second, products tend to enter foreign markets sequentially. If a firm knows that its product's quality exceeds the cut-off level for a given market, why does it wait to enter?

In this paper I propose a heterogeneous products model in which firms are uncertain about their products' export profitability—which is imperfectly correlated across destination markets—and enter markets sequentially to learn about their quality, updating their beliefs after each round. This model can explain why some firms make losses and why products are released sequentially to foreign markets. Both of these features are prominent in the movie industry, which is the empirical context of the study.

Four recent papers that make similar points are Eaton et al. (2012), Albornoz et al. (2012), Nguyen (2012), and Akhmetova and Mitaritonna (2013). Eaton et al. (2012) investigates export shipments from Columbia to the United States over time and documents a high degree of firm turnover; a large percentage of new exporters make small shipments and exit the export market shortly after entry. To reconcile this behavior with fixed export costs, the authors propose a model of search and learning, in which firms are initially uncertain about their profitability and learn about it after entry. The study is concerned with exports from a single origin country to a single destination market.

Albornoz et al. (2012) is closer to the present paper in that it considers firms that are uncertain about export profitability and can learn across export markets. The study highlights the theoretical strategic implications of learning—the option value of delaying entry to some markets as an incentive for sequential exporting—and empirically tests this idea indirectly by focusing on the consequences of sequential exporting: conditional on survival, growth rates are greatest between the first two periods in a firm's first export market.[2] Nguyen (2012) builds a structural model that fully takes into account the value of information from delayed entry. To feasibly simulate the model, the author makes the assumption that the correlation of demand across markets is equal for all country-

[2]The fact that growth is fastest between the first two periods suggests firms are learning relevant cost and demand parameters in the first period and adjusting scale accordingly. The fact that this effect is greatest in the first export market suggests firms are applying the new information in subsequent markets.

pairs. In the present study, the variation in these correlations is an interesting and apparently important feature of the data. Akhmetova and Mitaritonna (2013) also build and estimate a structural model of firm learning, in which firms are able to test new markets by paying a reduced entry cost, which is endogenous to the number of customers sampled as in Arkolakis (2010). In the model, demand uncertainty is limited to a bivariate distribution.

The model in this paper illustrates the incentives for firms to strategically delay entry to some markets in order to imperfectly learn about demand; however, the main empirical question is concerned with the implications of sequential entry rather than its determinants. In particular, given sequential entry, do movie distributors learn from prior-market performance and incorporate the new information in subsequent entry decisions?

Unlike other recent papers on export-demand uncertainty, this study focuses on a single product—U.S. movies—to empirically investigate learning via sequential entry. The analysis contributes in a number of ways. The first is that by considering a single product, the empirics are more in line with the theory. After all, quality (or appeal) applies at the product level. Other papers use the firm as the unit of analysis, but in a recent study on multi-product firms, Bernard et al. (2011) find that product-level demand shocks are salient features of the data, and measuring quality at the firm level can be misleading.

Second, movies are cultural products, and the export of movies is a form of trade in services. The model in this paper builds on other studies on the export of U.S. movies, in particular, Holloway (2013), which draws on Hanson and Xiang (2011) and Ferreira et al. (2012). These papers all investigate the nature and consequences of export costs in different ways, but none of them focuses on learning or entry timing. McCalman (2005) studies the determinants of the delay to release movies in foreign markets, but focuses on demand-side factors such as word-of-mouth and market-erosion due to piracy. Existing work on sequential exporting considers only manufacturing trade.

Third, I test directly for learning by incorporating a Bayesian-derived updating term into an entry regression. The Bayesian update is essentially a weighted average of the box-office surprises observed in the previous round of entry. Surprises comprise the difference between (log) actual revenue and (log) predicted revenue, where initial predictions are formed in a first-stage regression of box-office revenues on movie attributes and country fixed effects. Weights are determined by the degree of correlation between the markets and the variance of revenues within the markets. For example, suppose a movie is released in Spain and is a surprise success. This information is used to update predictions for other potential markets, say, France and Norway. Since the French market is highly correlated with the Spanish market, the performance in Spain provides a lot of information about potential French revenues. The Norwegian prior would not be affected much since Norwegian revenues are not highly correlated with those in Spain. Moreover, countries that exhibit large variation in revenues, conditional on movie attributes, provide less information than those with tighter variation.

The Bayesian update term enters significantly in the entry regression, suggesting that surprises in performance in the previous period affect the entry decisions in the current period. The point estimate implies that a one-standard-deviation increase in the update leads to a five percentage-point increase in the probability of entry, which represents a 25% increase over the average probability in the sample.

In addition to this main result, I document several facts in the data. In the long run, there is wide variation in the number of markets entered, and this number is correlated with the U.S. box-office performance. This is consistent with a model with fixed entry costs and revenues correlated across foreign markets. I also find that the production budget is a good predictor of box-office revenue and that low-budget movies are more likely to be released sequentially over several rounds. These facts are consistent with the learning story, in which firms that are more uncertain about profitability are more likely to enter new markets sequentially. The findings in this paper suggest an indirect cost of international movie piracy. If movies are increasingly released simultaneously in foreign markets to combat piracy, there is less scope to learn from one market to another, and thus a greater potential to make *ex post* unprofitable entries.

The paper proceeds as follows. In section 2 I derive a model of firm learning that guides the empirical specifications that follow. In section 3 I describe the data set and document features of the spatial-temporal pattern of entry for U.S. movies. The regressions are estimated in section 4, along with robustness checks. The conclusion summarizes the main findings.

2. Theory

The model builds on Holloway (2013), which assumes movie quality (i.e. revenue potential) is known, and draws on Ferreira et al. (2012) and Hanson and Xiang (2011).

Consider a risk-neutral distributor making entry decisions in K segmented markets. To enter any of the destination markets, indexed by d, the distributor of movie m must incur a fixed entry cost of F_{dm}. Movies are heterogeneous in quality, which is not directly observable even by their distributors. The applied quality of any given movie also varies between markets, due to country-specific idiosyncrasies in taste. Individuals in destination country d purchase a ticket for movie m if their indirect utility of doing so is greater than zero. As in Ferreira et al. (2012), indirect utility of individual i from country d consuming movie m is modelled as follows:

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

where q_m is the quality of the movie, β is the marginal utility of quality, y_d is per capita income in destination d, ρ captures how tastes for movies vary with income, p_{dm} is the price of movie m in destination d, α is the marginal utility of income, ψ_{dm} is the destination-movie-specific taste shock and u_{idm} is the individual's idiosyncratic utility.

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

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

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

Plugging 1 into 2,

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

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

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

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

Define the attractiveness of country d as $A_d \equiv \frac{M_d}{\alpha} e^{\lambda + \rho y_d - \alpha p_d}$ and let $Q_m \equiv e^{q_m}$ and $\Psi_{dm} \equiv e^{\psi_{dm}}$. We can then express operating profits succinctly as

$$\Pi_{dm} = Q_m^{\beta} A_d \Psi_{dm}. \tag{5}$$

Taking the logarithm of equation (5) gives the linear equation,

$$\pi_{dm} = \beta q_m + a_d + \psi_{dm}, \tag{6}$$

where lower-case letters represent logarithmic terms and $\psi_{dm} \sim N(0, \sigma^2_{\psi})$.

Although the quality of the movie is not known *ex ante*, there are known imperfect proxies. A firm might make reasonable predictions about future revenues in each of the prospective markets by substituting the known proxies in for unknown quality, and using historical data to estimate country fixed effects—to substitute for a_d—and the parameter β. That is, if the firms know the "law of revenues", they can substitute in their quality proxies to make initial predictions about potential revenues in each of the markets. In particular, suppose that quality, q_m, is a function of the logarithm of the movie's budget, $b_m = \ln B_m$:

$$q_m = \gamma b_m + \xi_m, \tag{7}$$

where $\xi_m \sim N(0, \sigma_\xi^2)$. Substituting equation (7) into (6), and replacing a_d by a set of destination fixed effects gives[3]

$$r_{dm} = \beta\gamma b_m + a_d + \nu_{dm}. \tag{8}$$

where $\nu_{dm} = \beta\xi_m + \psi_{dm}$.

Firms form beliefs for each market according to equation (8).[4] The normality assumptions on ξ and ψ—and thus on ν—imply a normal prior: $r_{dm} \sim N(\mu_{dm1}, \sigma_{d1}^2)$, where

$$\mu_{dm1} = \beta\gamma b_m + a_d \tag{9}$$

$$\sigma_{d1}^2 = \sigma_{\nu_d}^2. \tag{10}$$

For clarity of exposition, let us first assume there are only two destinations, A and B, and thus only two potential rounds of entry. Furthermore, market A is the more profitable market. Thus, in the first round, distributors choose whether to enter A alone or A and B simultaneously. If the movie enters only A in the first round, then distributors update their expectations about revenues in market B using realized revenues in market

[3]By an abuse of notation, I am calling the destination-specific constant (fixed effect), a_d, which is not equal to the conceptual $\ln A_d$. Also, since $R_{dm} = \alpha p_d \Pi_{dm}$, log revenues equal log profits plus a destination-specific constant, subsumed by a_d.

[4]That is, firms know the value of the compound parameter $\beta\gamma$ and the destination-specific constants.

A. According to Bayes' Law, $r_{Bm2} \sim N(\mu_{Bm2}, \sigma^2_{Bm2})$ with

$$\begin{aligned}
\mu_{Bm2} &= \mu_{Bm1} + \rho_{AB}\frac{\sigma_{B1}}{\sigma_{A1}}(r_{Am} - \mu_{Am1}) \qquad (11)\\
\sigma^2_{Bm2} &= \sigma^2_{B1}(1 - \rho^2_{AB}) \qquad (12)
\end{aligned}$$

where ρ_{AB} is the correlation between ν_{Am} and ν_{Bm}, σ_{B1} is the square root of $\sigma^2_{\nu_B}$, and $(r_{Am} - \mu_{Am1}) \equiv \nu_{Am}$ is the difference between the realized and expected log revenues for movie m in country A.

These Bayesian updating formulas provide intuition for how predictions in future potential markets depend on the surprises observed in entered markets. The surprises are tempered by the degree of correlation across the two countries, and the degree of variation within each of the countries. The posterior variance is always decreased after new information is attained, but again the amount of precision gained depends on the correlation between the markets involved.[5]

In the sequential entry case, movies will be released in market B in round 2 if the updated expected profits exceed the fixed costs of entry. To simplify notation I omit the subscript m in what follows:[6]

$$\begin{aligned}
\mathbb{E}[\Pi_B|R_A] &> F_B\\
e^{\mu_{B2}+\frac{\sigma^2_{B2}}{2}-k_B} &> F_B\\
\mu_{B1} + \rho_{AB}\frac{\sigma_{B1}}{\sigma_{A1}}(r_A - \mu_{A1}) + \frac{\sigma^2_{B2}}{2} - k_B &> \ln F_B \qquad (13)\\
\frac{\sigma_{A1}}{\rho_{AB}\sigma_{B1}}[\ln F_B - \mu_{B1} - \frac{\sigma^2_{B2}}{2} + k_B] + \mu_{A1} \equiv \hat{r}_A &< r_A, \qquad (14)
\end{aligned}$$

where $\hat{r}_A$ is the cut-off level of log revenues in A, above which expected profits are

[5] In practice, some movies enter more than one country per period. To aggregate the surprises in each of the entered markets, a matrix version of Bayes' Law is required. It is introduced in section 4.1.

[6] If $\log(X) \sim \mathrm{N}(\mu, \sigma^2)$ then $X \sim \text{Log-N}(\mu, \sigma^2)$ and $\mathbb{E}X = e^{(\mu + \frac{\sigma^2}{2})}$. The term $k_B \equiv \ln(\alpha c_B + 1)$ is included because μ_{B2} gives expected log box-office revenue but entry depends on expected profits.

positive for entry into market B. We can express the value of entering B in round 2 at round 1 by writing it as a discounted conditional expectation:

$$
\begin{aligned}
W_B &= \delta \mathbb{E}\left[\Pi_B - F_B | r_A > \hat{r}_A\right] \\
&= \delta \int_{\hat{r}_A}^{\infty} \left[e^{\mu_{B2} + \frac{\sigma_{B2}^2}{2} - k_B} - F_B \right] dG(r_A) \qquad (15) \\
&= \delta \int_{\frac{\hat{r}_A - \mu_{A1}}{\sigma_{A1}}}^{\infty} e^{\mu_{B1} + \rho_{AB}\sigma_{B1}s_A + \frac{\sigma_{B2}^2}{2} - k_B} d\Phi(s_A) - \delta F_B \left[1 - \Phi\left(\frac{\hat{r}_A - \mu_{A1}}{\sigma_{A1}} \right) \right] \qquad (16)
\end{aligned}
$$

For later convenience I have made the change of variables $s_A = \frac{\hat{r}_A - \mu_{A1}}{\sigma_{A1}}$, so the variable of integration is the surprise performance in market A scaled by its prior variance, which follows the standard normal distribution, $\Phi(\cdot)$. The first term represents the expected operating profits to be made by entering B conditional on revenues in A being above the cut-off level. The second term represents the expected entry costs, which equal the entry costs multiplied by the probability of entry. The leading factor δ is the discount factor.

The total expected profits from a sequential entry strategy equal the sum of expected net profits from entering A in round 1 and the discounted conditional expected profits from entering B in round 2: $\mathbb{E}\Pi_A - F_A + W_B$. The total expected profits from simultaneous release is equal to $\mathbb{E}\Pi_A - F_A + \mathbb{E}\Pi_B - F_B$, so simultaneous entry is preferred if:

$$
\begin{aligned}
\mathbb{E}\Pi_A - F_A + \mathbb{E}\Pi_B - F_B &> \mathbb{E}\Pi_A - F_A + W_B \\
\mathbb{E}\Pi_B &> F_B + W_B. \qquad (17)
\end{aligned}
$$

The term W_B represents the opportunity cost of entering B immediately without the benefit of information acquired in market A. This information value also affects the decision to enter market A in round 1: it is profitable to enter A if $\mathbb{E}\Pi_A + W_B > F_A$; that is, movies might enter A even if expected net profits are less than zero.

Suppose fixed entry costs are observable to the firms but not to us, because of idiosyncratic movie-destination market shocks. From inspecting equation 17, it isn't clear if higher entry costs will always make it less likely that movies will enter simultaneously rather than sequentially. This is because W_B is a decreasing function of F_B. Differentiating W_B with respect to F_B:[7]

$$
\begin{aligned}
\frac{\partial W_B}{\partial F_B} &= \frac{\partial}{\partial F_B}\left[\int_{\frac{\hat{r}_A-\mu_{A1}}{\sigma_{A1}}}^{\infty} \Pi(r_A;F_B)\phi(r_A)dr_A - F_B\left[1-\Phi\left(\frac{\hat{r}_A-\mu_{A1}}{\sigma_{A1}}\right)\right]\right] \\
&= \Phi\left(\frac{\hat{r}_A-\mu_{A1}}{\sigma_{A1}}\right) - 1; \qquad (18)
\end{aligned}
$$

thus, although W_B is falling in F_B, $F_B + W_B$ is increasing in F_B: larger entry costs will mean movies are less likely to be released in the current round.

In the empirics to follow, we wish to estimate the effect of updates to predicted revenues on the probability that a movie enters a destination in a given round of release. Unlike the stylized model above, there are more than two countries, and a typical destination market could potentially be followed by subsequent destinations. If we allow for a third market, C, and consider the decision to enter market B in round 2, we get a fuller picture. Predicted revenues for markets B and C are updated from market A performance, but market B also allows for further updating to predicted revenues in market C. The decision to enter market B in round 2 is then governed by the following inequality:

$$
\begin{aligned}
\mathbb{E}[\Pi_B|R_A] + W_C &> F_B \\
e^{\mu_{B2}+\frac{\sigma_{B2}^2}{2}-k_B} + \delta\int_{\frac{\hat{r}_B-\mu_{B2}}{\sigma_{B2}}}^{\infty}\left[e^{\mu_{C2}+\rho_{BC}\sigma_{C2}s_B+\frac{\sigma_{C3}^2}{2}-k_C} - F_C\right]d\Phi(s_B) &> F_B \qquad (19)
\end{aligned}
$$

Note that the surprise in market A enters in two places. First, it enters the conditional expected operating profits in market B through μ_{B2}; second, it enters W_C through μ_{C2}.[8] A positive surprise in market A will lead to a greater chance of entering market B in the next round (and a negative surprise will lead to a lower chance of entering market B).

Now consider the decision to enter market C in round 2 (simultaneously to market

[7] The second inequality follows from the Leibniz integral rule and the definition of $\hat{r}_A$.

[8] It also enters the lower limit of integration through $\hat{r}_B$, but this does not affect the derivative of the left-hand side of (19).

B). Analogously to 17 above, simultaneous entry in round 2 is optimal if:

$$\mathbb{E}[\Pi_C|R_A] > F_C + W_C \tag{20}$$

The implications for entry into market C from a surprise in A are not so obvious. On the one hand, predicted operating profits (the left-hand side of (20)) increase in the surprise so entry is more likely; on the other hand, the opportunity cost of not waiting and learning from market B (given by W_C) is also an increasing function of the surprise in A. It turns out that $\mathbb{E}[\Pi_C|R_A] - W_C$ is increasing in the market A surprise. To see this, we will take the derivative of both terms and compare them.

$$\begin{aligned}
\mathbb{E}[\Pi_C|R_A] &= e^{\mu_{C2}+\frac{\sigma_{C2}^2}{2}-k_C} \\
&= e^{\mu_{C1}+\rho_{AC}\sigma_{C1}s_A+\frac{\sigma_{C2}^2}{2}-k_C} \\
\frac{\partial \mathbb{E}[\Pi_C|R_A]}{\partial s_A} &= \rho_{AC}\sigma_{C1}e^{\mu_{C2}+\frac{\sigma_{C2}^2}{2}-k_C} \\
W_C &= \delta \int_{\frac{\hat{r}_B-\mu_{B2}}{\sigma_{B2}}}^{\infty} \left[e^{\mu_{C2}+\rho_{BC}\sigma_{C2}s_B+\frac{\sigma_{C3}^2}{2}-k_C} - F_C \right] d\Phi(s_B) \\
\frac{\partial W_C}{\partial s_A} &= \delta\rho_{AC}\sigma_{C1}e^{\mu_{C2}+\frac{\sigma_{C3}^2}{2}-k_C} \int_{\frac{\hat{r}_B-\mu_{B2}}{\sigma_{B2}}}^{\infty} \left[e^{\rho_{BC}\sigma_{C2}s_B}\right] d\Phi(s_B)
\end{aligned} \tag{21}$$

To make further progress, we can bound the size of the integral in the last line. Let $a = \rho_{BC}\sigma_{C2}$. Then,

$$\begin{aligned}
\int_{\frac{\hat{r}_B-\mu_{B2}}{\sigma_{B2}}}^{\infty} \left[e^{\rho_{BC}\sigma_{C2}s_B}\right] d\Phi(s_B) &= \frac{1}{\sqrt{2\pi}} \int_{\frac{\hat{r}_B-\mu_{B2}}{\sigma_{B2}}}^{\infty} e^{as_B-\frac{s_B^2}{2}} ds_B \\
&< \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{as_B-\frac{s_B^2}{2}} ds_B \\
&= e^{\frac{\rho_{BC}^2\sigma_{C2}^2}{2}}
\end{aligned} \tag{22}$$

By substituting back into the derivative of W_C, we obtain,

$$
\begin{aligned}
\frac{\partial W_C}{\partial s_A} &< \delta \rho_{AC}\sigma_{C1} e^{\mu_{C2}+\frac{\sigma_{C3}^2}{2}-k_C} e^{\frac{\rho_{BC}^2\sigma_{C2}^2}{2}} \\
&< \rho_{AC}\sigma_{C1} e^{\mu_{C2}+\frac{\sigma_{C2}^2}{2}(1-\rho_{BC}^2)+\frac{\rho_{BC}^2\sigma_{C2}^2}{2}-k_C} \\
&= \rho_{AC}\sigma_{C1} e^{\mu_{C2}+\frac{\sigma_{C2}^2}{2}-k_C} \\
&= \frac{\partial \mathbb{E}[\Pi_C|R_A]}{\partial s_A} \qquad (23)
\end{aligned}
$$

In summary, entry decisions are stochastic from our perspective because fixed entry costs are subject to movie-destination shocks that are observable to firms. Comparative statics on entry costs imply that higher costs are associated with less profitable entry. Comparative statics on the prior-release surprise indicate that the probability of entry is an increasing function of the performance surprise from the previous round.

3. Data Patterns

Box-office revenues for all movies making a cinematic release are available for a sample of countries from the web site boxofficemojo.com. I retain all U.S. movies that were shown in at least one of the thirteen other markets considered over the period 2002–2008.[9] The foreign markets are chosen based on data availability for these seven years. Reducing the time span to the latter three years would allow for greater geographic coverage but would greatly reduce the number of movies in the sample. Production budget data is taken from the web site the-numbers.com and is available for 761 of the movies. Categorical variables, including the main genre (comedy, drama, etc.) and MPAA rating (parental guidance, restricted to adults, etc.) are obtained from the-numbers.com and imdb.com, respectively.

In Figure 1, movies are sorted into bins representing the number of markets in the sample that they entered. The average U.S. box-office revenue over all movies in each bin is depicted, demonstrating a monotonic relationship between the number of markets

[9] The other 13 markets are Argentina, Australia, Czech Republic, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Spain, and United Kingdom.

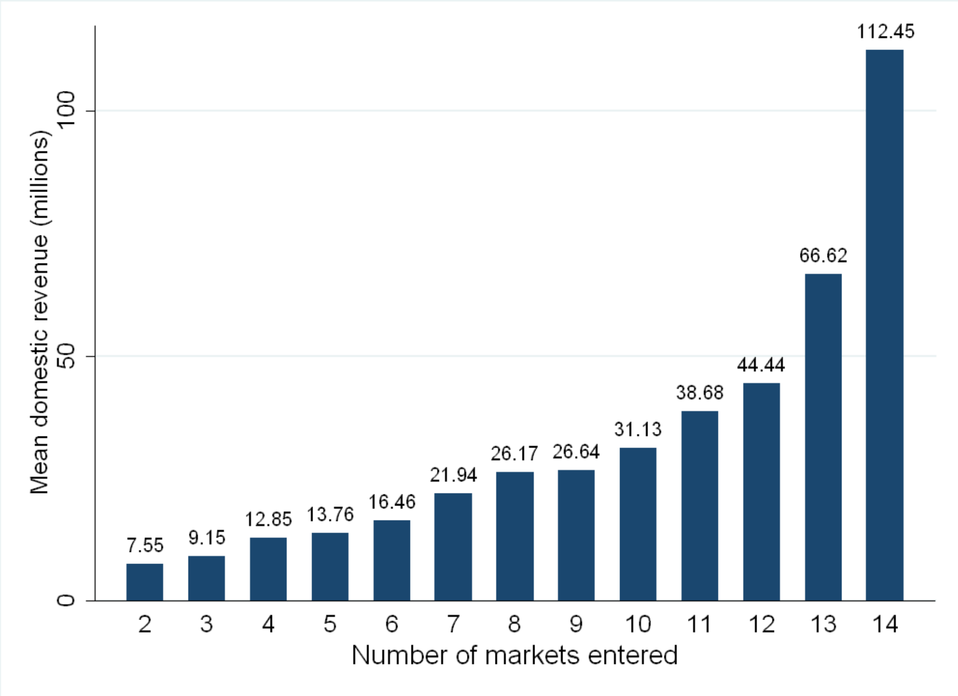

Figure 1: Mean Domestic Revenue by Number of Markets Entered

entered and the mean U.S. revenue. Thus, higher-quality movies (as measured by U.S. box-office revenues) tend to be exported to more foreign markets. This is consistent with a model with fixed export costs and positively correlated revenues across markets.[10]

Studios and distributors can't forecast precisely how well a movie will perform before it is released, but they can make reasonable predictions based on movie attributes and known relationships between these attributes and box-office performance. For instance, the revenue is correlated with the production budget, as shown in Figure 2 for the U.S.. Apart from a few low-budget surprise successes, the budget does quite well in predicting performance, with an R^2 of 0.43.[11]

Since big-budget movies are predicted to make larger revenues, there is less risk that they would not recover their entry costs upon entering a new market. Indeed, big-budget

[10]The long-run relationship between quality and foreign entry for U.S. movies is explored in more detail in Holloway (2013).

[11]The linear fit displayed in the figure is calculated by omitting the movies with a budget of less than \$100,000. The OLS slope-coefficient is 0.84; with the low-budget movies included it is 0.74.

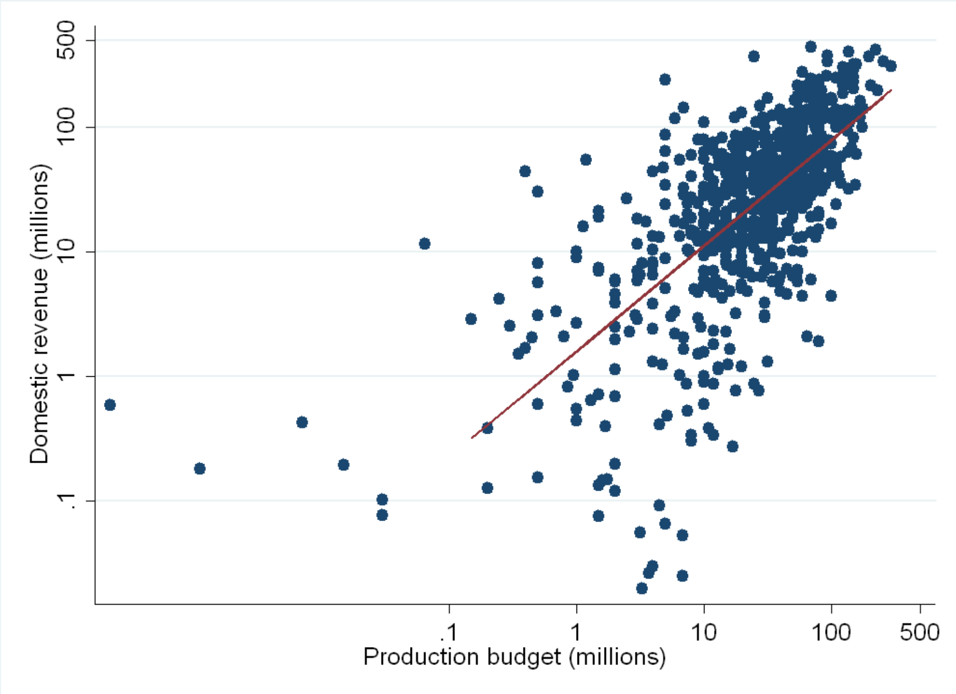

Figure 2: Domestic Box-Office Revenue vs. Production Budget

blockbusters are far more likely to have near-simultaneous release dates internationally. The median delay to foreign release since the U.S. premiere is decreasing in the size of the budget, despite the fact that big-budget movies enter *more* markets. Figure 3 plots the histograms of median delay by quartile of production budget, and demonstrates an increasing skewness towards early foreign release.

For a concrete illustration, Figure 4 charts the entry dates and performance (relative to initial prediction) of the 2003 Woody Allen production, *Anything Else*. With a budget of $18 million, it sits in the second quartile of the sample. In the first month, the movie disappointed in the U.S. but was a surprise success in Italy. The film then spread to France and Spain where it also played well. Three months later it was released in Argentina, to a neutral performance, before stumbling in Northern and Eastern Europe. It did not enter the remaining five markets in the sample.

Apart from the Italian release of *Anything Else*, which occurs in the same month as that of the U.S., Figure 4 exemplifies a pure sequential entry pattern. By this I refer

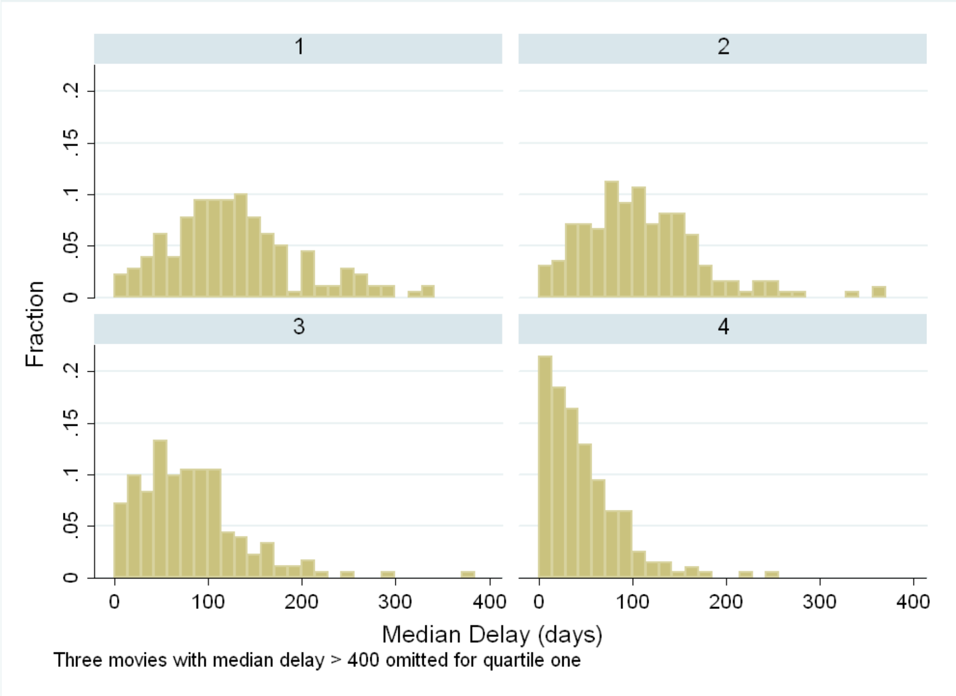

Figure 3: Histogram of Median Delay by Production Budget Quartile

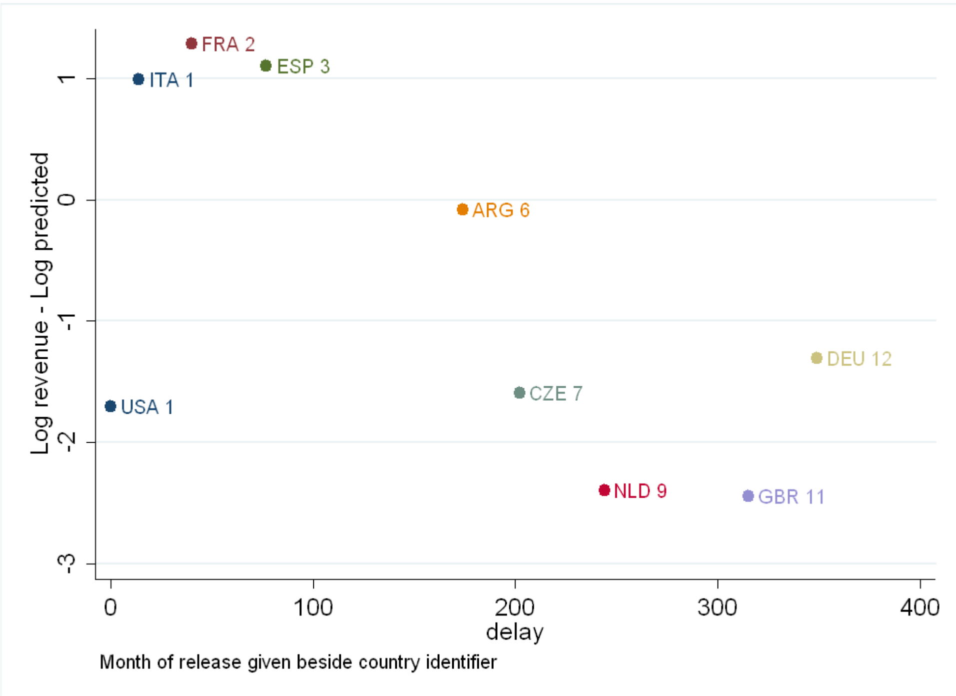

Figure 4: Entry Timing and Performance of “Anything Else”

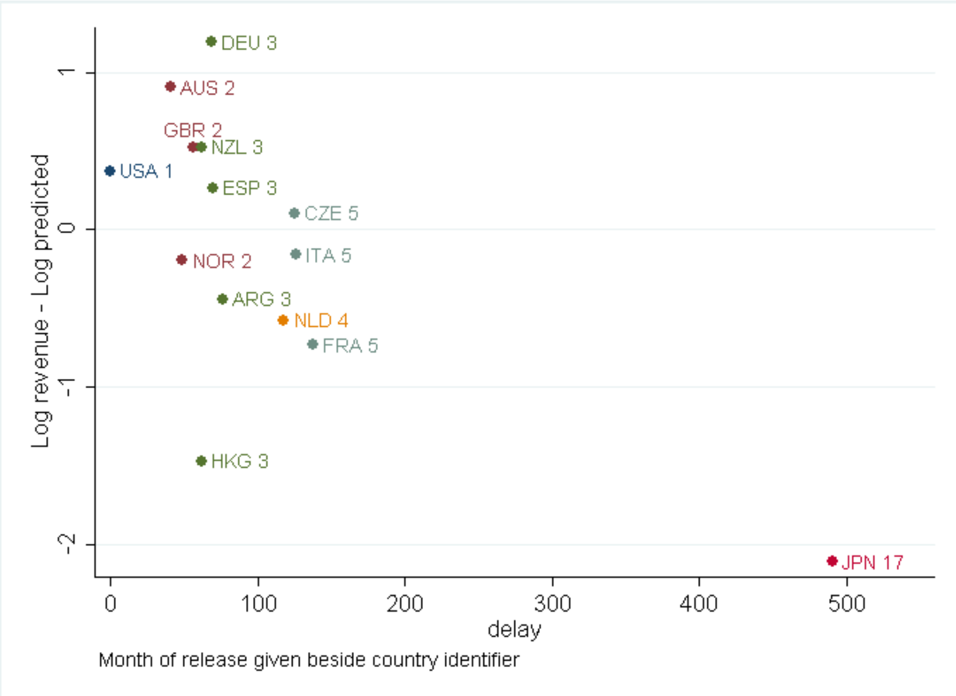

Figure 5: Entry Timing and Performance of "50 First Dates"

to the fact that each country was entered in a separate month. To illustrate another entry pattern, consider Figure 5, which plots the entry dates and performance for the 2004, seventy-five-million-dollar comedy, *50 First Dates*, starring Adam Sandler and Drew Barrymore. Here we see a mix between sequentiality and simultaneity, with multiple countries entered in each month.

To capture the degree to which a movie is released according to a sequential entry strategy, I compute a "sequential index" for each movie. First, I partition the release dates into months since the U.S. release (with month 1 indicating the month of the U.S. release). Any country that is entered in the same month as another is considered to be entered simultaneously with that other country. For most movies, there are gaps in the month in which new entry occurs. For example, a movie might go to two markets in month one, three markets in month two, but then only enter its last market in the fifth month. I refer to months in which the movie does enter new markets as "rounds" of release, so for this hypothetical movie, the fifth month would be considered round three.

The sequential index, Z, is computed as follows:

$$Z = \frac{N_{rounds} - 1}{N_{markets} - 1}, \tag{24}$$

where N_{rounds} is the number of rounds of release and $N_{markets}$ is the total number of markets entered for each movie. The index gives the ratio of the number of extra rounds taken to the number of foreign markets entered. Thus, if the movie enters ten countries and takes ten rounds of release to do so, the fraction is one, and this movie is characterized by pure sequential entry. If the movie entered all ten countries in one round, the fraction would be zero, indicating pure simultaneous entry. Interior values indicate the degree to which the movie followed a sequential entry strategy. For example, consider a movie that entered five markets. If it did so in three rounds, the index is $(3-1)/(5-1) = 0.5$, reflecting the fact that a mix of simultaneous and sequential entry is observed.

Figure 6 provides a histogram of the sequential index. It shows a large spike at one, reflecting the fact that more than one hundred of the movies exhibit pure sequential entry. Just twenty of the movies were released according to a pure simultaneous strategy (all within a month of the U.S. release). The remainder fall somewhat symmetrically around a value of one half.

We have established that movies with large production budgets tend to diffuse internationally more quickly. The longer delay for low-budget movies could be due to sequential entry, or it could occur if they are delaying all their foreign releases for some time, and then entering them all simultaneously. To investigate which movies are indeed entering sequentially, Figure 7 plots the sequential index against the production budget, along with a Lowess smoother. The figure confirms that low-budget movies do in fact employ a greater degree of sequential entry than their big-budget counterparts. Moreover, the effect is not driven by differences in budget by genre type, although comedies and dramas do show a higher propensity for sequential entry at any given budget level. This makes sense given their lower appeal in foreign markets (Epstein, 2006).

In addition to looking at which types of movies tend to be sequentially released, we

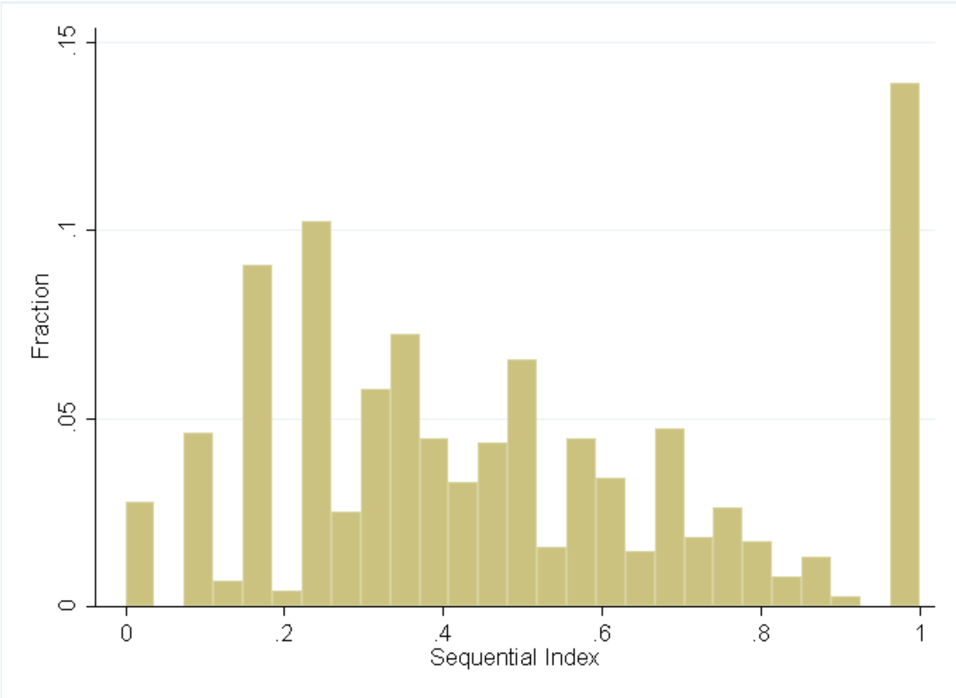

Figure 6: Histogram of Sequential Index

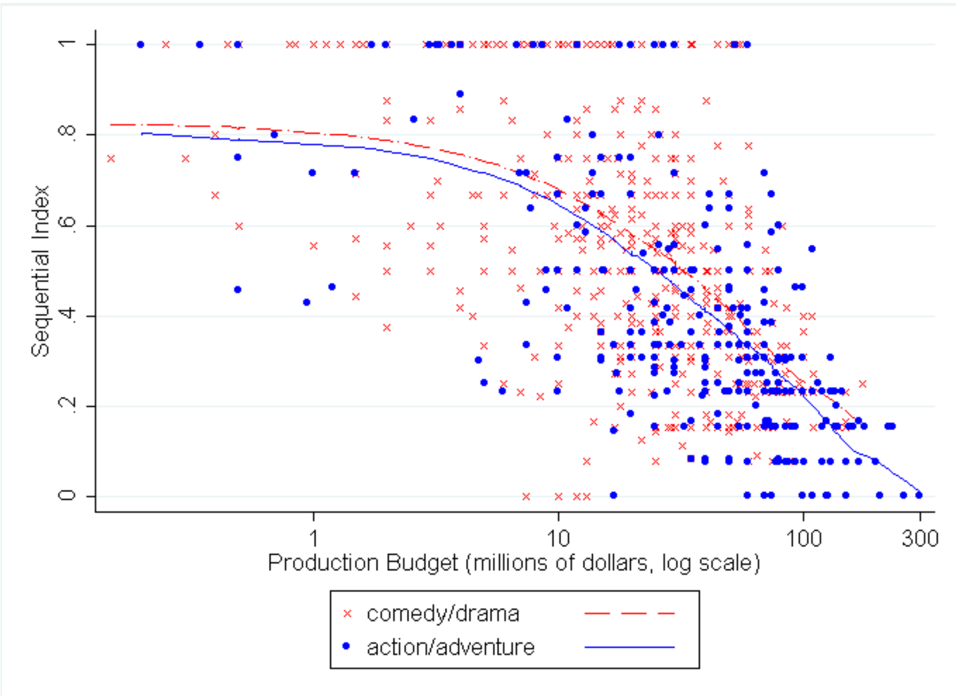

Figure 7: Sequential Index vs. Production Budget

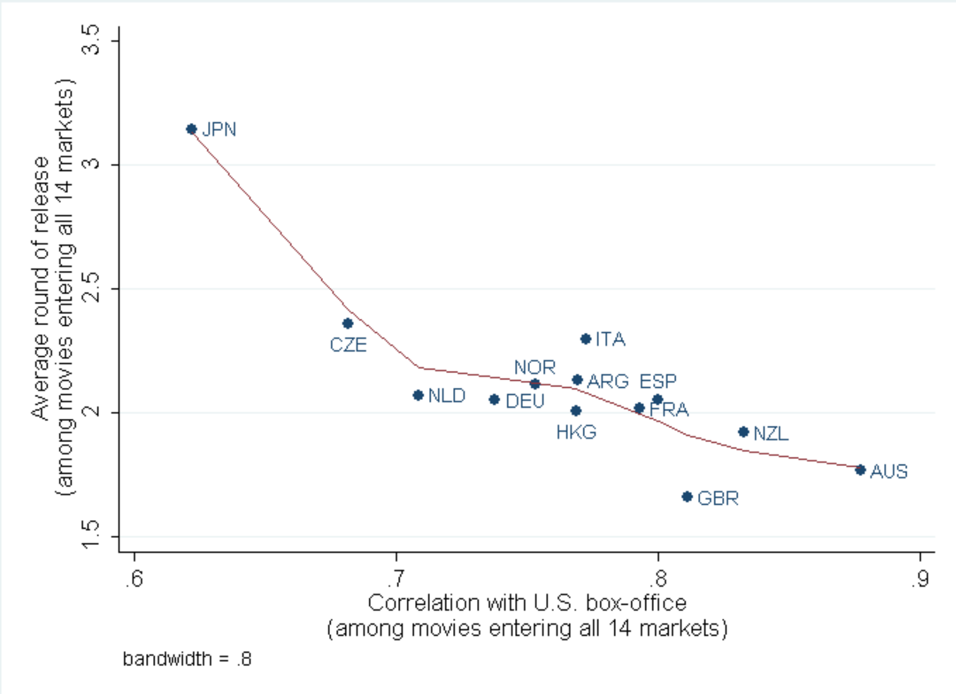

Figure 8: Average Round of Release vs. Correlation with U.S. Box-Office

can investigate the order in which countries tend to be entered. One simple measure of this is the average round of release among a country's imported movies. Figure 8 plots the average round of entry against the correlation between the countries' box-office revenues and those of the United States. To avoid possible bias associated with the fact that less profitable markets tend to attract bigger-budget movies, which tend to be released more quickly, only the movies that went to all thirteen foreign markets are considered in this figure. On average, countries with higher correlation in revenues with the U.S. are entered in earlier rounds than countries with lower correlation. Note that the four destinations with the lowest average round of entry are all English-speaking.

The data patterns illustrated in this section are consistent with the idea that firms that are uncertain about their export profitability may use sequential entry to learn and update expectations. The next section provides an empirical test of whether past performance surprises affect future entry decisions.

4. Results

The model of section 2 predicts that surprises in box-office revenue in previous markets affect the probability of entry into potential future markets. I test this prediction using regression analysis and consider alternative explanations for the results.

4.1. Firm learning and the decision to enter

First it is necessary to construct the appropriate variables, in particular the update to movie m at time t. Recall from the model that, initially, distributors form expected revenues for each potential destination based on movie characteristics such as the budget, and destination characteristics such as the country's historical expenditure on movies. I form *ex ante* predicted revenues for each movie-destination pair by regressing *ex post* actual (log) revenues on the movies' (log) budget and a set of genre and MPAA-ratings dummies, in addition to destination fixed effects. I allow the coefficients on the movie characteristics to differ across the destination countries:

$$\ln R_{dm} = \alpha_d + \beta_d \ln B_m + \gamma_d \text{ GENRE}_m + \delta_d \text{ MPAA}_m + \epsilon_{dm}, \tag{25}$$

where α_d is a destination fixed effect; $\ln B_m$ is log production budget; GENRE_m is a set of dummy variables indicating whether the main genre of the movie is action, adventure, comedy, musical, or thriller (drama is the omitted category); and MPAA_m is a set of dummy variables indicating whether the movie is rated G, PG, M, or R (PG-13 is the omitted category) by the Motion Picture Association of America. I then set the first-period predicted log revenues, μ^1_{dm}, equal to $\widehat{\ln R_{dm}}$.

Time periods are based on the month since the U.S. release. Although the data provide the precise day on which a movie was released in any given market, it is impractical to use days as the unit of time. Using daily time periods would introduce a lot of noise since there may be many idiosyncratic reasons for releasing on one day rather than the next. Recalling that the benefit to "pulling the plug" on a release is the saved fixed costs, the incentive to do so decreases as the period between learning that the movie will not make money in the market and the release date narrows. This is because advertising costs are sunk once they are spent. Similarly, adding a new market based on good performance would take time to organize and promote. I set the unit of time to be a month.[12]

For many movies, there are gaps in the month in which new entry occurs. According to the updating theory, there is no explanation for the magnitude of delay to each foreign entry. Indeed, the model is about information sets and not time. Accordingly, I collapse the data to the level of information sets—or *rounds* of entry—rather than keep all possible months for each movie. This procedure highlights the fact that we are not trying to explain the magnitude of the delay to foreign release, but rather to test whether new information affects the decision to release.

I compute the expected revenues and surprises for each destination-movie-round triple using an iterative procedure. The updating equations of section 2 apply if only one country is entered per period. In practice, many movies enter multiple countries per round and the surprises from each entered country must be aggregated to form the update for each remaining potential market. To do this we can employ the matrix versions of the Bayesian updating equations. Denote the set of countries entered in period $t-1$ by Y and the set of remaining potential destinations X.[13] The updating equations become:

$$\mu_X^t = \mu_X^{t-1} + \Sigma_{XY}^{t-1} \left(\Sigma_{YY}^{t-1}\right)^{-1} \left(r_Y - \mu_Y^{t-1}\right) \tag{26}$$

$$\Sigma_{XX}^t = \Sigma_{XX}^{t-1} - \Sigma_{XY}^{t-1} \left(\Sigma_{YY}^{t-1}\right)^{-1} \left(\Sigma_{XY}^{t-1}\right)', \tag{27}$$

where μ_X^t and μ_Y^t are vectors of predicted log revenues going into period t for the sets X and Y, respectively, r_Y is the vector of realized log revenues in Y, Σ_{XX}^t and Σ_{YY}^t are variance-covariance matrices, and Σ_{XY}^{t-1} is a cross-covariance matrix. All initial variance and covariance elements are calculated from the residuals, ϵ_{dm}, from equation (25).

[12]Paramount Pictures chief operating officer, Robert G. Friedman, notes that "television spot advertising is committed to three to four weeks prior to opening weekend" (Friedman, 2004, p. 290).

[13]These sets of course depend on the movie, m, and the period, t, but the subscripts are omitted for convenience of exposition. Note that the set of destinations entered before $t-1$ is irrelevant to the calculations since information from these entries is already incorporated into the $t-1$ prior.

Table 1: Correlations of Residuals between Markets

	ARG	AUS	CZE	DEU	ESP	FRA	GBR	HKG	ITA	JPN	NLD	NOR	NZL	USA
ARG	**1.32**	0.526	0.537	0.554	0.660	0.557	0.496	0.592	0.583	0.448	0.518	0.550	0.511	0.475
AUS	0.398	**2.53**	0.507	0.703	0.633	0.628	0.744	0.532	0.521	0.452	0.698	0.630	0.768	0.635
CZE	0.385	0.415	**1.37**	0.619	0.492	0.554	0.585	0.583	0.515	0.440	0.572	0.618	0.554	0.479
DEU	0.403	0.573	0.472	**2.74**	0.715	0.701	0.719	0.528	0.665	0.510	0.695	0.677	0.647	0.546
ESP	0.478	0.474	0.363	0.523	**2.60**	0.736	0.613	0.487	0.707	0.460	0.589	0.576	0.477	0.402
FRA	0.416	0.489	0.416	0.541	0.535	**2.98**	0.608	0.510	0.730	0.502	0.645	0.653	0.560	0.396
GBR	0.387	0.625	0.444	0.575	0.455	0.514	**2.40**	0.540	0.559	0.513	0.714	0.666	0.733	0.614
HKG	0.430	0.380	0.412	0.383	0.335	0.362	0.401	**1.27**	0.459	0.591	0.533	0.523	0.530	0.445
ITA	0.447	0.428	0.399	0.500	0.565	0.584	0.450	0.338	**3.28**	0.468	0.556	0.599	0.497	0.402
JPN	0.347	0.357	0.356	0.382	0.337	0.385	0.373	0.419	0.372	**2.26**	0.441	0.454	0.469	0.414
NLD	0.400	0.541	0.459	0.569	0.444	0.507	0.563	0.393	0.431	0.365	**1.84**	0.743	0.656	0.629
NOR	0.415	0.500	0.480	0.521	0.421	0.487	0.527	0.397	0.445	0.366	0.569	**2.01**	0.637	0.584
NZL	0.372	0.638	0.431	0.491	0.368	0.451	0.560	0.398	0.380	0.359	0.491	0.496	**1.13**	0.582
USA	0.334	0.540	0.365	0.455	0.337	0.358	0.502	0.349	0.330	0.341	0.488	0.439	0.469	**1.48**

Pearson correlation coefficients on upper triangle; Kendall's tau on lower triangle; variances on main diagonal

Table 1 provides correlation coefficients of ϵ_{dm} for each country pair. On the main diagonal, the variance of the residuals within each country is reported. The upper triangle reports Pearson correlation coefficients, which describe the strength of the linear relationships, and are directly related to the covariances between countries that are used in the updating equations. The country-pair with the highest correlation is Australia–New Zealand, at 0.768, followed by Australia–United Kingdom (0.744) and Netherlands–Norway (0.743). The country-pair with the lowest correlation is France–United States, at 0.396. In general, the correlations point to intuitive regional and colonial groupings: there are high correlations among Northern European and North American markets (U.S. statistics include box-office revenue in Canada); Southern European countries exhibit high correlation among themselves; the market in most agreement with Japan is Hong Kong; and Argentina's ties to Spain and Italy are reflected by high correlations among those countries. The lower triangle reports Kendall's tau, which provides a non-parametric measure of concordance of the ranking of movies for each country pair. The regional patterns are also evident using this alternative measure.

Table 2 reports the main result of the study. Each specification is a probit model and estimates the probability that a movie enters a destination in a given round, conditional on the movie not being released there previously. The table reports standardized average partial effects, so that it presents the change in the probability of release induced by a one-standard-deviation increase of the variable in question. The first column estimates the degree to which current expected revenue affects the decision to release. The first round of releases is excluded from the regression because this specification acts as a benchmark for the other columns, which include lagged variables. The coefficient implies that a one-standard-deviation increase in the (log) predicted revenue increases the probability of entry in the current period by 14.8 percentage points, compared to an average probability of 21.3%. As predicted, expected revenue is an important driver of the entry decision.

The second specification examines the constituent parts of the expected revenue, namely the expected log revenue in the previous round plus the update from the previous period. If firms do not adapt their entry strategies based on information learned in period

Table 2: Probability of Exporting to a New Market

probit model	(1)	(2)	(3)	(4)	(5)
depvar	released	released	released	released	released
pred. $\ln R$	0.148***				
	(0.006)				
lag pred. $\ln R$		0.144***	0.144***	0.148***	
		(0.006)	(0.006)	(0.006)	
lag update		0.050***			
		(0.003)			
per. 2 lag update			0.0514***		
			(0.004)		
per. $>$ 2 lag update			0.0489***		
			(0.005)		
negative update				-0.0321***	
				(0.004)	
positive update				0.0730***	
				(0.007)	
lag pred. Q1 (d)					-0.191*
					(0.080)
lag pred. Q2 (d)					-0.0624
					(0.080)
lag pred. Q3 (d)					0.0604
					(0.080)
lag pred. Q4 (d)					0.168*
					(0.080)
neg. update $\times$ pred Q1					-0.0089
					(0.012)
neg. update $\times$ pred Q2					-0.0372***
					(0.009)
neg. update $\times$ pred Q3					-0.0402***
					(0.007)
neg. update $\times$ pred Q4					-0.0474***
					(0.009)
pos. update $\times$ pred Q1					0.0501***
					(0.010)
pos. update $\times$ pred Q2					0.0695***
					(0.010)
pos. update $\times$ pred Q3					0.0671***
					(0.010)
pos. update $\times$ pred Q4					0.0542***
					(0.012)
N	24251	24251	24151	24251	24151
pseudo R^2	0.129	0.131	0.131	0.132	0.121

Standardized average partial effects; robust standard errors are adjusted for clusters in movies
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$(t-1)$ then we should not expect the coefficient on the update to be significant. In fact, the coefficient implies that a one-standard-deviation increase in the previous round's update is associated with a 5.0 percentage-point increase in the probability of entry. This is an increase of more than 23% over the average probability of entry. Column 3 includes interactions between the update and dummies for the first period and all other periods. This specification checks whether firms are learning only after the first round of entry, or whether subsequent entries also affect entry decisions. The coefficient on the update in periods greater than two is only slightly smaller, suggesting that learning is ongoing.

Columns 4 and 5 investigate whether the effect of a surprise in a movie's performance depends on whether the surprise is positive or negative. Column 4 indicates that the increase in the probability of entry due to positive news is more than twice as large in magnitude as the decrease in the probability due to negative news. This is likely due to how the expected revenues are distributed around the entry cutoffs. The result suggests that there is a larger mass of expected revenues within one standard deviation of update below the cutoffs than there is above. Column 5 breaks down the effect of positive and negative updates by quartile of lagged expected log revenue. Negative updates become more salient as the quartile increases. In fact, observations in the first quartile are unaffected by negative updates. Since these observations are unlikely to be associated with a release at all, the negative news does not have an impact. Positive updates have the greatest salience for observations in the middle quartiles. It is in this range that surprise good performances are most likely to push expectations above the entry thresholds.

4.2. Alternative Models

There is an alternative explanation for the main result that "surprise" performances affect further entry. It is probable that firms have information about the quality of their movies that is not captured by the first-stage regression of equation (25). In the extreme, they could know the quality perfectly, in which case any deviation from their expectations would be entirely due to idiosyncratic movie-destination demand shocks. Movies with seemingly big positive surprises would enter more countries in subsequent periods because they are good movies. Distributors would know this from the start and could be delaying for reasons other than learning. The methodology of this paper would erroneously attribute the correlation between "surprises" and future entry to learning.

To see whether this is driving the results, we can use the fact that this alternative hypothesis implies that firms would ignore surprises since they contain no relevant information for future markets. If no learning was taking place—and the correlation we observe is due to poor predictions in the first stage—then substituting the update from the current period (which isn't observed before current-period entry decisions are made) should produce similar results to including the lagged update. If the significance of the lagged update is due entirely to learning, then the current-round update should not enter significantly.

The first column of Table 3 estimates the effect of current expected log revenues on the probability of entry. The difference from column 1 of Table 2 is that first-round observations are included in the regression. This is to act as a benchmark for the specification of column 2, which includes the current predicted log revenue and the update derived from current entries. Column 2 indicates that a one-standard-deviation increase in the current update increases the probability of entry by 0.85 percentage points. This suggests that firms do have some information not accounted for in the initial forecast equation, but the estimated effect is about one-sixth of the size of the estimate for lagged updates, which is reproduced in column 3 for convenience. The fact that the effect of lagged updates is so much stronger than current (unrealized) updates supports the learning hypothesis.

In column 4, the variance of the prior distribution of log revenues is included. Recall from equation (13) of section 2 that the variance enters conditional expected profits positively. Mechanically, this is because of the assumed log-normal distribution for revenues. Intuitively, firms prefer to enter when the variance is high because their potential losses are capped by the entry cost, but there is no bound on the up side. On the other hand, the variance (for example, of country B) enters the option value of waiting, W_B, in two places. First, it enters the lower limit of the integral through $\hat{r}_A$, and second, directly in the integrand (see equations 14 and 15). In both cases, a higher variance increases the size of W_B and would thus lead to delayed entry. Intuitively, entering when the prior

Table 3: Probability of Exporting to a New Market

probit model	(1)	(2)	(3)	(4)
depvar	released	released	released	released
pred. $\ln R$	0.166***	0.166***		
	(0.006)	(0.006)		
current update		0.00852**		
		(0.003)		
lag pred. $\ln R$			0.144***	0.120***
			(0.006)	(0.005)
lag update			0.0504***	0.0422***
			(0.003)	(0.003)
variance $\ln R$				-0.165***
				(0.010)
N	34144	34139	24251	24251
pseudo R^2	0.134	0.135	0.131	0.150

Standardized average partial effects

Robust standard errors adjusted for clusters in movies

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

variance is high would be less valuable with respect to gaining information because the firm could not infer as much about quality as it could if the variance is low. This is because surprises could be due to large idiosyncratic shocks rather than high or low quality. Thus, the informational component of the value of entry would lead to firms favoring low-variance markets. Column 4 of Table 3 shows that high-variance observations are indeed less likely to be associated with entry, which might be taken as further evidence in favor of the learning story.

5. Conclusion

A growing body of work has suggested that manufacturing firms learn about their export profitability through exporting. This paper complements that literature by considering a different industry and a single, specific product. As cultural products, movies are subject to potentially large idiosyncratic differences in taste across markets, meaning inferences from prior observed performance must be far from perfect. Nonetheless, the results of this study suggest that distributors do adjust their entry strategies based on prior-market performance, adding markets after surprise successes and limiting further distribution after disappointments.

The correlation between past surprises and entry decisions could be due to omitted movie attributes in the initial forecasts. Movies with positive unobserved attributes will both perform better than expected (by the econometrician) and subsequently enter more foreign markets. Robustness checks suggest this is likely a factor, but the effect of unrealized surprises on entry decisions is just one-sixth the size of past surprises, suggesting that the methodology is picking up real learning.

This paper takes a reduced form approach to testing for adaptive entry strategies. The stylized model provides a mechanism through which firms have an incentive to potentially delay some foreign releases. The empirics, however, take sequential entry as given and investigate whether firms respond to surprises in performance by entering more or fewer markets in the subsequent period. A limitation of this approach is that it is not possible to run simulations of counter factuals. These might be useful if we wanted to know, for example, how a reduction in entry costs would affect entry timing.

The advantage of the reduced form approach is that channels outside the model might influence the entry strategy. It is entirely possible that distributors stagger release dates for other reasons, such as to hit different peak weekends or holidays in different countries (Einav, 2007), or because of financing constraints preventing worldwide simultaneous releases (Manova, 2013; Minetti and Zhu, 2011). The main empirical results indicate that firms do respond to surprises in performance, which suggests that one of the reasons for staggered releases is strategic delay.

As firms move toward a simultaneous release strategy to combat international piracy, they lose the ability to use the information from prior markets. Thus, firms face a trade-off between foregone revenues to illegal consumption if they delay foreign entry, and potentially loss-making foreign entries if they enter all markets simultaneously. Firm behavior is consistent with this trade-off: big-budget movies which are likely to draw higher box-office returns are much more likely to enter foreign markets simultaneously than smaller-budget movies that could be on the cusp of the break-even point.

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