Project in applied econometrics
Mid-term Report

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1 Introduction

Our project focuses on the identification of social learning effects into movie sales in the USA and in France. Social learning consists for people to rely on their peers' experience of consumption to make one's own consumption choice. This kind of behavior may arise in cases where there is uncertainty on the quality of a good or on the utility one will withdraw from consumption. In our case, we want to identify whether people choose to go watch a movie according to the behavior they have observed from their peers.

The project relies mainly on E. Moretti's paper "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales" (2011) in which he builds a theoretical model of social learning and apply it to aggregate data of movie sales in the USA. Our goal here is to replicate and comment his work, afterwards we will apply his model to similar French data.

2 Moretti's Model

2.1 Intuition

Moretti's model is based on the idea that people make a guess on how much they will like a movie before going to watch it. This guess is based upon public knowledge about elements like casting, film director etc. but also a private signal, the "feeling" they have about how much they will like the movie. Eventually, people have peers who went to see the movie and other who did not, and they might change their guess about the movie quality accordingly: this is social learning.

How can we identify social learning from aggregate movie sales? One can compute the probability for an individual to go see the movie: he does so if his expected utility is higher than the subjective cost of going. Before a film is released, theaters make expectations about the number of clients on the public knowledge they have. People receive an unbiased signal on the quality so a surprise in the number of entries might arise in the first week: the movie quality (understood as average the utility consumer obtain from viewing a film) could be higher or lower than what one would have forecasted from the objective data available. Social learning comes when people update their expected utility according to the feedbacks of their peers. It can be identified from aggregate data if we observe that a surprise in the first week has an effect on the following weeks, namely if a positive surprise in the first week increases the number of sales in the following weeks and conversely.

2.2 Mathematical Model

2.2.1 Utility Estimation Before A Movie Is Released

Actual Utility An individual i gets a utility $u_{i,j}$ watching the film j with

$$u_{i,j} = \alpha_j^* + v_{ij}, \tag{1}$$

where α_j^* is the quality of the movie for the average individual and $v_{ij} \sim \mathcal{N}(0, \frac{1}{d})$ represents how much individual i's appeal for movie j differs from the the average individual's taste for this movie.

Signal: Noisy Utility Moretti supposes that consumers don't measure $u_{i,j}$ but receives instead a noisy signal $s_{ij} = U_{ij} + \epsilon_{ij}$ with $\epsilon_{ij} \sim \mathcal{N}(0, \frac{1}{k_j})$. ϵ_{ij} is unbiased so on average, predictions are correct for a set of films with the same k_j.

Expected Utility The expected utility in the first week (ie before the film is being released) is estimated by the weighted average of the prior (objective) and the signal (personal but noisy), which are two different estimators of U_{ij} of different precision. Namely:

$$\mathbb{E}_1[U_{ij}|X_j'\beta, s_{ij}] = \omega_j X_j'\beta + (1-\omega_j)s_{ij}.$$

Cost of Watching In the model, a consumer decides to go and watch a film if her utility is higher than her subjective cost of watching (monetary cost and scarcity of free time) in the week considered (parameter t):

$$\mathbb{E}_1[U_{ij}|X_j'\beta, s_{ij}] > q_{it}. \tag{2}$$

To model the idea that the cost depends on the individual and on the week, Moretti supposes that $q_{it} = q + u_{it}$ with $u_{ij} \sim \mathcal{N}(0, \frac{1}{r})$ with all u_{it} independent. u_{it} is zero-mean so on average it is almost null over a large set of individuals for a given week, and over a set of weeks for a given individual.

Probability Of Watching The probability for individual i to go to see movie j in the first week is

$$P_1 = \mathbb{P}(\mathbb{E}_1[U_{ij}|X_j'\beta, s_{ij}] > q_{it}) = \Phi\left(\frac{(1-\omega_j)(\alpha_j^* - X_j'\beta) + X_j'\beta - q}{\sigma_{j1}}\right), \tag{3}$$

$$\sigma_{j1}^2 = (1-\omega_j)^2\left(\frac{1}{k_j} + \frac{1}{d}\right) + \frac{1}{r},$$

where Φ is the cumulative function of a standard normal distribution $\mathcal{N}(0,1)$. With neither social learning, nor decrease in utility for viewing a film again and again, the previous formula for P_1 remains valid as long as the movie can be watched.

2.2.2 Utility Estimation With Social Learning

Signal With Feedback We now consider social learning in the model. In week 2, we consider a consumer i who has N_i peers, n_i of which see the movie in Week 1. They all give their utility U_{pj}, $p \in [1, n_i]$ as a feedback to i after watching. Consumer i receives two information in the same time:
- the fact that his acquaintances who saw the film had a sufficiently high expected (ex-ante) utility to do so and that the remaining $N_i - n_i$ did not.
- and their ex-post utility itself.

From these information consumer i can estimate the real quality α_j^* by maximizing the associate maximum likelihood function. We denote the associated maximum likelihood estimator S_{ij2}. It is lower than the average of the ex-post utilities consumer i receives; this is the impact of non-viewers. It is also unbiased and asymptotically normal.

Expected Utility Consumer i will do a weighted average of the three information he has: $X_j'\beta$, s_{ij} and S_{ij2}. In week $t \geqslant 2$, the expected utility is

$$\mathbb{E}_t[U_{ij}|X_j'\beta, s_{ij}, S_{ij2}, ..., S_{ijt}] = \omega_{j1t}X_j'\beta + \omega_{j2t}s_{ij} + \sum_{w=2}^{t} \omega_{ij3w}S_{ijw}, \tag{4}$$

$$h_j = \frac{dm_j}{d+m_j}, z_{it} = \frac{b_{it}d}{b_{it}+d}.$$

This equation shows that a given piece of information has a decreasing importance in the final decision from week to week.

Probability of Watching Just like before, the probability of watching at week t is:

$$P_t = \Phi\left(\frac{(1-\omega_{j1t})(\alpha_j^* - X_j'\beta) + X_j'\beta - q}{\sigma_{jt}}\right), \tag{5}$$

$$\sigma_{jt}^2 = (\omega_{j2t})^2\left(\frac{1}{k_j} + \frac{1}{d}\right) + \frac{\sum_{p=2}^{t} z_{ip}}{(h_j + k_j + \sum_{s=2}^{t} z_{is})^2} + \frac{1}{r}$$

To study the evolution over time we can derivate P_t two times w.r.t t. If we suppose here that $X_j'\beta = q$ for simplicity, we obtain that P_t is increasing and concave over time if the surprise $\alpha_j^* - X_j'\beta$ is positive, decreasing and convex over time if the surprise is negative, and constant with no surprise. The evolution of the probability according to the surprise is the mark of a social learning multiplier. The concavity or convexity testifies that from one week to another, the quality becomes more and more precisely known, the variation in film attendance is less and less important. This effect is all the more important as the relative precision of the prior and of the signal is low compared to the added information's precision.

3 Data and Regressions

Data First, we will try to replicate the results of Moretti with his data set. The data is from movies released between 1982 and 2000 in the United-States. It includes sales and screens for 4,992 movies over a period of 8 weeks. It also comprises production cost, genre of the movie, informations on critic reviews and advertising, etc.

Then, using French data given by our supervisor, we will verify if we find similar results in France. The data include observations on 2,717 movies released between 2004 and 2008 in France. The data is similar to Moretti's. Number of entries and screens is observed for 13 weeks. Control variables such as genre, released date, sequel and rating are available.

Using the data The surprises are obtained by taking the residuals from the regression of the log of sales (or number of entries) on the log of screens. Then, using these residuals, we can check the main results of Moretti:

1. Sales of movies with positive surprise and sales of movies with negative surprise should diverge over time. To test this, we need to regress the log of sales on time and the interaction between time and surprise. If the coefficient of the interaction between time and surprise is significantly positive, then the sales of movies with positive surprise decrease slower than the sale of movies with negative surprise. If our results are consistent with those of Moretti, we should find that controlling for advertising, critic reviews and other variables does not affect significantly the results.

2. The effect of a surprise should be lower for movies with a more precise prior. To test this, we augment the previous regression equation with the interaction of time and the precision of the prior and the interaction of time, precision of the prior and surprise of the movie (whose coefficient is predicted to be negative). The precision of the prior can be a dummy for sequels (sequels are assumed to have a more precise prior) or can be measured by the variance of the first week surprise for movies of the same genre.

3. The effect of a surprise should be stronger for individuals with a larger social network. Teenagers are assumed to have a larger social network. Hence, we should find that the effect of a surprise is stronger for movies targeting teenagers. The effect of a surprise should also be stronger for movies opening in many theaters. As above, we can test this with the interaction of time, surprise and either a dummy for teen movies or the number of screens.

4. The marginal effect of a surprise on sales should decline over time. To test this, we include the square of time in the model. The second derivative of sales on time should be negative for movies with a positive surprise and positive for movies with a negative surprise.