Project in applied econometrics
Report

Lucas Javaudin, Robin Le Huérou-Kérisel, Rémi Moreau

March 2018

Abstract

This project has aimed at reproducing Moretti's 2011 paper on social learning effects in movie sales with R. We also blabla. Main results:

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1 Intuitions and detailed presentation of the model

1.1 Some intuitions

1.2 Presentation of the model

bonjour je m'appelle Rémi

2 Analysis and main results

Moretti's purpose is to provide evidence of social learning in consumption, that is to say that people tend to take into account their peers' experience to get a more precise idea of the value of a good. Economists, Moretti says, have had difficulties showing such social learning effects because of the absence of useful microdata on the matter. Moretti's innovation lies in his use of market-level data to identify social learning. He does so by defining what he calls "surprises" in movie sales: surprises, as their name suggests, consist in the difference between expected and actual sales. Moretti proposes that if we observe a surprise, we should also observe social learning effects: if a film is better or worse than expected, then by gathering experience through peers, people should reconsider their expectations and we might be able to see it in the data. In particular, Moretti makes five predictions on things we should be able to observe in presence of social learning:

1. in presence of social learning, sales of movies with positive and negative surprises should diverge: sales of better-than-expected movies should decrease at a lower rate than worse ones (see 2.2);
2. we should observe less social learning effects from a movie on which quality we have a precise idea and more social learning effects from movies which have a more uncertain quality (see 2.3);
3. we should observe more social learning effects when people have a greater social network (see 2.4);
4. we should be able to observe that the effects of a surprise decline over time: once the information on the quality of a movie has been shared, what was a surprise should not play a major role in sales (see 2.5);
5. we should not observe social learning effects when a surprise is due to elements other than quality of the film (let say weather).

We have replicated Moretti's work and tried to confront his predictions with French data.

2.1 Identification of the surprises

Surprises consist in the residuals of the regression of the log-number of sales in the first week on the log-number of screens available (opened by theaters). This definition of surprises holds because we suppose that theaters are profit-maximizing agents and make use of all the available information to predict the success of a movie. If this definition is correct, we should expect log-number of screens opened by theaters first week to be a good indicator of knowledge available on the movie quality before it is released. In the Table 1 we reproduce Moretti's regression of *log_sales_first_we* on *log_screens_first_week*. Each column is the result of the regression when we control with some variables (film genre, rating available, cost, distributor, weekday, month, week, year). The fact that adding control variables doesn't change the robustness of the regression proves Moretti's point which is that theaters take into account these factors when deciding their number of available screens.

Table 1: Regression of first-weekend sales on number of screens

	Dependent variable:						
	log_sales_first_we						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log_screens_first_week	0.893***	0.896***	0.883***	0.871***	0.803***	0.806***	0.813***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
R^2	0.907	0.909	0.910	0.912	0.932	0.936	0.938
Adjusted R^2	0.907	0.908	0.910	0.912	0.928	0.931	0.933
Note:							*p<0.1; **p<0.05; ***p<0.01

We have performed the same kind of regression on France data from 2004 to 2008 and find quite similar results (see table 2).

Table 2: Regression of first-week entries on number of screens for France

	Dependent variable:						
	log_entree_fr						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log_seance_fr	1.208***	1.237***	1.237***	1.279***	1.282***	1.287***	1.196***
	(0.009)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)
R^2	0.893	0.899	0.900	0.917	0.924	0.925	0.943
Adjusted R^2	0.893	0.898	0.898	0.910	0.915	0.916	0.935
Note:							*p<0.1; **p<0.05; ***p<0.01

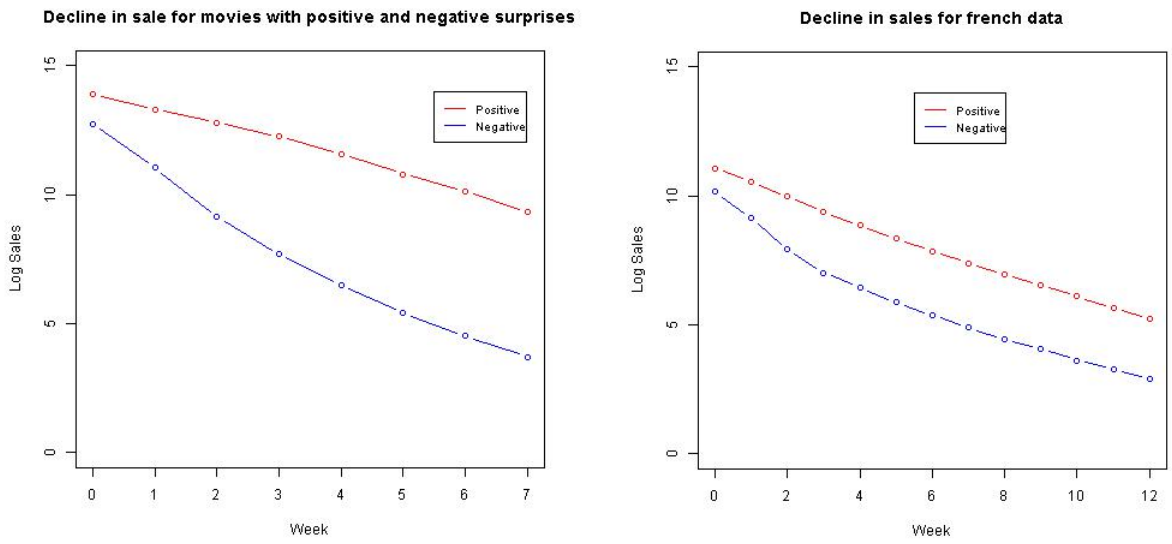
We can see that the number of sales in first week is highly explained by the number of screens opened. This result holds even when adding controls: each column corresponds to a regression in which we added a control variable (genre, ratings, distributors, month and week, year, and some other variables).

Figure 1: R code used to obtain French surprises

```
# Regression of first week sales on number of screens.
regSurprise1 <- lm(log_entree_fr ~ log_seance_fr, data = df, subset = (t==0))
# Including dummies for genre
regSurprise2 <- lm(log_entree_fr ~ log_seance_fr + genre, data = df, subset = (t==0))
# Including dummies for ratings
regSurprise3 <- lm(log_entree_fr ~ log_seance_fr + genre + interdiction, data = df, subset = (t==0))
# Including dummies for distributor
regSurprise4 <- lm(log_entree_fr ~ log_seance_fr + genre + interdiction + id_distributeur, data = df,
    subset = (t==0))
# Including dummies for month and week
regSurprise5 <- lm(log_entree_fr ~ log_seance_fr + genre + interdiction + id_distributeur + factor(mois
    ) + factor(semaine), data = df, subset = (t==0))
# Including dummies for year
regSurprise6 <- lm(log_entree_fr ~ log_seance_fr + genre + interdiction + id_distributeur + factor(mois
    ) + factor(semaine) + factor(annee), data = df, subset = (t==0))
# Including other variables
regSurprise7 <- lm(log_entree_fr ~ log_seance_fr + genre + interdiction + id_distributeur + factor(mois
    ) + factor(semaine) + factor(annee) + MoyennePresse + MoyenneSpectateur + PoidsCasting + pub, data
     = df, subset = (t==0))
```

2.2 Divergence of the sales

Figure 2: Comparing decline in sales between Moretti's and French data



The first prediction of Moretti is that if there are social learning effects in movie sales, we should observe diverging trajectories between movies with positive and negative surprises. The idea is simple: without social learning, sales of movies with positive and negative surprises should decrease at the same rate; in other words, surprises would not have any effect on sales. Indeed, people would not take surprises as a new information on the movie quality.

Moretti estimates models of the form:

$$\ln(y_{jt}) = \beta_0 + \beta_1 * t + \beta_2(t * S_j) + d_j + u_{jt} \tag{1}$$

where $\ln(y_{jt})$ is the log of box-office sales in week t; S_j is surprise; d_j is a movie fixed effect. The variable of interest is β_2 because we want to identify an effect of the surprise on the dynamic of sales over time.

In the figure 2, we have reproduced Moretti's graph and plotted the graph for French data. In Moretti's graph we clearly see the diverging trajectories of the sales. Our graph also shows diverging trajectories

Table 3: Decline in box-office sales by opening week surprise for French data

	Dependent variable:			
	log_entree_fr			
	(1)	(2)	(3)	(4)
t	-0.526^{***}	-0.526^{***}	-0.571^{***}	
	(0.002)	(0.002)	(0.003)	
t:surprise		0.076^{***}		
		(0.004)		
t:positive_surprise			0.087^{***}	
			(0.004)	
t:bottom_surpriseFALSE				-0.459^{***}
				(0.004)
t:bottom_surprise				-0.574^{***}
				(0.004)
t:middle_surprise				-0.088^{***}
				(0.005)
Observations	26,598	26,598	26,598	26,598
R^2	0.851	0.853	0.853	0.854
Adjusted R^2	0.838	0.841	0.841	0.841
Note:				*p<0.1; **p<0.05; ***p<0.01

En fait je crois que je comprends pas tout ici.

Figure 3: R code used to obtain French sales dynamics

```
##############################################
#  Prediction 1: Surprises and Sale Dynamics  #
##############################################

# In this part, we study the difference in rate of decline between movies with a positive surprise and
    movies with a negative surprise.

# Regression of sales on the interaction between time and surprises.
# We use the command felm of the package lfe to compute linear regressions with thousands of dummies.
regSaleDynamics1 <- felm(log_entree_fr ~ t | X, data = df)
regSaleDynamics2 <- felm(log_entree_fr ~ t + t : surprise | X, data = df)
regSaleDynamics3 <- felm(log_entree_fr ~ t + t : positive_surprise | X, data = df)
regSaleDynamics4 <- felm(log_entree_fr ~ t : bottom_surprise + t : middle_surprise | X, data = df)

# Print a table with the results of the regressions.
stargazer(regSaleDynamics1, regSaleDynamics2, regSaleDynamics3, regSaleDynamics4, omit.stat=c("f", "ser
    "), title='Decline in box-office sales by opening week surprise')
```

2.3 Precision of the prior

Another prediction of Moretti is that the effect of surprises should vary with the precision of the prior people have on movies.

Moretti estimates models of the form:

$$\ln(y_{jt}) = \beta_0 + \beta_1 * t + \beta_2(t * S_j) + \beta_3(t * precision_j) + \beta_4(t * S_j * precision_j) + d_j + u_{jt} \quad (2)$$

Table 4: Precision of the prior

	Dependent variable:		
	log_entree_fr		
	(1)	(2)	(3)
t	-0.570^{***}	-0.698^{***}	-0.678^{***}
	(0.003)	(0.013)	(0.004)
t:positive_surprise	0.105^{***}	0.109^{***}	0.009
	(0.005)	(0.018)	(0.006)
t:saga	-0.027		
	(0.016)		
t:positive_surpriseTRUE:saga	-0.145^{***}		
	(0.019)		
t:var_surprise		0.370^{***}	
		(0.035)	
t:positive_surpriseTRUE:var_surprise		-0.062	
		(0.050)	
t:art_essai			0.259^{***}
			(0.006)
t:positive_surpriseTRUE:art_essai			0.066^{***}
			(0.008)
Observations	26,598	26,546	26,598
R^2	0.855	0.854	0.880
Adjusted R^2	0.843	0.842	0.870
Note:			*p<0.1; **p<0.05; ***p<0.01

2.4 Size of the Social Network

Consumers with a larger social network receive more feedbacks from their peers and thus they are able to evaluate more precisely the quality of the movie. Hence, social learning should be stronger for consumers with a larger social network. More formally, this prediction can be tested by estimating the models of the form:

$$\ln(y_{jt}) = \beta_0 + \beta_1 t + \beta_2(t \times S_j) + \beta_3(t \times NS_j) + \beta_4(t \times S_j \times NS_j) + d_j + u_{jt} \quad (3)$$

where S_j is a dummy for positive surprise and NS_j is a variable representing the network size of the movie j's audience. If social learning is stronger with higher values of NS_j, then the coefficient β_4 of the triple interaction between the time trend, the surprise and the network size should be positive.

In his article, Moretti uses two different measurement of network size. First, he makes the assumption that teenagers have a more developed social network than adults and he estimates the model of equation 3 with a dummy for teen movies. He finds that the estimate of the coefficient β_4 is indeed positive. However, the estimate is very weakly significant. Additionally, there is no indicator for teen movies in the data and the way Moretti build a dummy for teen movies is quite surprising. He uses *genre1* (one of the three variables indicating the genre of the movies) and he considers that teen movies are movies of the genre action, adventure, comedy, fantasy, horror, sci-fi and suspense. We would have appreciated more justification for the assumption that teenagers have a larger social network and for the way teen movies are defined. To investigate further these issues, we used the two other variables indicating the genre of the movies: *genre2* and *genre3*. Both variables have a category *Children* and a category *Youth*. We used these two categories to define new dummies for teen movies. Using *genre2*, we find that the estimate of β_4 is significantly negative. Using *genre3*, we find that the estimate of β_4 is significantly positive. We conclude that using teen movies is not a good way to test this prediction.

A second measurement of the size of the social network used by Moretti is the number of theaters broadcasting the movie during the opening week. If a movie opens in lots of theater, the consumers should receive more feedbacks from their peers. As expected, he estimates that the coefficient of β_4 is significantly positive. We estimated the same model with the French data. The results are reported in column (2) of table 5. We find that the coefficient of the triple interaction is indeed significantly positive.

In the French data, the variable *tout public* is a dummy indicating movies which are suitable for any kind of audience. We can assume that consumers have more feedbacks from their peers for movies opened to anyone. Hence, we estimated the model of equation 3 using the *tout public* dummy to measure network size. The results of the estimated are reported in column (1) of table 5. Consistently with our assumption, the coefficient of the triple interaction is significantly positive.

2.5 Does learning decline over time?

The model predicts that the effects of positive and negative surprises should decline over time. More precisely, sales profile should be a concave function of time for positive surprises and a convex function of time for negative surprises. To test this prediction, we need to estimate the sales profile which is assumed to be a quadratic function of time. Therefore, we estimate the following model:

$$\ln(y_{jt}) = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3(t \times S_j) + \beta_4(t^2 \times S_j) + d_j + u_{jt}$$

where S_j is a dummy for positive surprise. The results are reported in table 6. The second derivative of log of entries for negative-surprise movies is

$$\left.\frac{\partial^2 y_{jt}}{\partial t^2}\right|_{S_j=0} = 2\beta_2.$$

The second derivative of log of entries for positive-surprise movies is

$$\left.\frac{\partial^2 y_{jt}}{\partial t^2}\right|_{S_j=1} = 2(\beta_2 + \beta_4).$$

Table 5: Precision of peers' signal

	Dependent variable:	
	log_entree_fr	
	(1)	(2)
t	-0.663^{***}	-0.451^{***}
	(0.007)	(0.005)
t×positive_surprise	0.061^{***}	0.076^{***}
	(0.010)	(0.006)
t×tout_public	0.115^{***}	
	(0.008)	
t×positive_surprise×tout_public	0.031^{***}	
	(0.011)	
t×seance_fr_first_week		-0.033^{***}
		(0.001)
t×positive_surprise×seance_fr_first_week		0.011^{***}
		(0.001)
Observations	26,598	26,598
R^2	0.856	0.867
Adjusted R^2	0.844	0.856
Note:	*p<0.1; **p<0.05; ***p<0.01	

We can test the hypothesis of convexity ($2\beta_2 > 0$) and the hypothesis of concavity ($2(\beta_2 + \beta_4) < 0$) with Student tests. For instance, to test $H_0 : \ 2(\beta_2 + \beta_4) < 0$ against $H_1 : \ 2(\beta_2 + \beta_4) > 0$, the t statistic is

$$t = \frac{2(\hat{\beta}_2 + \hat{\beta}_4)}{\text{se}(2(\hat{\beta}_2 + \hat{\beta}_4))}$$

where $\text{se}(2(\hat{\beta}_2 + \hat{\beta}_4)) = 2[\text{Var}(\hat{\beta}_2) + \text{Var}(\hat{\beta}_4) + 2 \cdot \text{Cov}(\hat{\beta}_2, \hat{\beta}_4)]^{1/2}$ is the standard error of $2(\hat{\beta}_2 + \hat{\beta}_4)$.

With the US data, both hypotheses cannot be rejected with a good confidence. With French data, the p-value for the test of convexity of negative-surprise movies is really close to 0 ($t \approx 36.72$ and $p \approx 0$). However, the hypothesis of concavity of positive-surprise movies must be rejected ($t \approx 9.41$ and $p \approx 1$). What we can say however is that the sales profile of positive-surprise movies is *more concave* than the sales profile of negative-surprise movies because the estimates show that the coefficient β_4 is significantly negative. These statements are confirmed by the graphs of the sales profile of figure 2 where the sales profile of negative-surprise movies is clearly convex and the sales profile of positive-surprise movies seems linear.

Table 6: Convexity of the sales profile

	Dependent variable:
	log_entree_fr
t	-0.978^{***}
	(0.011)
t^2	0.034^{***}
	(0.001)
t×positive_surprise	0.393^{***}
	(0.016)
t^2×positive_surprise	-0.026^{***}
	(0.001)
Observations	26,598
R^2	0.861
Adjusted R^2	0.850
Note:	*p<0.1; **p<0.05; ***p<0.01

3 Conclusion: some comments

A R codes

Data cleaning

```
####################
#  Data Cleaning  #
####################

# In this part, we change the dataset to make it closer to the dataset of Moretti.

# Remove the movies without any screen in France during the first week (667 movies).
fr_df <- fr_df[!is.na(fr_df$seance_fr1),]
# Remove the movies without any id_distributeur (4 movies).
fr_df <- fr_df[!is.na(fr_df$id_distributeur),]

# Set MoyennePresse and MoyenneSpectateur to the mean if no value is specified.
mean_moy <- mean(fr_df[!is.na(fr_df$MoyennePresse), 'MoyennePresse'])
fr_df[is.na(fr_df$MoyennePresse), 'MoyennePresse'] <- mean_moy
mean_moy <- mean(fr_df[!is.na(fr_df$MoyenneSpectateur), 'MoyenneSpectateur'])
fr_df[is.na(fr_df$MoyenneSpectateur), 'MoyenneSpectateur'] <- mean_moy

# Repeat each columns 13 times.
n <- nrow(fr_df)
df <- fr_df[rep(1:n, each=13),]

# Add a column to indicate the week.
df$t <- rep(0:12, n)

# Replace the variables for each week (e.g. 'entree_paris1') with a global variable (e.g. 'entree_paris')
for (i in 0:12) {
for (variable in c('entree_paris', 'seance_paris', 'entree_fr', 'seance_fr')) {
# Concatenate the variable name with and indicator for the week (e.g. 'entree_paris1').
variable_t <- paste(c(variable, toString(i+1)), collapse='')
# For each week, the variable in the new df (e.g. 'entree_paris') is taken from the old df (e.g. 'entree_paris1').
df[df$t==i, variable] <- fr_df[,variable_t]
}
}

# Keep only the useful variables.
df <- df[,c(1:6, 33:43, 70:85)]

# Replace the NAs in seance_fr with zeros.
df[is.na(df$seance_fr), 'seance_fr'] <- 0

# Generate logarithm of sales and screens.
df$log_entree_paris <- log(df$entree_paris + 1)
df$log_seance_paris <- log(df$seance_paris + 1)
df$log_entree_fr <- log(df$entree_fr + 1)
df$log_seance_fr <- log(df$seance_fr + 1)

# Variable id_distributeur is a factor.
df$id_distributeur <- as.factor(df$id_distributeur)

# Variable id is a factor (this is used for movie dummies with the package life).
df$X <- as.factor(df$X)
df$X.eff <- rnorm(nlevels(df$X))
```