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:

Contents

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.

We have performed the same kind of regression on France data from 2004 to 2008 and find quite similar results (Table 2 for France data and Table 3 for Paris data only[1]).

FRANCE

PARIS

2.2 Divergence of the sales

2.3 Precision of the prior

[1] Data available for Paris are richer of 600 movies than France.

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

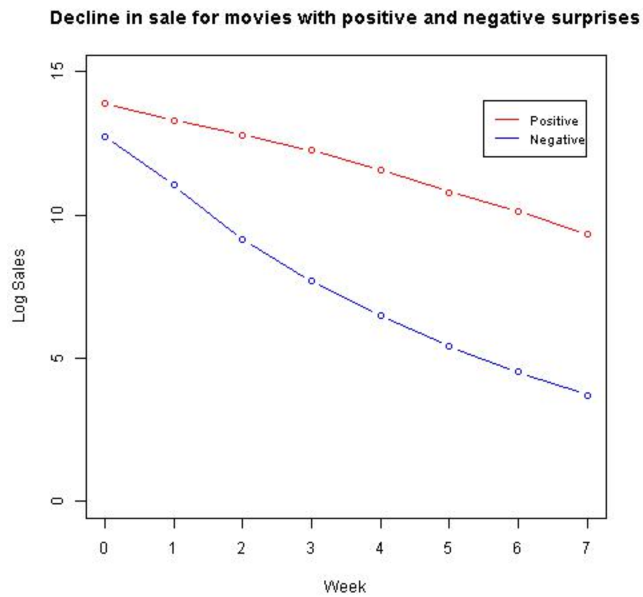
Table 2: Regression of first-week entries on number of screens for France

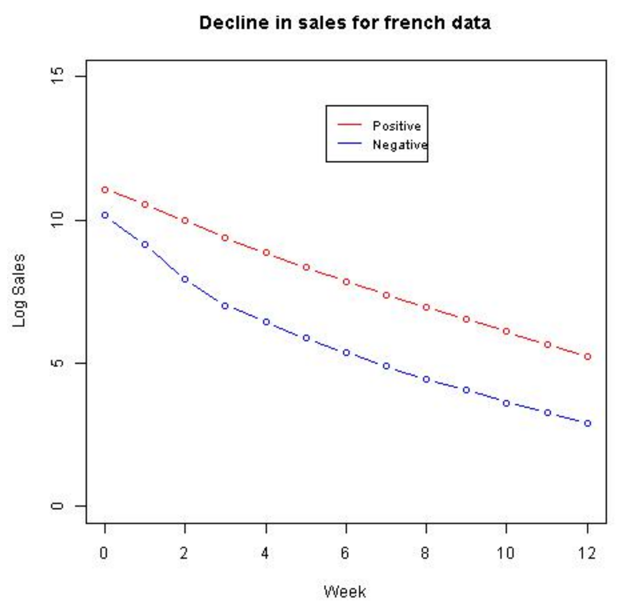
	Dependent variable:						
	log_entree_fr						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log_seance_fr	1.208***	1.237***	1.237***	1.279***	1.282***	1.287***	1.196***
	(0.009)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	2,046	2,046	2,046	2,046	2,046	2,046	2,046
R^2	0.893	0.899	0.900	0.917	0.924	0.925	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

Table 3: Regression of first-week entries on number of screens for Paris only

	Dependent variable:						
	log_entree_paris						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log_seance_paris	1.342***	1.336***	1.337***	1.281***	1.281***	1.284***	1.152***
	(0.010)	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	2,701	2,701	2,701	2,701	2,701	2,701	2,701
R^2	0.875	0.880	0.881	0.901	0.908	0.909	0.927
Adjusted R^2	0.875	0.879	0.880	0.892	0.897	0.898	0.918
Note:							*p<0.1; **p<0.05; ***p<0.01

Figure 1: We find the same graph as Moretti





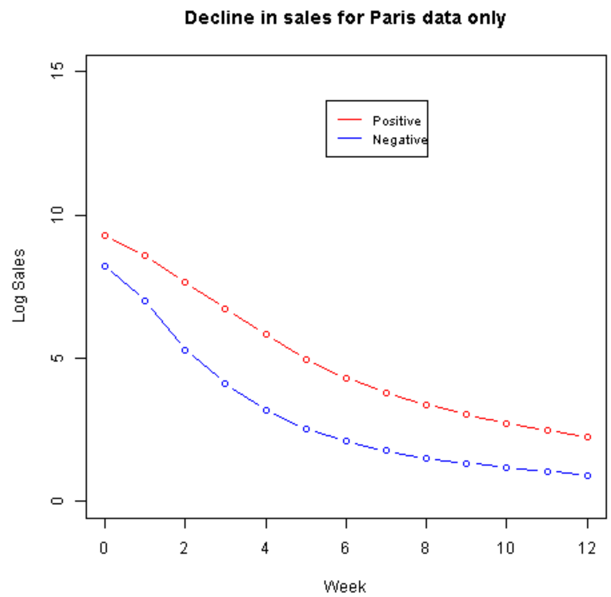


Table 4: Decline in box-office sales by opening week surprise

	Dependent variable:			
	log_sales			
	(1)	(2)	(3)	(4)
t	-0.952^{***}	-0.952^{***}	-1.289^{***}	
	(0.007)	(0.006)	(0.009)	
t:surprise		0.475^{***}		
		(0.009)		
t:positive_surprise			0.640^{***}	
			(0.013)	
I(t ∗bottom_surprise)				-1.353^{***}
				(0.011)
I(t ∗middle_surprise)				-1.011^{***}
				(0.011)
I(t ∗top_surprise)				-0.491^{***}
				(0.011)
Observations	39,936	39,936	39,936	39,936
R^2	0.772	0.788	0.787	0.790
Adjusted R^2	0.739	0.758	0.756	0.760
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Precision of the prior

	Dependent variable:	
	log_sales	
	(1)	(2)
t	-1.291^{***}	-1.267^{***}
	(0.010)	(0.087)
t:positive_surprise	0.654^{***}	-0.061
	(0.013)	(0.121)
t:sequel	0.037	
	(0.038)	
t:positive_surpriseTRUE:sequel	-0.225^{***}	
	(0.053)	
t:var_surprise		-0.045
		(0.174)
t:positive_surpriseTRUE:var_surprise		1.416^{***}
		(0.243)
Observations	39,936	39,936
R^2	0.787	0.787
Adjusted R^2	0.756	0.757
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6: Decline in box-office sales by opening week surprise

	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		

Table 7: 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

Table 8: Decline in box-office sales by opening week surprise

	Dependent variable:			
	log_entree_paris			
	(1)	(2)	(3)	(4)
t	-0.583^{***}	-0.583^{***}	-0.564^{***}	
	(0.002)	(0.002)	(0.003)	
t:surprise		-0.032^{***}		
		(0.004)		
t:positive_surprise			-0.039^{***}	
			(0.005)	
t:bottom_surpriseFALSE				-0.594^{***}
				(0.004)
t:bottom_surprise				-0.541^{***}
				(0.004)
t:middle_surprise				-0.021^{***}
				(0.006)
Observations	35,113	35,113	35,113	35,113
R^2	0.810	0.810	0.810	0.811
Adjusted R^2	0.794	0.794	0.794	0.795
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Precision of the prior

	Dependent variable:		
	log_entree_paris		
	(1)	(2)	(3)
t	-0.560^{***}	-0.772^{***}	-0.616^{***}
	(0.003)	(0.017)	(0.005)
t:positive_surprise	-0.030^{***}	-0.213^{***}	-0.126^{***}
	(0.005)	(0.024)	(0.007)
t:saga	-0.118^{***}		
	(0.017)		
t:positive_surpriseTRUE:saga	-0.022		
	(0.020)		
t:var_surprise		0.576^{***}	
		(0.045)	
t:positive_surpriseTRUE:var_surprise		0.480^{***}	
		(0.065)	
t:art_essai			0.087^{***}
			(0.006)
t:positive_surpriseTRUE:art_essai			0.156^{***}
			(0.009)
Observations	35,113	35,074	35,113
R^2	0.811	0.814	0.819
Adjusted R^2	0.795	0.798	0.804
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.

Table 10: Precision of peers' signal

	Dependent variable:	
	log_entree_fr	
	(1)	(2)
t	-0.663^{***}	-0.451^{***}
	(0.007)	(0.005)
$t\times$positive_surprise	0.061^{***}	0.076^{***}
	(0.010)	(0.006)
$t\times$tout_public	0.115^{***}	
	(0.008)	
$t\times$positive_surprise$\times$tout_public	0.031^{***}	
	(0.011)	
$t\times$seance_fr_first_week		-0.033^{***}
		(0.001)
$t\times$positive_surprise$\times$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	

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:

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

The results are reported in table 11. The second derivative of log of entries for negative-surprise movies is

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

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

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

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

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

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. However, the hypothesis of concavity of positive-surprise movies must be rejected (p-value $= 1$). 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.

Table 11: Convexity of the sales profile

	Dependent variable:
	log_entree_fr
t	-0.978^{***}
	(0.011)
t^2	0.034^{***}
	(0.001)
$t\times$positive_surprise	0.393^{***}
	(0.016)
$t^2\times$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