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## Social influence and the Matthew mechanism: The case of an artificial cultural market

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*Social Influence and the Matthew  
Mechanism: The Case of an Artificial  
Cultural Market*

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SOCIAL INFLUENCE AND THE MATTHEW MECHANISM:  
THE CASE OF AN ARTIFICIAL CULTURAL MARKET

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# **Social Influence and the Matthew Mechanism: The Case of an Artificial Cultural Market<sup>1</sup>**

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June 10<sup>th</sup>, 2013

We show that the Matthew effect, or Matthew mechanism, was present in the artificial cultural market Music Lab when social influence between individuals was allowed, whereas this was not the case when social influence was not allowed. We also sketch on a class of social network models, derived from social influence theory, that may generate the Matthew effect. Thus, we propose a theoretical framework that may explain why the most popular songs were much more popular, and the least popular songs were much less popular, than when disallowing social influence between individuals.

JEL codes: C31, C65, Z19.

Keywords: Matthew effect, Music Lab, social influence, social network.

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## 1 Introduction

Salganik, Dodds and Watts (2006) created the artificial cultural market Music Lab, in which more than 14,000 individuals participated. The participants were asked to listen to, rate, and, if they chose, download songs by bands they had never heard of. One group of individuals did not receive any information about the popularity, in the form of download statistics, of different songs, whereas this information was given to individuals in eight other groups, or “worlds,” in the experiment. The aim of this experimental design was for the former group of individuals to determine the quality of the songs, whereas the individuals in the different “worlds” determined the success of the songs, allowing for social influence between individuals.

Salganik et al. (2006) found that the success of a song was only partly determined by its quality. In fact, the most popular songs were much more popular, and the least popular songs were much less popular, than when disallowing social influence between individuals. Moreover, the particular songs that became popular were different in the different “worlds,” which led the authors to conclude that *“when individual decisions are subject to social influence [...] there are inherent limits on the predictability of outcomes”* (Salganik et al. 2006:856). A striking example of the large variation in the outcome of a specific song in the different “worlds” was the song Lockdown. In terms of quality, the song was ranked 26<sup>th</sup> out of 48 songs. However, in one “world,” the same song was ranked 1<sup>st</sup>, whereas in another “world,” it was ranked 40<sup>th</sup> (Watts 2007).

In addition, in reference to his findings in Salganik et al. (2006), Watts (2007) wrote the following in the New York Times:

“[W]hen people tend to like what other people like, differences in popularity are subject to what is called ‘cumulative advantage,’ or the ‘rich get richer’ effect. This means that

if one object happens to be slightly more popular than another at just the right point, it will tend to become more popular still. As a result, even tiny, random fluctuations can blow up, generating potentially enormous long-run differences among even indistinguishable competitors—a phenomenon that is similar in some ways to the famous ‘butterfly effect’ from chaos theory. Thus, if history were to be somehow rerun many times, seemingly identical universes with the same set of competitors and the same overall market tastes would quickly generate different winners: Madonna would have been popular in this world, but in some other version of history, she would be a nobody, and someone we have never heard of would be in her place.”

Bask and Bask (2013) argue in detail that a dynamic process characterized by the “butterfly effect” is also associated with the Matthew effect, which is the effect of the Matthew mechanism. The term Matthew effect is derived from the Gospel of Matthew, in which Jesus says, “[f]or unto every one that hath shall be given, and he shall have abundance: but from him that hath not shall be taken away even that which he hath” (Matthew 25:29). It was Merton (1968; 1988) who coined this term due to his observation that better-known scientists tend to receive more academic recognition than lesser-known scientists for similar achievements. Consequently, better-known scientists attract more resources at the expense of lesser-known scientists, which widens the gap between the two groups’ resources and achievements:

“[T]he Matthew effect is the accruing of large increments of peer recognition to scientists of great repute for particular contributions in contrast to the minimizing or withholding of such recognition for scientists who have not yet made their mark. The biblical parable generates a corresponding sociological parable” (Merton 1988:609).

We show (in Section 2) in this short paper that the Matthew mechanism was present in the artificial cultural market Music Lab when social influence between individuals was allowed,

whereas this was not the case when social influence was not allowed. We also sketch (in Section 3) on a class of social network models, derived from social influence theory, that may generate the Matthew effect. Thus, we propose a theoretical framework that may explain why *“Madonna would have been popular in this world, but in some other version of history, she would be a nobody, and someone we have never heard of would be in her place”* (Watts 2007).

## 2 The Music Lab experiment and the Matthew mechanism

The bounded dynamic process  $f : \mathbb{R}^{n_f} \rightarrow \mathbb{R}^{n_f}$  generates

$$(1) \quad \mathcal{S}_{t+1} = f(\mathcal{S}_t),$$

where  $\mathcal{S}_t$  is the state of the Music Lab experiment in one “world.” For an  $n_f$ -dimensional process as in (1), there are  $n_f$  Lyapunov exponents that are ranked from the largest to the smallest value:  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{n_f}$ . Bask and Bask (2013) argue in detail that the Matthew mechanism is in play when the largest Lyapunov exponent is positive,  $\lambda_1 > 0$ . Thus, the Matthew mechanism is *“capable of magnifying small differences over time and makes it difficult for an individual or group that is behind at a point in time [...] to catch up”* (DiPrete and Eirich 2006:272).

Because the actual form of the dynamic process  $f(\cdot)$  is unknown, it may seem impossible to estimate the Lyapunov exponents of the process, including the largest Lyapunov exponent. However, we can reconstruct the dynamics by using a scalar time series and then estimate the Lyapunov exponents of the reconstructed process. To do so, associate  $f(\cdot)$  with the observer function  $g : \mathbb{R}^{n_f} \rightarrow \mathbb{R}$  that generates

$$(2) \quad s_t = g(\mathcal{S}_t) + \varepsilon_t,$$

where  $s_t \in \mathbb{R}$  is a song's market share of downloads (e.g., the song Lockdown in the Music Lab experiment) and  $\varepsilon_t \in \mathbb{R}$  is the measurement error, which means that the time series  $\{s_t\}_{t=0}^{t_{max}}$  is observed. The  $t_{max} + 1$  observations in the time series contain information on unobserved state variables that can be utilized to define a state in the present time. For this reason, let

$$(3) \quad \mathcal{T} = (\mathcal{T}_0, \mathcal{T}_1, \dots, \mathcal{T}_{n_{\mathcal{T}}-1})'$$

be the reconstructed trajectory that describes how the reconstructed state  $\mathcal{T}_t \in \mathbb{R}^{n_h}$  evolves over time; additionally, let  $n_{\mathcal{T}}$  be the number of states in the reconstructed trajectory. Moreover, the reconstructed state at time  $t$  is

$$(4) \quad \mathcal{T}_t = \{s_t, s_{t+1}, \dots, s_{t+n_h-1}\},$$

where  $n_h$  is the embedding dimension. Thus,  $\mathcal{T}$  is an  $n_{\mathcal{T}} \times n_h$  matrix, and the constants  $n_{\mathcal{T}}$ ,  $n_h$ , and  $t_{max}$  are related as  $n_{\mathcal{T}} = t_{max} - n_h + 2$ . Takens (1981) proved that the function

$$(5) \quad \Phi(\mathcal{S}_t) = \{g(f^0(\mathcal{S}_t)), g(f^1(\mathcal{S}_t)), \dots, g(f^{n_h-1}(\mathcal{S}_t))\},$$

which maps the  $n_f$ -dimensional unobserved state  $\mathcal{S}_t$  onto (and not only into) the  $n_h$ -dimensional reconstructed state  $\mathcal{T}_t$ , is an embedding when  $n_h > 2n_f$  (but be aware that this condition is a sufficient, but not necessary, condition for an embedding; Sauer, Yorke and Casdagli 1991). Thus, the function  $\Phi : \mathbb{R}^{n_f} \rightarrow \mathbb{R}^{n_h}$  is a smooth function that performs a one-to-one coordinate transformation and has a smooth inverse. Moreover, the function preserves topological information about the unknown dynamic process  $f(\cdot)$ , such as the Lyapunov exponents. In particular, the function induces another function,  $h : \mathbb{R}^{n_h} \rightarrow \mathbb{R}^{n_h}$ , on the reconstructed trajectory,

$$(6) \quad \mathcal{T}_{t+1} = h(\mathcal{T}_t),$$



which is topologically conjugate to the unknown dynamic process  $f(\cdot)$ :

$$(7) \quad h^j = \Phi \circ f^j \circ \Phi^{-1}(\mathcal{T}_t).$$

$h(\cdot)$  is, therefore, a reconstructed dynamic process that has the same Lyapunov exponents as the unknown dynamic process  $f(\cdot)$ .

To estimate the Lyapunov exponents of the unknown dynamic process  $f(\cdot)$ , we first reconstruct the dynamic process  $h(\cdot)$ . However, because

$$(8) \quad h : \begin{pmatrix} s_t \\ s_{t+1} \\ \vdots \\ s_{t+n_h-1} \end{pmatrix} \rightarrow \begin{pmatrix} s_{t+1} \\ s_{t+2} \\ \vdots \\ h'(s_t, s_{t+1}, \dots, s_{t+n_h-1}) \end{pmatrix},$$

the reconstruction of the dynamic process  $h(\cdot)$  reduces to the estimation of  $h'(\cdot)$ :

$$(9) \quad s_{t+n_h} = h'(s_t, s_{t+1}, \dots, s_{t+n_h-1}),$$

which is a non-linear autoregression of order  $n_h$  (with no error term). Moreover, because the Jacobian  $Dh(\cdot)$  on the reconstructed state  $\mathcal{T}_t$  is

$$(10) \quad Dh(\mathcal{T}_t) = \begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ \frac{\partial h'}{\partial s_t} & \frac{\partial h'}{\partial s_{t+1}} & \frac{\partial h'}{\partial s_{t+2}} & \dots & \frac{\partial h'}{\partial s_{t+n_h-1}} \end{pmatrix},$$

we use a feed-forward neural network to estimate the above derivatives and, thus, to estimate the Lyapunov exponents consistently (Dechert and Gençay 1992; Gençay and Dechert 1992).

We do so because Hornik, Stinchcombe and White (1990) showed that a function and its derivatives of any unknown functional form can be approximated arbitrarily accurately by such a neural network. Specifically, after estimating the derivatives in (10) with a neural network, we estimate the Jacobian  $Dh(\cdot)$ . Having repeated this procedure at each point in time along

the reconstructed trajectory  $\mathcal{T}$ , we estimate the Lyapunov exponents of the reconstructed dynamic process  $h(\cdot)$ , which are the same as the Lyapunov exponents of the unknown dynamic process  $f(\cdot)$ :

$$(11) \quad \hat{\lambda}_i = \lim_{n_{\mathcal{T}} \rightarrow \infty} \frac{1}{n_{\mathcal{T}}} \sum_{k=0}^{n_{\mathcal{T}}-1} \log_e |Dh(\mathcal{T}_k)|,$$

where each limit is taken in the direction identified with the corresponding eigenvector in tangent space. Of course, our interest is restricted to the estimate of the largest Lyapunov exponent,  $\hat{\lambda}_1$ , because the positivity of this exponent means that the Matthew mechanism is present in the dynamic process that generates songs' market shares of downloads in the Music Lab experiment.

Finally, how can we test whether the Matthew mechanism is present in one “world” in the Music Lab experiment? Shintani and Linton (2004) derived the asymptotic distribution of a neural network estimator of the Lyapunov exponents:

$$(12) \quad \sqrt{n_{\mathcal{T}}}(\hat{\lambda}_i - \lambda_i) \Rightarrow \mathbb{N}(0, \mathcal{V}_i),$$

where  $\{\hat{\lambda}_i\}_{i=1}^{n_h}$  is the estimator of the  $i$ th Lyapunov exponent, based on the  $n_{\mathcal{T}}$  reconstructed states on the trajectory  $\mathcal{T}$ , and  $\{\mathcal{V}_i\}_{i=1}^{n_h}$  is the variance of the  $i$ th Lyapunov exponent. To test the hypothesis that the Matthew mechanism is present in the dynamic process that generates songs' market shares of downloads in the Music Lab experiment, we consider the null and alternative hypotheses,

$$(13) \quad \begin{cases} H_0 : \lambda_1 \leq 0, \\ H_1 : \lambda_1 > 0, \end{cases}$$

where our interest is restricted to the sign of the largest Lyapunov exponent. The test statistic

is  $\hat{t} = \frac{\hat{\lambda}_1}{\sqrt{\hat{\mathcal{V}}_1}}$ , where  $\hat{\mathcal{V}}_1$  is a consistent estimator of  $\mathcal{V}_1$  (Andrews 1991). Thus, the null hypothesis

(no Matthew mechanism) is rejected when  $\hat{t} \geq z_\alpha$ , where the significance level is  $Pr[\mathbb{Z} \geq z_\alpha] = \alpha$  and  $\mathbb{Z}$  is the standard normal random variable.<sup>4</sup>

Following Salganik et al. (2006), we used a song’s market share of downloads as the measure of how successful a song was. Specifically, in each of the nine “worlds”—including eight social influence “worlds” and one “world” that disallowed social influence between individuals—we used the song Lockdown’s market share of downloads as our reconstruction variable. After removing the first 200 observations in each of the nine time series—one time series for each “world”—to avoid transients in the dynamics (because there was a clearly defined beginning in each “world”), we estimated the largest Lyapunov exponent, making use of 4, 8, and 12 inputs to the neural network, where the number of hidden units ran, in each case, from 2 to 12 units (which means that we estimated 33 neural networks for each “world”). We then selected the estimate of the largest Lyapunov exponent associated with the neural network that minimized the Schwarz Information Criterion for each “world.” The estimation results for the “worlds” in the Music Lab experiment by Salganik et al. (2006) can be found in Table 1.

[Table 1 about here.]

We found that the Matthew mechanism was (statistically significantly) present in two social influence “worlds:” 1) the 7<sup>th</sup> “world,” with  $\hat{\lambda} = 0.4879$  ( $p$  value = 0.0244), and 2) the 8<sup>th</sup>

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<sup>4</sup> NETLE 4.1 software can be used to estimate the Lyapunov exponents and make statistical inferences. This software was developed by R. Gençay, C.-M. Kuan, and T. Liu, and it can be downloaded from <http://tliu.iweb.bsu.edu/download/index.html>. NETLE 4.1 was also used when we tested for the presence of the Matthew mechanism in the artificial cultural market Music Lab. The Music Lab data can be downloaded from <http://opr.princeton.edu/archive/cm/>, which also contains a careful description of the project and data documentation. It is the second experiment in Salganik et al. (2006) that we examine herein.

“world,” with  $\hat{\lambda} = 0.0721$  ( $p$  value = 0.0473). The latter “world” was also the “world” with the greatest inequality in the popularity of songs (see Figure 1B in Salganik et al. 2006). Interestingly, the Matthew mechanism was (statistically significantly) not present when social influence between individuals was disallowed ( $\hat{\lambda} = -0.0085$ ;  $p$  value = 0.0001). Also of note is that the magnitude of  $\hat{\lambda}$  was very large in the 7<sup>th</sup> “world.”

### 3 Social influence and the Matthew mechanism

Undoubtedly, a theoretical model that explains the Matthew mechanism in the Music Lab experiment must be a heterogeneous agent model. One class of heterogeneous agent models that fits well for this aim are social network models derived from social influence theory (Friedkin and Johnsen 1990; 2003). This class of models is described by the following dynamic process:

$$(14) \quad \mathbf{y}_{t+1} = \mathbf{A}_t \mathbf{W}_t \mathbf{y}_t + (\mathbf{I} - \mathbf{A}_t) \mathbf{y}_0,$$

where  $\mathbf{y}_t \in \mathbb{R}^p$  is a vector of the opinions (e.g., about a song in the Music Lab experiment) of the  $p$  individuals who are in the social network,  $\mathbf{A}_t \in \mathbb{R}^{p \times p}$  is a diagonal matrix of the individuals’ susceptibilities to inter-individual influences, and  $\mathbf{W}_t \in \mathbb{R}^{p \times p}$  is a matrix of inter-individual influences. Moreover, the elements in  $\mathbf{W}_t$  are fractions,  $0 \leq w_{ijt} \leq 1$ , and  $\sum_{j=1}^p w_{ijt} = 1$ . Finally,  $\mathbf{y}_0 \in \mathbb{R}^p$  is a vector of the initial opinions of the individuals who are in the social network.

Under what conditions is the social influence process in (14) able to generate the Matthew effect? First,  $\mathbf{W}_t$  must be truly time-dependent so that the inter-individual influences change over time. Second, if the inter-individual influences depend on the individuals’ opinions,  $\mathbf{W}_t = k(\mathbf{y}_t)$ , where  $k : \mathbb{R}^p \rightarrow \mathbb{R}^{p \times p}$ , we may observe the Matthew effect because there are

bounded dynamic processes with  $\lambda_1 > 0$  that can be described by a difference equation of order 1 (such as the logistic map).

Note that individuals' susceptibilities to inter-individual influences,  $\mathbf{A}_t$ , directly affect the degree of social influence between individuals in the social network. We have two special cases of the social influence process in (14): (i) maximal susceptibility among individuals,  $\mathbf{A}_t = \mathbf{I}$  in (14),

$$(15) \quad \mathbf{y}_{t+1} = \mathbf{W}_t \mathbf{y}_t;$$

and (ii) no susceptibility among individuals,  $\mathbf{A}_t = \mathbf{0}$  in (14),

$$(16) \quad \mathbf{y}_{t+1} = \mathbf{y}_0.$$

Thus, the degree of social influence between individuals in the social network is strongest in the process in (15), whereas there is no social influence in the process in (16). Hence, the latter process corresponds to the 9<sup>th</sup> “world” in the Music Lab experiment when social influence between individuals was not allowed. Also of note is that the process in (16) is not dynamic, which means that the process is *not* able to generate the Matthew effect.

Lastly, individuals' opinions affect the state of the Music Lab experiment since the opinions affect songs' market shares of downloads. Thus, if  $\mathbf{W}_t = k(\cdot)$  is chosen carefully, the social influence process in (14) (or (15)) may generate the Matthew effect. Of course,  $\mathbf{W}_t = k(\cdot)$  must not be limited to only depend on individuals' opinions about a song at time  $t$ . It is our belief that research along these lines may provide a deeper understanding of why there are inherent limits on the predictability of outcomes when individuals' opinions are subject to social influence.

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**Table**

“World” <sup>1</sup>	Observations <sup>2</sup>	$\hat{\lambda}$	$p$ value <sup>3</sup>
1	817	-0.0077	0.6675
2	764	0.5124	0.2820
3	680	-0.0077	0.2907
4	899	-0.0061	0.1298
5	905	0.0020	0.9132
6	733	-0.0086	0.0001
7	945	0.4879	0.0244
8	722	0.0721	0.0473
9	1 989	-0.0085	0.0001

1 1-8 are social influence “worlds,” and 9 is the “world” that disallowed social influence between individuals.

2 The number of observations after the first 200 observations has been removed from the original time series.

3 The  $p$  value is based on the quadratic spectral standard error.

**Table 1** Estimation results for the “worlds” in the artificial cultural market Music Lab.



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