

Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market

Matthew J. Salganik,^{1,2*} Peter Sheridan Dodds,^{2*} Duncan J. Watts^{1,2,3*}

Hit songs, books, and movies are many times more successful than average, suggesting that “the best” alternatives are qualitatively different from “the rest”; yet experts routinely fail to predict which products will succeed. We investigated this paradox experimentally, by creating an artificial “music market” in which 14,341 participants downloaded previously unknown songs either with or without knowledge of previous participants’ choices. Increasing the strength of social influence increased both inequality and unpredictability of success. Success was also only partly determined by quality: The best songs rarely did poorly, and the worst rarely did well, but any other result was possible.

How can success in cultural markets be at once strikingly distinct from average performance (1–4), and yet so hard to anticipate for profit-motivated experts armed with extensive market research (4–8)? One explanation (9) for the observed inequality of outcomes is that the mapping from “quality” to success is convex (i.e., differences in quality correspond to larger differences in success), leading to what has been called the “superstar” effect (9), or “winner-take-all” markets (10). Because models of this type, however, assume that the mapping from quality to success is deterministic and that quality is known, they cannot account for the observed unpredictability of outcomes. An alternate explanation that accounts for both inequality and unpredictability asserts that individuals do not make decisions independently, but rather are influenced by the behavior of others (11, 12). Stochastic models of collective decisions that incorporate social influence can exhibit extreme variation both within and across realizations (4, 13, 14), even for objects of identical quality (3, 15). Unfortunately, empirical tests of these predictions require comparisons between multiple realizations of a stochastic process, whereas in reality, only one such “history” is ever observed.

We adopted an experimental approach to the study of social influence in cultural markets. We created an artificial “music market” (16) comprising 14,341 participants, recruited mostly from a teen-interest World Wide Web site (17), who were shown a list of previously unknown songs from unknown bands (18). In real time, arriving participants were ran-

domly assigned to one of two experimental conditions—*independent* and *social influence*—distinguished only by the availability of information on the previous choices of others. In the *independent* condition, participants made decisions about which songs to listen to, given only the names of the bands and their songs. While listening to a song, they were asked to assign a rating from one star (“I hate it”) to five stars (“I love it”), after which they were given the opportunity (but not required) to download the song. In the *social influence* condition, participants could also see how many times each song had been downloaded by previous participants. Thus, in addition to their own musical preferences, participants in the *social influence* condition received a relatively weak signal regarding the preferences of others, which they were free to use or ignore. Furthermore, participants in the *social influence* condition were randomly assigned to one of eight “worlds,” each of which evolved independently of the others. Songs in each world accumulated downloads only from participants in that world, and subsequent participants could only see their own world’s download counts.

Our experimental design has three advantages over both theoretical models and observational studies. (i) The popularity of a song in the

independent condition (measured by market share or market rank) provides a natural measure of the song’s quality, capturing both its innate characteristics and the existing preferences of the participant population. (ii) By comparing outcomes in the *independent* and *social influence* conditions, we can directly observe the effects of social influence both at the individual and collective level. (iii) We can explicitly create multiple, parallel histories, each of which can evolve independently. By studying a range of possible outcomes rather than just one, we can measure inherent unpredictability: the extent to which two worlds with identical songs, identical initial conditions, and indistinguishable populations generate different outcomes. In the presence of inherent unpredictability, no measure of quality can precisely predict success in any particular realization of the process.

We report the results of two experiments in which we study the outcomes for 48 songs by different bands (18). In both experiments, all songs started with zero downloads (i.e., all initial conditions were identical), but the presentation of the songs differed. In the *social influence* condition in experiment 1, the songs, along with the number of previous downloads, were presented to the participants arranged in a 16×3 rectangular grid, where the positions of the songs were randomly assigned for each participant (i.e., songs were not ordered by download counts). Participants in the *independent* condition had the same presentation of songs, but without any information about previous downloads. In experiment 2, participants in the *social influence* condition were shown the songs, with download counts, presented in one column in descending order of current popularity. Songs in the *independent* condition were also presented with the single column format, but without download counts and in an order that was randomly assigned for each participant. Thus, in each experiment, we can observe the effect of social influence on each song’s success, and by comparing results across the two experiments, we can measure the effect of increasing the “strength” of the relevant information signal.

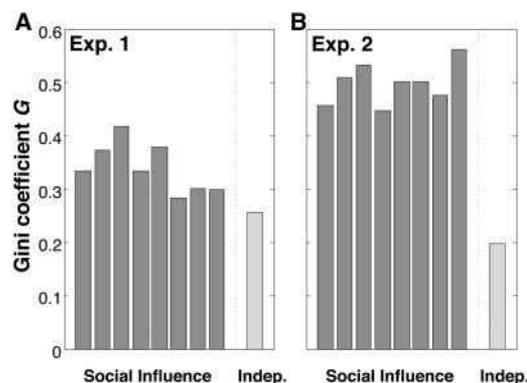


Fig. 1. Inequality of success for social influence (dark bars) and independent (light bars) worlds for (A) experiment 1 and (B) experiment 2. The success of a song is defined by m_i , its market share of downloads ($m_i = d_i / \sum_{k=1}^S d_k$, where d_i is song i 's download count and S is the number of songs). Success inequality is defined by the Gini coefficient $G = \frac{\sum_{i=1}^S \sum_{j=1}^S |m_i - m_j|}{2S \sum_{k=1}^S m_k}$, which represents the average difference in market share for two songs normalized to fall between 0 (complete equality)

and 1 (maximum inequality). Differences between independent and social influence conditions are significant ($P < 0.01$) (18).

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Our results support the hypothesis that social influence, which here is restricted only to information regarding the choices of others, contributes both to inequality and unpredictability in cultural markets. Figure 1 displays the effects of social influence on market inequality, as measured by the Gini coefficient (19) (other measures yield similar results). In both experiments, we found that all eight social

influence worlds (dark bars) exhibit greater inequality—meaning popular songs are more popular and unpopular songs are less popular—than the world in which individuals make decisions independently (light bars). Comparing Fig. 1, A and B, we also note that inequality increased when the salience of the social information signal was increased from experiment 1 to experiment 2. Thus our results suggest not

only that social influence contributes to inequality of outcomes in cultural markets, but that as individuals are subject to stronger forms of social influence, the collective outcomes will become increasingly unequal.

Social influence also generates increased unpredictability of outcomes (Figs. 2 and 3). In each experiment, the average difference in market share (fraction of total downloads) for a song between distinct social influence worlds is higher than it is between different subpopulations of individuals making independent decisions (Fig. 2). Because these different outcomes occur even with indistinguishable groups of subjects evaluating the same set of songs, this type of unpredictability is inherent to the process and cannot be eliminated simply by knowing more about the songs or market participants. Figure 3 displays the market share (left column) and market rank (right column) of each song in each of the eight social influence worlds as a function of its “quality” (i.e., its market share and rank, respectively, in the independent condition). Although, on average, quality is positively related to success, songs of any given quality can experience a wide range of outcomes (Fig. 3). In general, the “best” songs never do very badly, and the “worst” songs never do extremely well, but almost any other result is possible. Unpredictability also varies with quality—measured in terms of market share, the “best” songs are the most unpredictable, whereas when measured in terms of rank, intermediate songs are the most unpredictable (this difference derives from the inequality in success noted above). Finally, a comparison of Fig. 3, A and C, suggests that the explanation of inequality as arising from a convex mapping between quality and success (9) is incomplete. At least some of the convexity derives not from similarity of pre-existing preferences among market participants, but from the strength of social influence.

Our experiment is clearly unlike real cultural markets in a number of respects. For example, we expect that social influence in the real world—where marketing, product placement, critical acclaim, and media attention all play important roles—is far stronger than in our experiment. We also suspect that the effects of social influence were further diminished by the relatively small number of songs, and by our requirements (which aided control) that subjects could participate only once and could not share opinions. Although these differences limit the immediate relevance of our experiment to real-world cultural markets, our findings nevertheless suggest that social influence exerts an important but counterintuitive effect on cultural market formation, generating collective behavior that is reminiscent of (but not identical to) “information cascades” in sequences of individuals making binary choices (20–22). On the one hand, the more information participants have regarding the decisions of others, the greater agreement

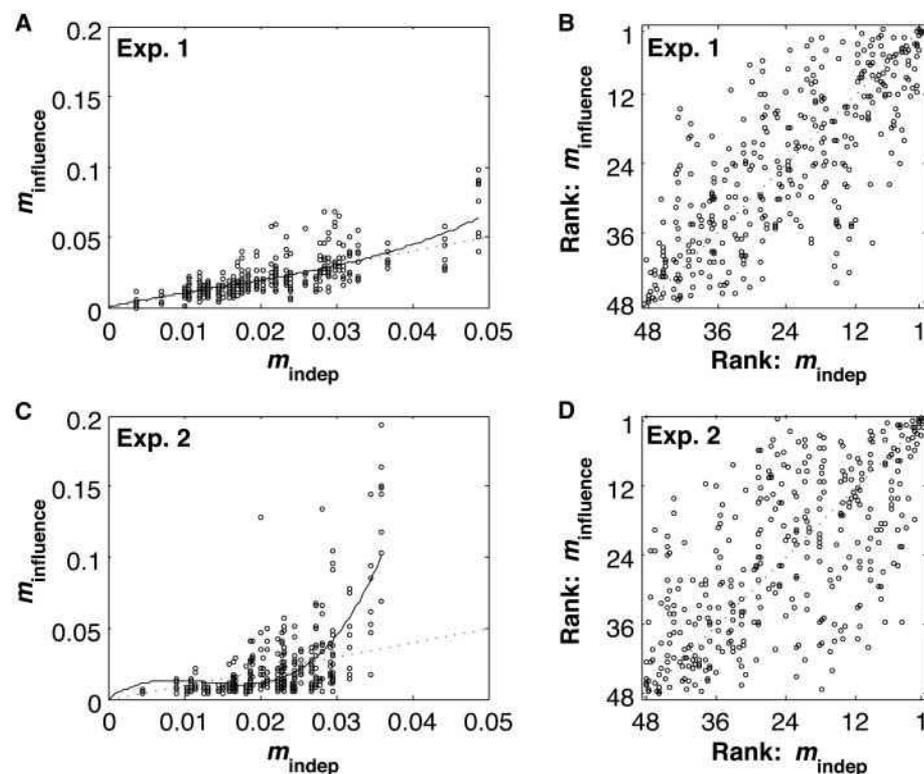
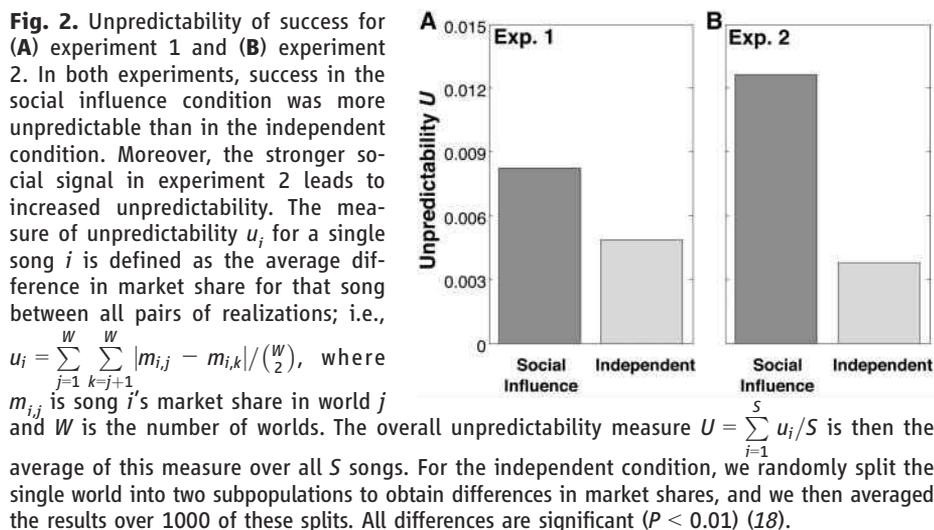


Fig. 3. Relationship between quality and success. (A) and (C) show the relationship between m_{indep} , the market share in the one independent world (i.e., quality), and $m_{influence}$, the market share in the eight social influence worlds (i.e., success). The dotted lines correspond to quality equaling success. The solid lines are third-degree polynomial fits to the data, which suggest that the relationship between quality and success has greater convexity in experiment 2 than in experiment 1. (B) and (D) present the corresponding market rank data.

they will seem to display regarding their musical preferences; thus the characteristics of success will seem predictable in retrospect. On the other hand, looking across different realizations of the same process, we see that as social influence increases (i.e., from experiment 1 to experiment 2), which particular products turn out to be regarded as good or bad becomes increasingly unpredictable, whether unpredictability is measured directly (Fig. 2) or in terms of quality (Fig. 3). We conjecture, therefore, that experts fail to predict success not because they are incompetent judges or misinformed about the preferences of others, but because when individual decisions are subject to social influence, markets do not simply aggregate pre-existing individual preferences. In such a world, there are inherent limits on the predictability of outcomes, irrespective of how much skill or information one has.

Although Web-based experiments of the kind used here are more difficult to control in some respects than are experiments conducted in physical laboratories (18), they have an important methodological advantage for studying collective social processes like cultural market formation. Whereas experimental psychology, for example, tends to view the individual as the relevant unit of analysis, we are explicitly interested in the relationship between individual (micro) and collective (macro) behavior;

thus we need many more participants. In order to ensure that our respective worlds had reached reasonably steady states, we required over 14,000 participants—a number that can be handled easily in a Web-based experiment, but which would be impractical to accommodate in a physical laboratory. Because this “micro-macro” feature of our experiment is central to all collective social dynamics (23), we anticipate that Web-based experiments will become increasingly useful to the study of social processes in general.

References and Notes

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Supporting Online Material

www.sciencemag.org/cgi/content/full/311/5762/854/DC1
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Tables S1 to S4
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The Nucleosomal Surface as a Docking Station for Kaposi's Sarcoma Herpesvirus LANA

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Kaposi's sarcoma-associated herpesvirus (KSHV) latency-associated nuclear antigen (LANA) mediates viral genome attachment to mitotic chromosomes. We find that N-terminal LANA docks onto chromosomes by binding nucleosomes through the folded region of histones H2A-H2B. The same LANA residues were required for both H2A-H2B binding and chromosome association. Further, LANA did not bind *Xenopus* sperm chromatin, which is deficient in H2A-H2B; chromatin binding was rescued after assembly of nucleosomes containing H2A-H2B. We also describe the 2.9-angstrom crystal structure of a nucleosome complexed with the first 23 LANA amino acids. The LANA peptide forms a hairpin that interacts exclusively with an acidic H2A-H2B region that is implicated in the formation of higher order chromatin structure. Our findings present a paradigm for how nucleosomes may serve as binding platforms for viral and cellular proteins and reveal a previously unknown mechanism for KSHV latency.

Kaposi's sarcoma-associated herpesvirus (KSHV) has an etiological role in Kaposi's sarcoma (KS), the predominant AIDS malignancy; primary effusion lymphoma (PEL); and multicentric Castleman's disease (1–4). KSHV persists as a multicopy episome in latently infected tumor cells (5, 6). Viral genomes lack centromeres, which govern faithful DNA partitioning in eukaryotic cells,

and use a distinct segregation mechanism in which the 1162-amino acid KSHV latency-associated nuclear antigen (LANA) tethers episomes to mitotic chromosomes. LANA is required for episome persistence, and interaction with mitotic chromosomes is essential for its function. The first 22 residues comprise the dominant LANA chromosome-association region, because the C-terminal chromosome tar-

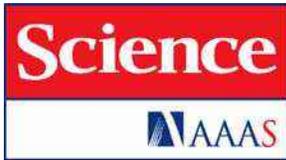
geting domain is unable to rescue chromosome association in mutants that are deleted for or contain specific mutations within the N-terminal region (7–10). We therefore sought to determine the chromosome docking partner of the LANA N terminus.

Genetic analysis of LANA's chromosome binding region was central to our strategy for characterization of putative docking partners. Transient assays have shown that alanine substitutions at LANA residues 5 to 7 [original amino acids were GMR (11)], 8 to 10 (originally LRS), or 11 to 13 (originally GRS) (termed LANA₅GMR₇, LANA₈LRS₁₀, and LANA₁₁GRS₁₃, respectively) (Fig. 1A) lack chromosome association, whereas LANA with alanine substitutions at amino acids 17 to 19 (originally PLT) or 20 to 22 (originally RGS) (termed LANA₁₇PLT₁₉ and LANA₂₀RGS₂₂,

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Supporting Online Material for

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This PDF file includes:

Materials and Methods

SOM Text

Figs. S1 to S10

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Experimental design

As stated in the main text, subjects entering the experiment were randomly assigned into either the *independent* condition or the *social influence* condition. Subjects in the independent condition had no information about the previous behavior of others and so were forced to make their decisions about the songs independently. However, subjects in the social influence condition were given information about the behavior of others which they could use, or ignore, when making their decisions. Any difference in success outcomes for the songs between these two groups can be attributed to presence of social influence.

Our design also had an additional step. In order to better understand unpredictability, subjects in the social influence condition were further randomly assigned into one of eight influence “worlds.” Each subject was given information only about the behavior of others in their influence world. We thus created multiple “histories” to determine to what extent indistinguishable groups of subjects, starting at the same initial condition, and choosing from the same set of songs can generate different success outcomes. We only needed one independent condition world because the behaviors of the subjects in this condition were independent. A schematic of the experimental design is shown in Fig. S1.

The assignment of subjects was done such that 20% of the subjects were assigned the independent condition and 10% were assigned to each of the eight social influence worlds. For each experiments, this allocation resulted in about 700 subjects in each of the social influence worlds and about 1,400 in the independent condition. The reason for this allocation scheme will become clear when we discuss our measure of unpredictability.

Subject experience during the experiment

The entire framework of the experimental design was unknown to the subjects. Upon entering the website (<http://musiclab.columbia.edu>) subjects were presented with a welcome screen telling them that they

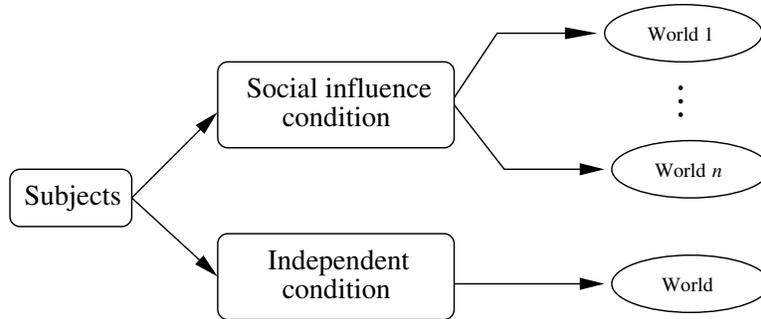


Figure S1: Schematic of the experimental design.

were about to participate in a study about musical tastes and that in exchange for participating they would be offered the chance to download some free songs by up-and-coming artists. Subjects next gave their informed consent, filled out a brief survey, and were shown a page of instructions. Finally, subjects were presented with a menu of 48 songs.

In experiment 1, the songs were presented in a three column jukebox-type design (see Fig. S2) and displayed in a random order to each subject. By randomizing the order for each subject we avoided favoring any songs by placing them in advantageous screen-locations. However, the specific order for each subject was fixed for the entire experiment. Subjects in the social influence condition were also presented with the song download counts in their world while subjects in the independent condition were not.

In experiment 2, the songs were presented in a one column design (see Fig. S3). Subjects in the social influence worlds were presented the songs sorted by number of downloads, along with the download counts in their world. If several songs shared the same number of downloads, the ordering of the songs was determined randomly for each user. Subjects in the independent condition in experiment 2 were presented with the songs in the same one column design, but in random order and without the download counts.

Once at the menu of songs, if a subject clicked on a specific song, they were taken to a new screen where the song automatically began playing in a Macromedia Flash Player, streamed in the mp3 format encoded at 96kbps (Fig. S4). While a subject listened to the song they were asked to rate it on a scale from 1 star (“I hate it”) to 5 stars (“I love it”) which could be done at any time while the song was playing; subjects did not need to wait for the song to complete. After the rating was recorded, subjects were asked if they would like to download the song (Fig. S5). After making the download decision, subjects were returned to the menu of 48 songs and were able to choose again.

Once a subject had listened to as many songs as they wished, they could click “log off” and were taken to a screen thanking them for participating and providing them links to the webpages of all 48 bands. Subjects who returned to the website while the experiment they participated in was still underway were automatically

	# of down loads	[Help] [Log off]	# of down loads	# of down loads
HARTSFIELD: "enough is enough"	20	GO MORECAL: "it does what its told"	12	UNDO: "while the world passes"
DEEP ENOUGH TO DIE: "for the sky"	17	PARKER THEORY: "she said"	47	UP FOR NOTHING: "in sight of"
THE THRIFT SYNDICATE: "2003 a tragedy"	20	MSS OCTOBER: "pink aggression"	27	SILVERFOX: "gnaw"
THE BROKEN PROMISE: "the end in friend"	19	POST BREAK TRAGEDY: "florencia"	14	STRANGER: "one drop"
THIS NEW DAWN: "the belief above the answer"	12	FORTHFADING: "fear"	24	FAR FROM KNOWN: "route 9"
NOONER AT NINE: "walk away"	6	THE CALEFACTION: "trapped in an orange peef"	20	STUNT MONKEY: "inside out"
MORAL HAZARD: "waste of my life"	8	S2METRO: "lockdown"	17	DANTE: "lifes mystery"
NOT FOR SCHOLARS: "as seasons change"	27	SIMPLY WAITING: "went with the count"	16	FADING THROUGH: "wish me luck"
SECRETARY: "keep your eyes on the ballistics"	5	STAR CLIMBER: "tell me"	38	UNKNOWN CITIZENS: "falling over"
ART OF KANLY: "seductive atto, melodic breakdown"	10	THE FASTLANE: "il death do us part (i dont)"	31	BY NOVEMBER: "if i could take you"
HYDRAULIC SANDWICH: "separation anxiety"	20	A BLINDING SILENCE: "miseries and misacles"	17	DRAWN IN THE SKY: "tap the ride"
EMBER SKY: "this upcoming winter"	25	SUM RANA: "the bolshevik boogie"	15	SELSIUS: "stars of the city"
SALUTE THE DAWN: "i am emo"	13	CAPE RENEWAL: "baseball warlock v1"	12	SIBRIAN: "eye patch"
RYAN ESSMAKER: "detour...be still"	14	UP FALLS DOWN: "a brighter burning star"	11	EVAN GOLD: "robert downey jr"
BEERBONG: "father to son"	12	SUMMERSWASTED: "a plan behind destruction"	17	BENEFIT OF A DOUBT: "run away"
HALL OF FAME: "best mistakes"	19	SILENT FILM: "all i have to say"	61	SHIPWRECK UNION: "out of the woods"

Figure S2: Screenshot of the song menu in the social influence world in experiments 1. Screenshot from the independent condition (not shown) was identical except that the download counts to the right of each song are removed.

	# of down loads
PARKER THEORY: "she said"	159
THE FASTLANE: "il death do us part (i dont)"	103
SELSIUS: "stars of the city"	62
STUNT MONKEY: "inside out"	56
BY NOVEMBER: "if i could take you"	55
FORTHFADING: "fear"	49
HYDRAULIC SANDWICH: "separation anxiety"	43
SILENT FILM: "all i have to say"	40
UNDO: "while the world passes"	36
BENEFIT OF A DOUBT: "run away"	32
A BLINDING SILENCE: "miseries and misacles"	27
MSS OCTOBER: "pink aggression"	26
STAR CLIMBER: "tell me"	24
FAR FROM KNOWN: "route 9"	22
HALL OF FAME: "best mistakes"	21
EMBER SKY: "this upcoming winter"	19

Figure S3: Screenshot of the song menu in the social influence world in experiments 2. Screenshot from the independent condition (not shown) was identical except that the download counts to the right of each song are removed.

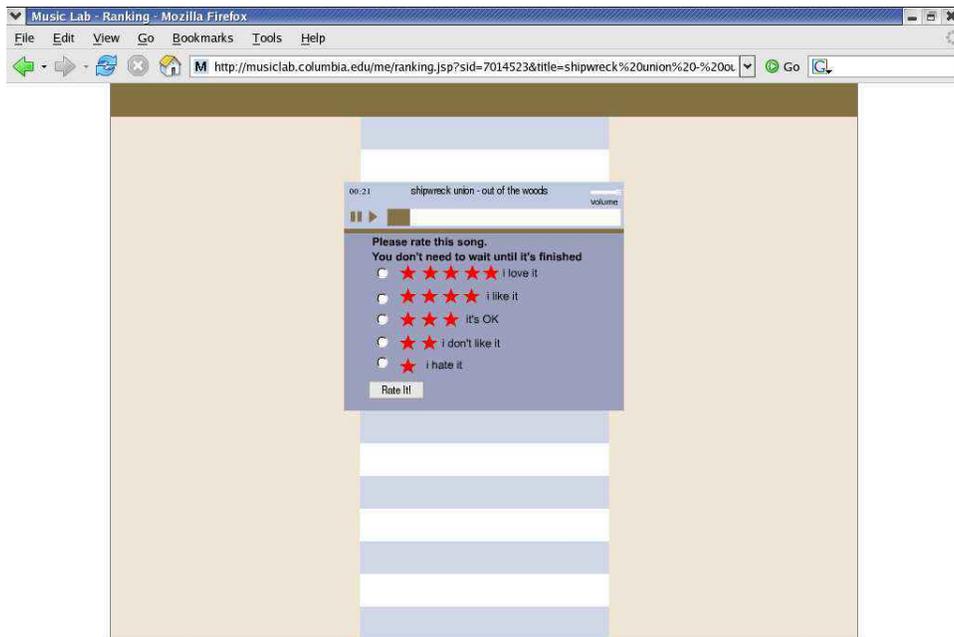


Figure S4: Screenshot of the listening screen. While a song was playing subjects were required to rate it on a scale of 1 to 5 stars. This rating could be submitted before the song was finished playing.

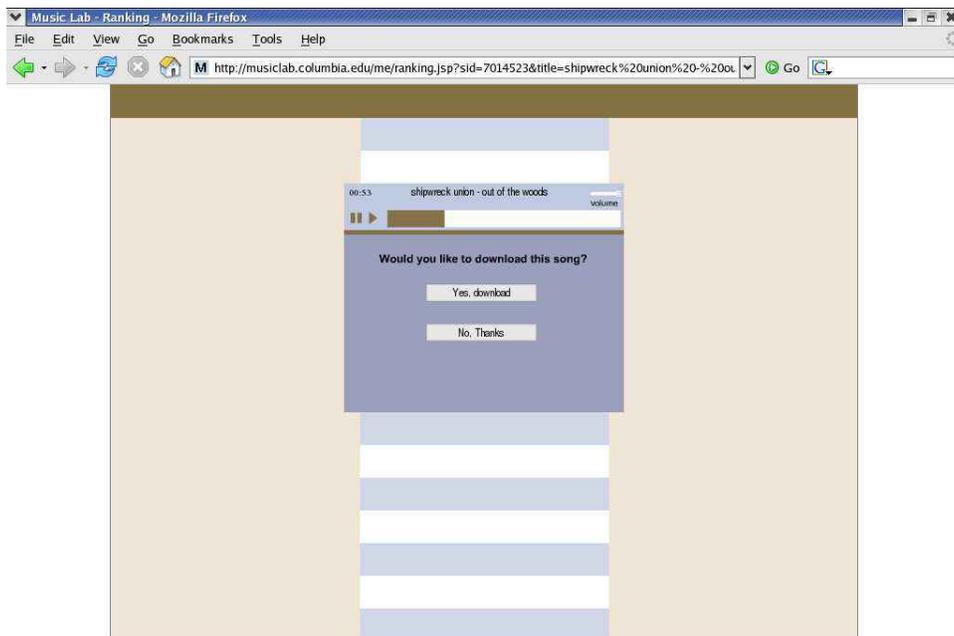


Figure S5: Screenshot of the download decision screen. After rating the song, subjects had to decide to download the song or not.

Category	Experiment 1 ($n = 7,149$) (% of participants)	Experiment 2 ($n = 7,192$) (% of participants)
Female	36.4	73.9
Broadband connection	74.1	69.0
Has downloaded music from other sites	60.4	62.4
Country of Residence		
UNITED STATES	79.8	81.8
CANADA	4.5	4.4
UNITED KINGDOM	4.4	4.7
OTHER	11.3	9.1
Age		
14 AND YOUNGER	11.5	16.0
15 TO 17	27.8	34.9
18 TO 24	38.5	39.2
25 AND OLDER	22.3	9.9

Table S1: Descriptive statistics about the subjects.

	Experiment 1			Experiment 2		
	Influence ($n = 5,708$)	Independent ($n = 1,441$)	Total ($n = 7,149$)	Influence ($n = 5,746$)	Independent ($n = 1,446$)	Total ($n = 7,192$)
Number of listens	21,971	5,394	27,365	20,217	5,643	25,860
Mean per subject	3.8	3.7	3.8	3.5	3.9	3.6
Median per subject	1	1	1	1	1	1
Number of downloads	6,626	1,578	8,203	8,106	2,192	10,298
Mean per subject	1.2	1.1	1.1	1.4	1.5	1.4
Median per subject	0	0	0	0	0	0

Table S2: Descriptive statistics on subject behavior in the two conditions and overall.

returned to their world and taken to the appropriate song menu without the need to re-register. Subjects from experiment 1 who returned to the website during experiment 2 were prevented from participating.

Subject recruitment

Experiment 1 took place from October 7, 2004 to December 15, 2004 (69 days) and involved 7,149 subjects. Immediately after completing experiment 1, we began experiment 2 which ran from December 15, 2004 to March 8, 2005 (83 days) and involved 7,192 subjects. Most subjects were recruited from <http://www.bolt.com>, a website popular with teens and young adults from the United States. Demographics about these subjects are presented in Table S1 and summary statistics about their behavior is presented in Table S2.

We note that there was a change in percentage of females from experiment 1 to experiment 2. Subjects in both experiments were drawn from <http://www.bolt.com>, but they were drawn from different parts of the website. A majority of the subjects in experiment 1 were likely drawn from the “music” and “free-

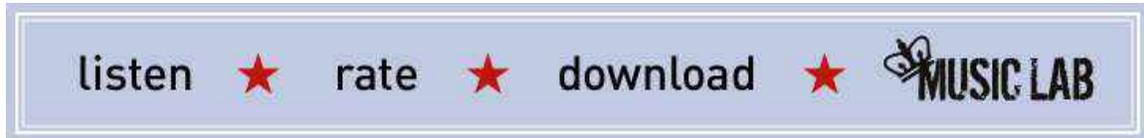


Figure S6: Banner used to recruit subjects from <http://www.bolt.com> for experiment 2.

stuff” sections while a majority of the subjects in experiment 2 were likely drawn from a special email sent to a set of Bolt users and from banner ads in all sections of the site (for example, Fig. S6). Another potential reason for the difference is that while experiment 1 was underway, the project was mentioned on the popular blog <http://www.kottke.org> which probably has an older, more male readership. Ideally these differences in recruitment between experiments would not have occurred, but we do not believe that they had a substantial effect on our findings.

Music selection

The music for the experiment comes from <http://www.purevolume.com>, a website where bands can create homepages and post their music for download. In July 2003 there were approximately 42,000 bands with homepages. Preliminary research revealed that the quality of the music of these bands was extremely variable with a large number having very poor audio quality. However, <http://www.purevolume.com> also hosted of a set of premium member bands who paid approximately \$10 per month for additional features on their homepages. There were approximately 1,000 premium bands, and we took a random sample from these bands.

Initially, about 200 bands were selected. The experiments required bands that are unknown to the subjects so we screened out any band that had played in more than 10 states, or had played more than 15 concerts in the past 30 days, or had appeared on the Warped Tour, or had 30,000 or more hits on their purevolume page. These screening criteria are ultimately arbitrary, but they are reasonable. We have no reason to believe that the results would be any different if other reasonable criteria were used. In all, these criteria removed 51 bands. In addition, 17 bands could not be contacted because they did not have a publicly available email address. The remaining 133 bands were contacted via email (results summarized in Fig. S7A). In order to minimize non-response bias, all non-responding bands received two follow-up emails spaced at one week intervals. In the end, 51 of these bands agreed to be in the study and provided us with a song of their choice, the other bands becoming ineligible for a variety of reasons (results summarized in Fig. S7B).

Preliminary pilot testing revealed that, for the song menu used in experiment 1 (Fig. S2), the maximum number of songs that could be legibly presented on a typical computer screen was 48. Thus, we took a

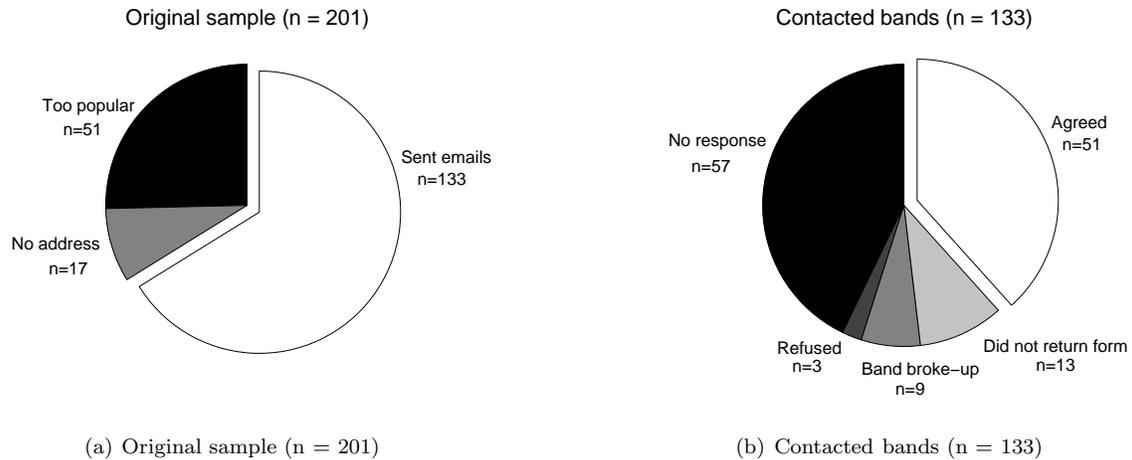


Figure S7: Pie charts showing various aspects of attrition for the sample of bands selected from the music website <http://www.purevolume.com>. Approximately, 40% of the contacted bands agreed to be in the study.

sample of 48 of the 51 bands to be in the experiments. A list of these bands and songs can be found in table S3.

In order to check that our initial screening criteria filtered out music that might be known to the subjects, we presented the list of bands and songs to two different experts in popular music: a DJ at the Barnard College student radio station and the music editor for <http://www.bolt.com>. Neither expert recognized any of the bands or songs. As an additional test, we surveyed subjects about their familiarity with the 3 bands who agreed to participate, but were ultimately not included because we were limited to 48 bands. We chose to ask only about the bands that were ultimately not included because having the same bands in the survey and experiment might have biased subjects' music preferences.

In table S4 we compare the subjects' familiarity with three bands from our pool of potential bands to one fake band. The data suggest that there was a large amount of social desirability bias in responses — 14% of subjects reported hearing of the fake band Peter on Fire and 2% reported being familiar with their music. The responses for the fake band are very similar to the responses for the real bands. The high recognition rate for the band Remnant Soldier is probably a question ordering effect; this question was asked immediately after a question about familiarity with the very popular band U2. In future studies we recommend randomization to avoid this problem. Taken together, these results, along with our screening, lead us to believe that the music used in the experiment was essentially unknown. Also, while the experiments were in progress, we monitored the success of the bands and found nothing which would lead us to believe that there were any significant changes.

Band name	Song name
52metro	Lockdown
A Blinding Silence	Miseries and Miracles
Art of Kanly	Seductive Intro, Melodic Breakdown
Beerbong	Father to Son
Benefit of a Doubt	Run Away
By November	If I Could Take You
Cape Renewal	Baseball Warlock v1
Dante	Life's Mystery
Deep Enough to Die	For the Sky
Drawn in the Sky	Tap the Ride
Ember Sky	This Upcoming Winter
Evan Gold	Robert Downey Jr.
Fading Through	Wish me Luck
Far from Known	Route 9
Forthfading	Fear
Go Mordecai	It Does What Its Told
Hall of Fame	Best Mistakes
Hartsfield	Enough is Enough
Hydraulic Sandwich	Separation Anxiety
Miss October	Pink Aggression
Moral Hazard	Waste of my Life
Nooner at Nine	Walk Away
Not for Scholars	As Seasons Change
Parker Theory	She Said
Post Break Tragedy	Florence
Ryan Essmaker	Detour_(Be Still)
Salute the Dawn	I am Error
Secretary	Keep Your Eyes on the Ballistics
Selsius	Stars of the City
Shipwreck Union	Out of the Woods
Sibrian	Eye Patch
Silent Film	All I have to Say
Silverfox	Gnaw
Simply Waiting	Went with the Count
Star Climber	Tell Me
Stranger	One Drop
Stunt Monkey	Inside Out
Sum Rana	The Bolshevik Boogie
Summerswasted	A Plan Behind Destruction
The Broken Promise	The End in Friend
The Calefaction	Trapped in an Orange Peel
The Fastlane	Til Death do us Part (I don't)
The Thrift Syndicate	2003 a Tragedy
This New Dawn	The Belief Above the Answer
Undo	While the World Passes
Unknown Citizens	Falling Over
Up Falls Down	A Brighter Burning Star
Up for Nothing	In Sight Of

Table S3: List of the 48 bands used in the experiment. These bands were randomly selected from the website <http://www.purevolume.com>. Several tests were conducted which allow us to conclude that these bands were essentially unknown.

	How familiar are you with the following bands?		
	Don't know it at all (% of subjects)	Heard of it (% of subjects)	Know it pretty well (% of subjects)
Real Bands			
GUYS ON COUCH	87.9	11.0	1.1
GROVER DILL	88.4	10.5	1.1
REMNANT SOLDIER	77.2	19.9	2.9
Fake Band			
PETER ON FIRE	84.5	13.7	1.8

Table S4: Comparing the popularity of the potential bands from our sample to a fake band. Subjects reported being about as familiar with an fake band (Peter on Fire) as three potential bands from our sample. The high recognition rate for Remnant Soldier is likely a question ordering effect — it was asked immediately after the well known band U2.

Data analysis

We measured success based on the market share of downloads that belonged to a specific song. The market share, m_i of song i is defined as,

$$m_i = \frac{d_i}{\sum_{k=1}^S d_k} \quad (1)$$

where d_i is the number of downloads for song i and S is the number of songs. This definition of success is based on the subjects' behavior, rather than their self-reported liking of the songs, as measured by their ratings from 1 to 5 stars. As a check, we compared these two measures and found them to be consistent. In Fig. S8A we see that songs which received higher average ratings (measured in stars) had higher probabilities that a listen would result in a download ($r = 0.87$). In Fig. S8B we see that the higher rating a subject gave a song, the more likely that the subject downloaded the song. Results from experiment 2 are essentially identical (results not shown). Overall, the similarity between these two measures gives us confidence that our behavioral measure is meaningful.

Given that we use the market share of songs as a measure of success, we measure inequality of success with one of the most common metrics, the Gini coefficient, G , which is defined as follows,

$$G = \frac{\frac{1}{S^2} \sum_{i=1}^S \sum_{j=1}^S |m_i - m_j|}{2 \cdot \frac{\sum_{k=1}^S m_k}{S}}. \quad (2)$$

The Gini coefficient can be interpreted as the expected difference in market share between two randomly chosen songs scaled so that it falls between 0 and 1 with 0 representing complete equality and 1 representing complete inequality. As stated previously, the independent condition has twice the number of subjects ($n \approx 1,400$) as each social influence world ($n \approx 700$), for reasons that will be clear when we present our measure of unpredictability. In order to ensure that our comparison between the two conditions was based

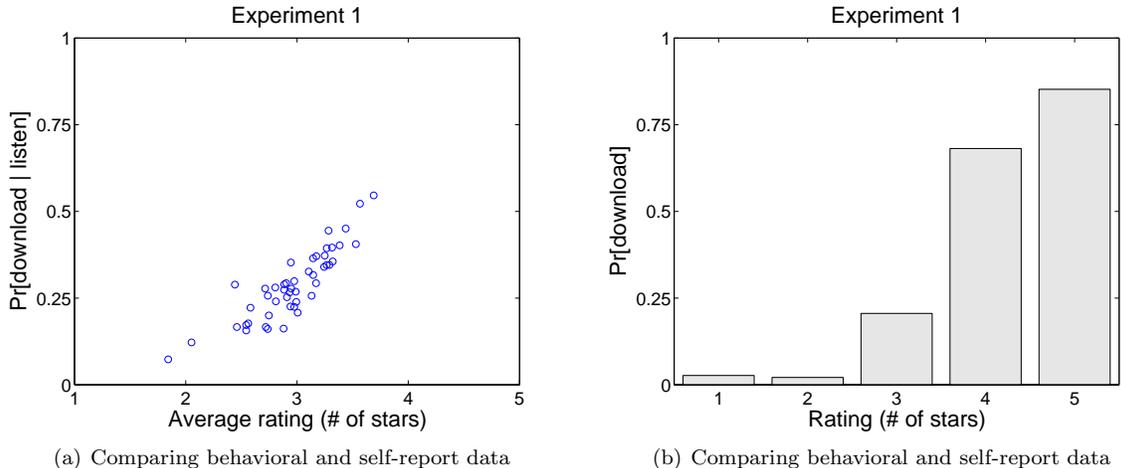


Figure S8: Plots comparing the download decisions to the rating decisions. These results suggest that the two measures are consistent. Results from experiment 2 (not shown) were essentially the same.

on a similar number of subjects, we randomly split the independent condition into two groups and then calculated the Gini coefficient for one of these groups. We repeated this splitting procedure 1,000 times and produced a distribution of replicate values of G . The value of G reported in Fig. 1 for the independent condition is the mean of these 1,000 replicate values. Also, we used the distribution of replicate values to conduct a test of statistical significance. The difference between a randomly chosen Gini coefficient from one of the eight influence worlds and a randomly chosen replicate Gini coefficient from the independent world was less than 0 with $p < 0.01$ in experiment 1 and $p < 0.001$ in experiment 2. Thus, the difference in observed Gini coefficients between the two conditions is statistically significant in both experiments. Finally, we can examine the dynamics of the Gini coefficient as the experiment progresses (Fig. S9). The final values of each trajectory are the values reported in Fig. 1. The Gini coefficients were relatively stable indicating that we probably would not have observed substantially different results with more subjects.

In addition to the Gini coefficient, we measured inequality using two other common measures, the coefficient of variation and the Herfindahl index. The results were qualitatively unchanged. We could not consider any of the logarithm-based measures, standard deviation of the logarithms and Theil entropy, because these measures are not defined in cases where a song has 0 downloads which occurred in one of the social influence worlds in experiment 1. For more on all of these measures of inequality see Coulter (1989).

To measure unpredictability we examined the variation in success of a song across worlds. If a song had the same outcome in all worlds then its unpredictability was 0. However, if the outcomes varied across worlds, then there was an inherent unpredictability in the success of the song. We defined u_i as a measure of the unpredictability of song i to be the average difference in market share across all possible pairs of worlds.

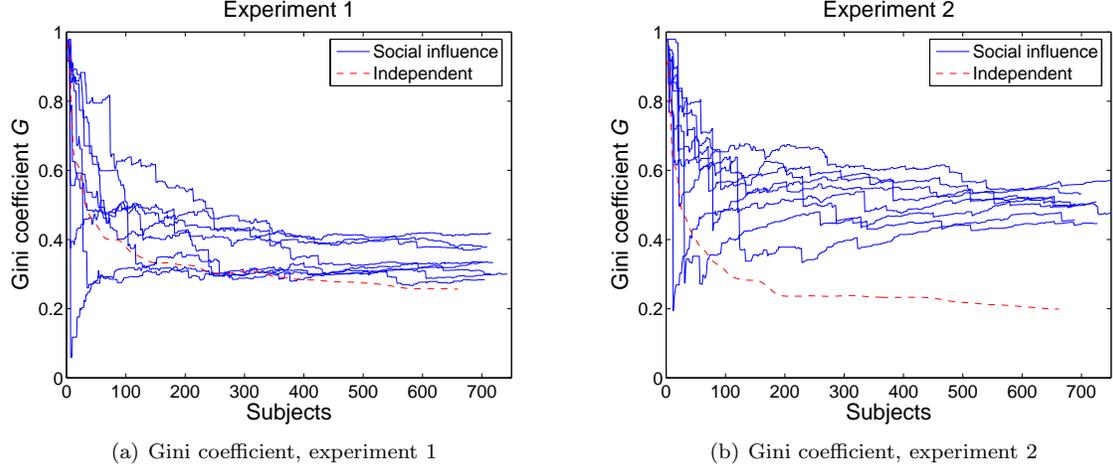


Figure S9: Dynamics of the Gini coefficient G in experiment 1 and 2. The final values of each trajectory are the values reported in the Fig. 1.

That is,

$$u_i = \frac{\sum_{j=1}^W \sum_{k=j+1}^W |m_{i,j} - m_{i,k}|}{\binom{W}{2}}, \quad (3)$$

where $m_{i,j}$ is song i 's market share in world j , and $\binom{W}{2}$ is the number of pairs of worlds. The unpredictability, U , for an experimental condition is then the average of the unpredictability of the songs in that condition,

$$U = \frac{\sum_{i=1}^S u_i}{S}. \quad (4)$$

In the independent condition we have only one world, but, as noted previously, it has twice as many subjects as each social influence world. Thus, for the independent condition, we randomly split the subjects into two independent realizations and calculated u_i and U with these two realizations. We repeated this splitting procedure 1,000 times and produced a distribution of replicate values of U . The value of U reported in Fig. 2 is the mean of this distribution. To calculate a measure of statistical significance we compared the distribution of replicate values from the independent condition to the distribution of calculated U values for the 28 $\left(\frac{8 \times 7}{2}\right)$ possible pairs of influence worlds. The difference between the measured unpredictability based on a randomly chosen pair of social influence worlds and the measured unpredictability based on a random split of the independent world was less than 0 with a probability of $p < 0.01$ in experiment 1 and $p < 0.001$ in experiment 2. Thus, the difference in unpredictability across conditions is statistically significant. Finally, we can examine the dynamics of the unpredictability U as the experiment progresses (Fig. S10). The final values of each trajectory are the values reported in Fig. 2. As with our measure of inequality, the unpredictability was relatively stable indicating that we probably would not have observed substantially different results with more subjects.

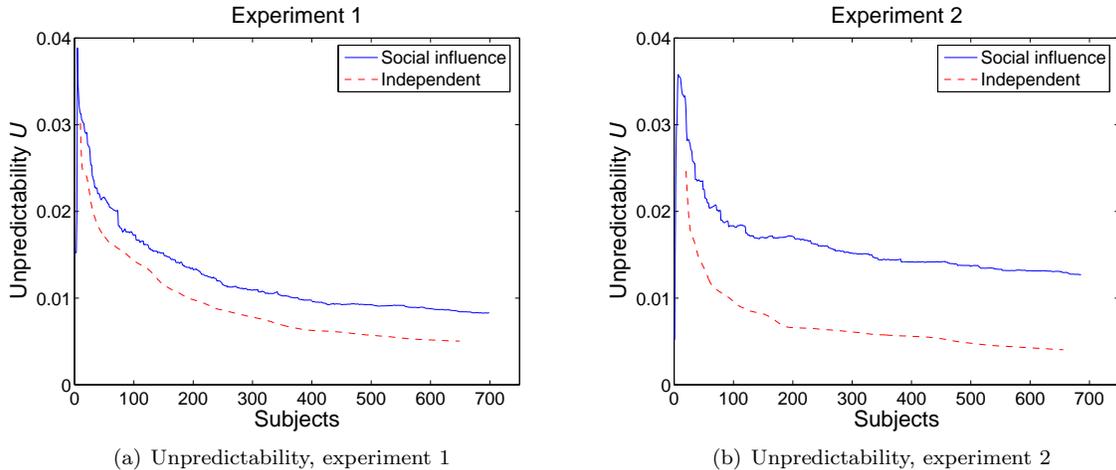


Figure S10: Dynamics of unpredictability U in experiment 1 and 2. The final values of each trajectory are the values reported in Fig. 2.

Measures to ensure data quality

In all experiments researchers must take steps to ensure that data are generated by the appropriate set of subjects in situations that match the experimental design and that the subjects have no malicious intent. These problems can be more difficult to deal with in web-based experiments where researchers have less control over subject recruitment and behavior than they would have in a standard laboratory-based experiment. Because of this limited control, some of the data from our experiments are possibly unsound. Instead of preventing this unsound data generation, and hence giving subjects incentive to provide us with false information, we allowed all subjects to participate in all situations, but flagged data that could have been unsound and excluded them from our analysis.

For example, our experimental design required that a subject’s information about the behavior of others be limited to what we provided them (or did not provided them). Information contamination leading to unsound data could have occurred a number of ways: 1) between two subjects from different two influence worlds 2) between two subjects from the independent condition and 3) between a subject in the independent condition and a subject in an influence world. Unlike in a traditional laboratory-based experiment, we were not able to physically isolate the subjects to prevent this information contamination. As such, we flagged for exclusion data generated in several cases where the subject behavior could have possibly been influenced by information that was outside of the experimental design.

The first step in this data-flagging process was based on a survey that all subjects completed. On this survey subjects were asked to select, from a list of choices, all of the ways that they heard about the experiment. If a subject reported “friend told me about a specific song” or “friend told me about a specific

band” all data generated by that subject were flagged. However, data generated by subjects who reported “friend told me about the experiment in general” were not flagged. We also flagged all data generated after either the subject clicked “log-off” or 2 hours had passed since the subject registered. These data were flagged in order to exclude data where the subject could have participated, discussed the music with friends, and then returned with outside information.

In addition, to prevent information contamination within and between experiments, we placed several cookies — small pieces of information — into the subject’s web browser. These cookies ensured that if a subject returned to the experiment, the subject would be placed in the same condition and same world without having to re-complete the registration process. The cookies also limited the possibility of subjects from experiment 1 participating in experiment 2.

Our flagging criteria were quite strict and so we probably flagged data which was not contaminated. However, we cannot rule out the possibility that some contaminated data was not flagged. Any information contamination across influence worlds would have likely had the effect of decreasing the differences across worlds and thus decreasing our unpredictability measure. Information contamination within the independent condition would have likely increased the inequality in the independent condition. Finally, information contamination between a social influence world and the independent condition would likely increase the correlation between quality and success. Thus, our findings on inequality, unpredictability, and the relationship between quality and success represent a lower-bound on the possible values that could have occurred in a perfectly clean experiment.

In addition to problems with the isolation of subjects, when doing a web-based experiment, or any other experiment, one has to take a number of steps to guard against the possibility of malicious subjects who intend to disrupt the experiment. This problem, while not limited to web-based experiments, is perhaps a larger issue in this set of experiments than in most. For example, members of one of the bands might have tried to artificially inflate the download count of their song. To prevent this possibility, each subject was allowed to download a specific song as many times as they liked, but could only add one to the displayed download count for that song. Members of the bands might have also tried to manipulate the results by sending their fans to the experiment. As such, we flagged all data generated by people who reported on our survey that they heard about the experiment from “one of the bands.” We also checked our web-server log to ensure that we were not receiving subjects from the websites of any of the bands. In two cases, links to the experiment was posted on bands’ websites, but these links were detected quickly and both bands complied with our email request to remove the link.

An additional class of malicious subjects could have simply wished to disrupt the experiment for no specific reason. To prevent against these subjects, the experiment was run appropriate security precautions

using the latest software (Apache 2.0, MySQL 4.0, and Tomcat 5.0) with strict firewall settings.

Despite all of our security precautions it was still possible for a subject to manipulate our results. For example, there is no way that we could prevent the same person from registering from several different computers and providing us with false information each time. However, given that subjects have little incentive to undertake this behavior, we think that this probably did not occur. Taken together our data-quality measures give us confidence that our data are reasonably clean. Of course we cannot rule out all possible problems, but we have not seen any patterns in the data that indicate data contamination or malicious manipulation occurred.

Robustness of results to specific design choices

These two experiments represent only a small portion of the parameter space of all possible experiments using this design. For example, system parameters like the strength and type of social signal, the subject population, the distribution of quality of the songs, and the number of songs probably influence the magnitude of the observed outcomes. Based on our experience with these experiments, we offer a few predictions.

We suspect that other methods of strengthening the social signal would increase the inequality and unpredictability. For example, in our experiment we chose to present the number of previous downloads, the band name, and song name all in the same size font. If, for example, we had presented the download counts in a larger font we suspect that the inequality and unpredictability would be greater.

However, other methods of changing the social signal may have ambiguous effects on outcomes. For example, in our experiments, the social signal was anonymous, in the sense that subjects did not have any information about the characteristics and behavior of previous subjects. If the social signal was instead somehow linked to the identities of the previous subjects, one could imagine that since subjects may be more strongly influenced by “people like them,” the cumulative advantage process could be weakened or strengthened depending on the distribution of subjects’ identities.

Given the type of signal that we chose to use, we suspect that the process of social influence observed in the experiments is relatively general, but may be more pronounced with our subject pool (teenagers from the U.S.). We suspect that if the experiment was re-run using a different subject pool that different songs would become successful, but that the overall amount of inequality and unpredictability would be similar. Further empirical work in this area is needed.

Switching from characteristics of the subjects to characteristics of the songs, we expect that if the songs were more similar in quality, then the inequality in success would be less, but the unpredictability would be greater. Recall, that in these experiments we did not directly set the distribution of quality; rather, it was

determined by the songs on <http://www.purevolume.com>.

Another key system parameter for the songs is the number used. Because choice overload is so pervasive in cultural markets, we chose to use 48 songs in the experiments — the maximum that could fit on a computer screen when presented with the song menu used in experiment 1 (Fig. S2). We conjecture that if we had used more songs, the observed inequality and unpredictability would increase. Whatever the final number of songs used, it is likely important that this number is much larger than the number of songs that each subject listens to.

These speculations are suggestive, and clearly more research is needed. However, the speculations do suggest that the qualitative findings of the experiments are likely robust to reasonable design choices.

References

Coulter, P. B. (1989). *Measuring Inequality: A Methodological Handbook*. Westview Press, Boulder.