Modeling Diffusion of Many Innovations via Multilevel Diffusion Curves: Payola in Pop Music Radio

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Modeling Diffusion of Many Innovations via Multilevel Diffusion Curves: Payola in Pop Music Radio

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Abstract:
We introduce a new statistical method – multilevel diffusion curves – to model how multiple innovations spread through an industry. Specifically, we analyze when radio stations begin broadcasting 534 pop singles. Ordinarily radio stations imitate one another, an endogenous process producing a characteristic "s-curve." However, payola can dwarf this process and produce a characteristic negative exponential curve, controlling for the song artist's number of successful songs in the past year. Therefore the shape of a song's cumulative adoption function indicates whether its rise involved corruption. We validate this heuristic against a panel of songs with a documented history of payola and a comparable set of songs with no such allegations. Compared to earlier methods, multi-level diffusion curves allow testing of more types of hypotheses, model a greater range of data, and are statistically more efficient and precise.

Keywords: Diffusion, Multilevel Analysis, Internal-Influence, External-Influence, S-curve, Payola, Bribery, Radio

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Introduction

How innovation spreads through social systems is one of the most fascinating and distinctly social issues in sociology. States adopt policies, firms enter markets and adopt management practices, and individual people learn news, change their beliefs, and begin to practice new behaviors. Analyzing the rate at which ideas, behaviors, or institutional structures spread across the actors in a social system (diffusion curve analysis) is a particularly powerful approach for exploring these issues. By abstracting from the actor's adoption, diffusion curve analysis shows cascades of behavior where actors are sensitive to the number of peers who have adopted the innovation. For instance, many systems have a "tipping point" or a critical mass at which its rate of adoption drastically accelerates (Schelling 1971, Gladwell 2000, Rogers 2003). In other cases however, actors derive neither externalities nor information from one another's behavior but are instead motivated by some exogenous force. Analysis of the relationship between the slope and height of the cumulative adoption distribution can help distinguish between these two types of models.

In nearly any aspect of society one can find individual or corporate actors adopting not only one innovation but multiple innovations. Often we are interested in innovations not for themselves but because they are indicative of some larger latent trend. States do not adopt neo-liberalism, but deregulate particular industries in particular ways (Henisz et. al. 2005). Banks do not practice market entry; they enter specific financial markets (Haveman 1993). Engineers do not adopt information technology; they begin using calculators or computers (Randles 1983). Hence, diffusion curve analyses that aggregate information across several innovations are particularly useful. These analyses allow one to distinguish the unique traits of a specific innovation from common properties of an entire class of innovations. For example, one can distinguish what is characteristic of a broad trend and what is merely particular to the depoliticization of electrical utilities, entry to the consumer non-mortgage loan market, or the use of second generation calculators.

Furthermore, one can identify contingencies in diffusion patterns. The first study to formally aggregate several innovations showed that the rate at which industrial firms adopt new technologies is a function of the efficiency of those technologies (Mansfield 1961). Likewise, the rate at which municipalities adopt civil service reform is contingent on whether the state capitol has mandated them to do so (Tolbert and Zucker 1983).

Existing techniques for aggregating innovations suffer two drawbacks. First, they are cumbersome and inefficient. This inefficiency not only requires larger sample sizes, but introduces a "success bias" since only innovations that diffuse widely can be analyzed (Rogers 2003). Second, many parameters cannot be tested with them. For instance, current methods cannot easily estimate period effects or the outsize influence of particularly powerful actors. In this paper we introduce a new method, multilevel diffusion curves, which addresses these problems. We demonstrate its benefits by comparing its analyses with a traditional method on a data set estimating payola in the music industry.

An Example: Payola in the music industry

Organizations facing uncertainty strive to stabilize their environment to mitigate the potentially adverse effects of disruptive changes (Thompson 1967, Pfeffer and

Salancik 1978). In culture industries, firms often raise the exposure of their products by manipulating the third-party endorsements of gatekeepers in ancillary industries (Hirsch 1972). For recorded music, radio is the primary way to introduce products to the general public. “There is no better guarantor of a band’s success than a hit single on the radio luring listeners into record stores to buy the album” (Slichter 2004, p. 76).

Record labels therefore go to great lengths (legal and illegal) to encourage radio stations to play their artists' songs (Coase 1979, Dannen 1990, Caves 2000, Slichter 2004). Record labels engage in a broad family of practices in which they give valuable commodities to radio stations because the latter hold something of tremendous value to the former and can therefore extract rents (Coase 1979). Legally, a record company can provide radio stations with a sample copy of a record, a press packet, and contact men who visit the stations to talk up the record. In contrast, illegal influence, or “payola,” is giving cash or something of value in exchange for a radio station playing a particular song without disclosing the transaction on the air. Even without an explicit *quid quo pro,* record label gifts and services to radio stations are legally ambiguous. Another gray area is the common practice of labels contracting with “independent radio promoters” (IRP) or “indies” to promote a record. Indies are so named because they are not directly employed by the record company but are independent consultants. They commonly pay radio stations on a retainer basis for the privilege of advising them about their playlists, and this access in turn makes their services valuable to record labels (Dannen 1990, Slichter 2004). Although the IRP does not usually pay the station for each song, presumably a station that consistently rejected the indie’s suggestions would lose its retainer fees and thus these dealings form a sort of embedded payola.

Although the practice is arguably much older, payola first became a political issue in the United States in 1959 (Coase 1979). In the House of Representatives, the “Harris Committee” on Legislative Oversight held hearings on how quiz show producers had rigged their programs by coaching Charles Van Doren and other contestants. In the course of this investigation the committee uncovered evidence that record labels had bribed disk jockeys to play their records, and that this practice had facilitated the rise of rock and roll. The ensuing controversy implicated two influential rock-and-roll disk jockeys, Alan Freed and Dick Clark, destroying the career of the former. In 1960, Congress closed a loophole that technically allowed firms to legally bribe agents of a broadcaster (although not the broadcaster itself). On their side, radio stations began restricting the autonomy of disk jockeys and placing all creative control under “programmers.”

However these legal changes and modified business practices failed to eradicate payola. Like clockwork, it was discovered anew every fifteen years.[1] In 1974, the federal government found evidence that Clive Davis and David Wynshaw used independent radio promoters to give disk jockeys and programmers a quarter of a million dollars in cash and narcotics. In 1989, federal prosecutors indicted independent radio promoters such as Joe Isgro (a member of the Gambino crime syndicate) for payola (Dannen 1990). In 2004, Eliot Spitzer (now governor and then Attorney General of New York State) subpoenaed evidence that all four of the major record companies (EMI, Sony, Universal,

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[1] This pattern is revealed by querying “payola” in the *New York Times* file in Proquest and Lexis-Nexis. In most years only a few stories contain the word. At least ten payola stories were printed in each of the following years: 1960, 1961, 1973, 1990, 2005, and 2006.

and Warner Brothers) and at least two major radio companies (Entercom and CBS) had systematically engaged in payola. Using this evidence, Spitzer extracted consent decrees from the companies that established *de facto* regulatory regimes. Specifically, the firms agreed to severely restrict their business practices and to make multi-million dollar charitable donations.

The Spitzer investigation not only produced consent decrees, but also a large set of subpoenaed files detailing the songs targeted by the payola. These files included emails and other documents in which record company personnel discussed amongst themselves or with radio personnel, *quid quo pro* transactions of valuable commodities in exchange for airplay of songs. Examples include a radio station programmer acknowledging receipt of an in-kind bribe or a record company official filing invoices for the same. In the modal case, the bribe was an in-kind gift worth a few hundred dollars to be given to a contest winner in exchange for which the radio station would play a specific artist. These files form the basis for this paper's data collection frame.

We identified all songs mentioned in the EMI, Sony, Universal, and Warner settlements and queried them in Mediabase, a commercial radio airplay dataset. If an artist, but no specific song, was mentioned then we recorded whatever song was in the Mediabase airplay charts on the date of the email.[2] Ultimately this produced a set of 150 songs implicated by Spitzer in payola, or simply "Spitzer songs." We also identified a panel of control songs. To choose comparable songs we first noted on which Mediabase chart and on which date each payola song peaked. We then identified the two songs ranked above and the two songs ranked below each Spitzer song. This produced 384 control songs.[3] See appendix A for summary statistics.

For each of the Spitzer and control songs, we used Mediabase to record the date on which each station first played the song, or what in radio is known as an "add." These data allow us to construct a cumulative adoption function for each song.

This study has methodological, theoretical, and practical implications. Methodologically, this study introduces a more powerful, more precise, and more efficient estimation technique: multi-level diffusion curves (MDC). MDC can model explanatory variables at all levels while assessing the diffusion of multiple innovations simultaneously. Through a synthesis of diffusion of innovation, production of culture, and contingency theory, this study shows how "internal" and "external" diffusion processes reflect 3rd party interventions that use monetary incentives (payola) to increase adoption of innovations (songs). At the practical level, we develop a technique for uncovering such illegitimate practices. Using these documents, we show that our new method, multilevel diffusion curves, can uncover payola without relying on the extraordinary (but intermittent) powers of a Congressional committee or prosecutor to subpoena documents and testimony.

Internal- vs. external-influences on diffusion

A wide literature across the social sciences examines how innovations diffuse among actors in a social system. In the case of radio, the actors are radio stations and the

[2] To the extent that this introduces measurement error it will introduce a conservative bias to our estimates.
[3] Theoretically, there could have been as many as 600 control songs. However many songs identified in the two up, two down, frame were either themselves Spitzer songs or were identified as controls for several songs.

innovations are pop songs. Radio is an ideal field for exploring diffusion because of its especially high level of novelty compared to other fields. The typical radio station adds one to five songs to its playlist every week.[4] In other cases, firms might adopt a specific business practice, peasants might adopt a public health measure, or governments might adopt a specific policy (Rogers 2003). In general, diffusion processes can be categorized as internal or external influence (Mahajan and Peterson 1985, Valente 1993).

Many studies have shown that actors adopt innovations after seeing peers doing the same (*internal-influence*). A seminal study interviewed hundreds of Iowa farmers to see when and why they first began planting "hybrid corn," a high-yield variety of maize (Ryan and Gross 1943). Although most of the farmers first learned of the corn from sources outside the community such as mass media or salesmen, they often actually planted it only after a neighbor told them of their satisfactory experience with the crop. As more farmers tried the corn, more neighbors could learn about its virtues. When only one farmer used the corn he could describe it to only a handful of neighbors. After the next harvest however, the neighbor farmers who used the corn could describe it to still more farmers. Thus in this manner of diffusion, every new convert becomes an evangelist. The adoption of the corn was slow at first but then spread rapidly. When many farmers planted the corn, they became less likely to meet a neighbor who had not tried the corn, and the innovation begins to saturate the system. As this occurs, the risk set of persons yet to adopt the innovation shrinks and the rate of adoption declines. Overall, the hybrid corn adoption rate was slow initially (1924-1933), increased rapidly (1934-1939), and finally tapered off (after 1939).

Mathematically, the instantaneous rate of adoption is a function of the number of prior adopters times the remaining risk pool, in which t is time, N_t is adopters at t, $\underline{N}$ is the maximum number of adopters, and b is the coefficient of adoption.

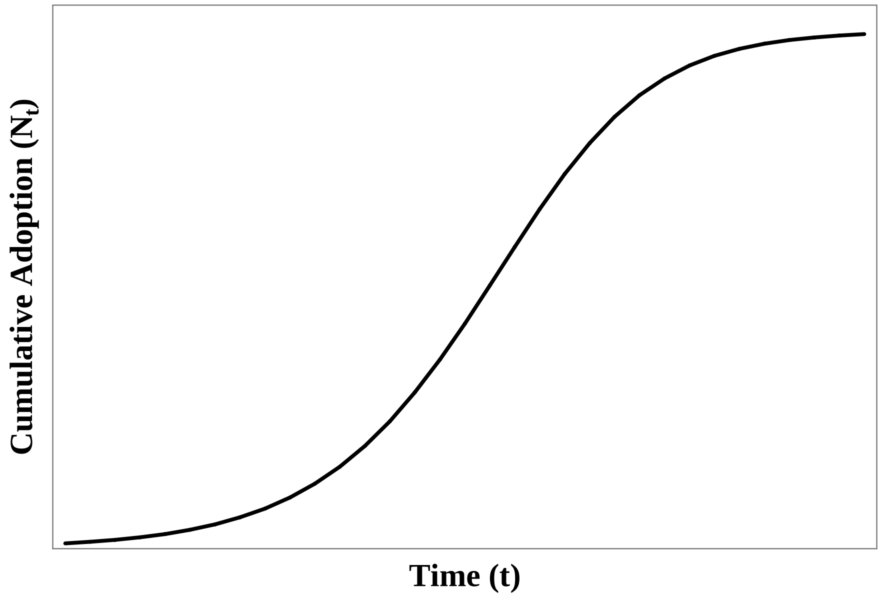
$$(dN_t/dt) = bN_t\ (\underline{N} - N_t) \qquad (1)$$

Integrating this function produces a cumulative adoption function known as an "s-curve" or "logistic curve" where N_0 indicates the value of N at t_0.

$$N_t = \underline{N}\ /[1+ (\exp[-b\underline{N}(t-t_0)])\ (\underline{N} - N_0)\ /N_0] \qquad (2)$$

[4] This estimate is based on generating Mediabase 7-day station playlists for a dozen radio stations in an arbitrary week. It reflects the number of songs on each station's playlist with a value of "first played" occurring within the current week.

Figure 1: Internal-influence



This curve is characterized by slow initial growth, then a period of rapid growth, and then a final period of slow growth. Contagion and threshold models have different mechanisms for explaining exactly why each actor adopts the innovation at various times, Nevertheless, under a wide range of assumptions, both models predict that the adoption rate of an innovation is a function of the prior number of adopters, and thus the cumulative adoption function will follow the s-shaped pattern. Most common is a "contagion" or "meme" model in which adopters directly evangelize to future potential adopters (Tarde 1903, Ryan and Gross 1943, Dawkins 1976). "Information cascade" or "herd behavior" models assume that the actor is using peer adoption of the innovation as a measure of its quality (Banerjee 1992, Bikhchandani et. al. 1992). Network externality models assume that the more prior adopters an innovation has, the more useful it becomes and therefore the faster the rate of growth in the future (Katz and Shapiro 1985, Adler 1985). Both cascade and externality models are special cases of "threshold models" in which actors have different thresholds or reservation prices for how popular an innovation must become before they adopt it (Grannovetter 1978). If actors have an underlying normal distribution of thresholds, then such a process will produce an s-shaped diffusion curve. In fact, the overwhelming consensus of the theoretical and empirical literature is that endogenous diffusion processes will almost always produce an s-shaped diffusion curve (Mahajan and Peterson 1985, Rogers 2003).

Internal-influence in radio can occur through both direct peer-to-peer influence and pop chart mediation. In an ongoing study, most Contemporary Hits Radio (a.k.a. "Top 40") programmers report that they are aware of the programming decisions of about ten of their peers, either by having regular personal conversations with them, by listening to their stations, or by reading about these peer stations in trades or databases. In fact, several report weekly conference calls in which they trade information with several other programmers at once. Internal-influence is also mediated through the charts published in *Radio & Records* magazine, an industry trade journal. These charts summarize how popular different songs are in various genres of radio. During the period of this study, *R&R* charts were based on the same Mediabase data used in this study.[5] Thus a single piece of information, the *R&R* chart, efficiently summarizes field trends, or as a programmer expressed in an interview "The chart is God!" Another programmer described the core of his job as "pounding through *R&R* trying to figure out what songs looked like they are on their way up" (Lynch and Gillispie 1998, p. 101).

Programmers are attentive to the behavior of their rivals to obtain information and to exploit public's acclimation to novelty via rival's airplay. Programmers assume that the consensus carries meaningful information about quality that their own taste alone is unable to divine (*herd* function, Banerjee 1992, Bikhchandani et. al. 1992). A country programmer claims that "If I hear something that blows me away I'll play it. But most of the time I wait for other stations that I trust and let them break things. Then I get on it later just to make sure I'm not making as many mistakes as other stations do. It's a safer way to go" (Lynch and Gillispie 1998, p. 122). There is also an important issue of externalities. Programmers believe that audiences are hostile to songs that they have never heard before. "A lot of times [disk jockeys] will come in and say 'I'm so sick of this song!' And I'll say 'Well that's about the time your listeners are starting to get into it.' … [Y]ou have to have at least 100 spins on a record before your audience is going to have heard it enough times to really decide whether they like it or not" (Lynch and Gillispie 1998, p. 123).Therefore, programmers have an incentive to play a song after listeners have acquired a comfortable familiarity with it from one's rivals (free riding on rivals). Similarly, the *R&R* chart is a good indication of whether a song's uncomfortable novelty has been mitigated by repetition. In short, internal-influence is likely the default pattern in radio programming.

In contrast, external-influence processes yield a different diffusion pattern. Under external-influence, actors in a system look not to each other but to something outside of their group in considering whether to adopt. Civil rights enforcement in American industry illustrates this process clearly (Dobbin and Sutton 1998). In the mid-1960s, most American employers understood both their moral obligations and the 1964 Civil Rights Act as eschewing the most egregiously discriminatory practices, but not affirmative action and not eliminating subtle barriers to minority employment. Beginning in the late 1960s, and especially in 1971, the federal government dramatically expanded the scope and enforcement of civil rights law, and firms responded to the external-influence of federal regulations. The number of firms with an Equal Employment Opportunity/ Affirmative Action (EEO/AA) compliance officer was very small in 1967, rose sharply after the policy shocks in 1968 and 1972, and thereafter rose at a declining rate (Dobbin and Sutton 1998).

Unlike the slow growth-fast growth-slow growth pattern of internal-influence (e.g., hybrid corn adoption, Ryan and Gross 1943), external-influence (EEO/AA officers) has a fast growth-slow growth pattern. Mathematically, the instantaneous rate of adoption is a constant function times the remaining risk pool where *a* is the coefficient of adoption:

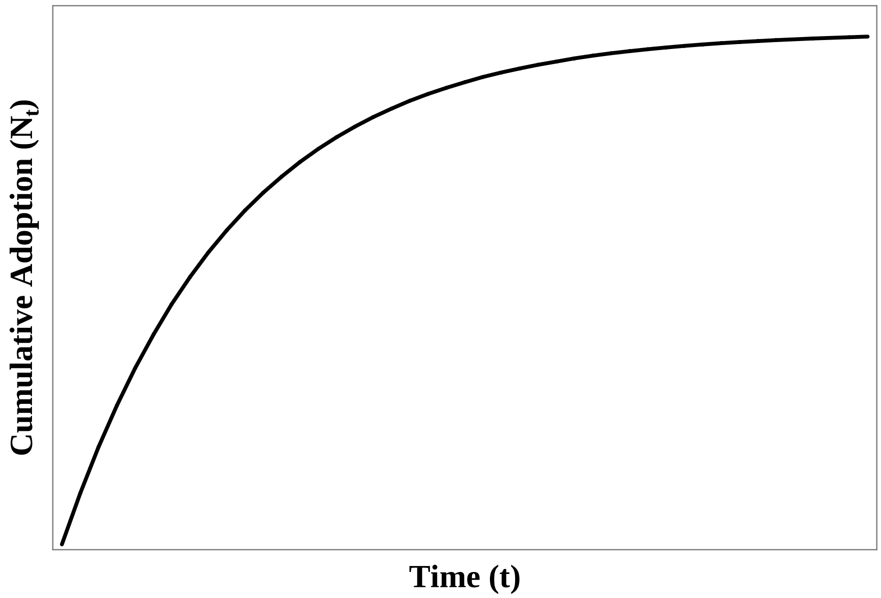
$$(dN_t/dt) = a\,(\underline{N} - N_t) \qquad (3)$$

[5] In August of 2006, *Radio & Records* was purchased by Nielsen, which began using its own Broadcast Data Systems (BDS) data as the basis for *R&R* charts. As the methodologies and scope of Mediabase and BDS are very similar, this has produced no meaningful change in the *R&R* chart.

Integrating this function produces a negative exponential, cumulative adoption function.

$N_t = \underline{N}\ (1- e^{-at})$ (4)

Figure 2: External-Influence



When individual people are the unit of analysis, policy mandates and mass media campaigns might be important external-influences.

External-influence can also be a factor in radio programming. The most important exogenous impact on radio comes from the promotion efforts of record labels. These efforts can be quite substantial. For instance, in 1998, MCA spent $700,000 dollars promoting the song "Closing Time" by the band Semisonic (Slichter 2004). About half of this money went for legitimate expenses like filming a music video and sending the band to live radio appearances but the rest was simply payola. Such promotion efforts are not a function of prior adoptions, nor do they otherwise build over time. Rather, promotion efforts are aimed at getting a wave of adds. Slichter (2004) even claims that his promotional campaign *delayed* some adds so as to make them closer to the targeted add date. Thus payola is not only conceptually external to radio but should also have a pattern revealing it.

Internal-influence and external-influence can occur in the same system, as in the case of small-town physicians first prescribing the antibiotic tetracycline (Coleman et. al. 1966). Dividing the physicians into those who read few vs. many medical journals revealed distinct diffusion patterns. Heavy journal-readers adopted tetracycline rapidly after the drug's introduction and slowly afterwards. Among light journal-readers, adoption was slow, then fast, then slow again. Thus physicians who were exposed to a mass media influence showed an external-influence pattern whereas physicians without such exposure showed an internal-influence pattern (Valente 1993). Similar contingencies occur when municipalities adopted civil service reform to reduce patronage (Tolbert and Zucker 1983). If the state government mandated adoption, the municipalities responded to the dictates of the state capitol and showed an external-influence pattern.

Without a state mandate, the municipalities imitated one another, showing an internal-influence adoption pattern.

As the presence of external vs. internal-influence varies between studies, and occasionally even within them, Mahajan and Peterson (1985) modeled both external-influence ("a") and internal-influence ("b") within a "mixed-influence" model:

$$(dN_t/dt) = (a + bN_t)(\underline{N} - N_t) \qquad (5)$$

Integration yields the following formula.

$$N_t=\{\underline{N}-[a(\underline{N}-N_0)/(a+bN_0)]\exp[-(a+b\underline{N})(t-t_0)]\}/(1+b[\underline{N}-N_0]/(a+bN_0)\exp[-(a+b\underline{N})(t-t_0)]) \qquad (6)$$

The shape of the resulting curve depends on the relative strength of the two parameters. The relative size of the parameters *a* and *b* indicates the degree to which a diffusion curve approximates the two ideal types. For instance, the model of EEO/AA officers would have a relatively large *a* (external-influence), while the model of hybrid-corn adoption would have a relatively large *b* (internal-influence).

This model can be extended to multiple innovations to identify common patterns among them. Such an approach not only allows one to pool information across innovations, but to treat the parameters themselves as objects of analysis. For instance, Mansfield (1961) interpreted the rate at which large firms adopted twelve different new technologies. He first regressed the shape of each innovation's curve to solve for *b*. Then, he treated these twelve values of *b* as a new dataset which he in turn regressed on the cost-effectiveness of the technologies.[6] As regression coefficients have standard errors however, using regression coefficients as outcome variables is statistically inefficient (Kay 1993). Moreover, this method does not model the effect of time-level variables on internal-influence, external-influence, or total potential users. Likewise, it does not allow interaction effects between time level variables and song level variables.

We further extend Mansfield's (1961) model by changing the two-stage macro analysis (Mansfield 1961, Mahajan and Peterson 1985) to a multilevel diffusion curve (MDC) analysis that is both efficient and flexible. A brief overview of the older technique serves as a useful preface. As radio station programmers often plan their playlist one week at a time (Lynch and Gillispie 1998), we examine the weekly diffusion of songs. Hence, we incorporate discrete time periods of equal length to equation 5, resulting in the following equation:

$$N_{t+1} - N_t = a\underline{N} + (b\underline{N} - a)N_t - bN_t^{\,2} \qquad (7)$$

Note that this is a quadratic equation of N_t.

$$N_{t+1} - N_t = A + BN_t + CN_t^{\,2} \qquad (8)$$

We then solve for the parameters of external-influence (a), internal-influence (b), and estimated total potential users ($\underline{N}$).

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[6] Note that Mansfield (1961) refers to *b* as *φ* (phi). Our nomenclature is adapted from Mahajan and Peterson (1985) and Valente (1993).

$b = –C$ (9)

$\underline{N} = [–B \pm (B^2–4AC)^{0.5}] / 2C$ (10)

$a = A_1 / \underline{N}$ (11)

$a = A_1*2C / [–B \pm (B^2–4AC)^{0.5}]$ (12)

Consider an analysis of the music data with a combination of Mahajan and Peterson's (1985) mixed influence model and Mansfield's (1961) method.

Internal-influence = $\delta_0 + \Sigma\delta_i X_i + e_b$ (13)

External-influence = $\chi_0 + \Sigma\chi_i X_i + e_a$ (14)

Number of potential users = $\eta_0 + \Sigma\eta_i X_i + e_N$ (15)

For 534 songs, we did 534 regressions to estimate the external-influence, internal-influence, and total number of potential users for each song (see table 1). See appendix A for the correlation-variance-covariance matrix. Fourteen songs had less than 3 weeks of adds, showing initial fast growth. Consistent with our hypotheses, all fourteen were Spitzer songs. Also, 41 songs yielded quadratic equations whose coefficients did not have real roots. Thus, these 55 songs were removed from this version of the analyses.

Table 1.
The external-influence, internal-influence, and total number of potential users for 534 songs.

Song	Internal-influence	External-influence	Total potential users
1. (I Got That) Boom Boom by BRITNEY SPEARS	0.00007	0.10397	1237
2. (I Hate) Everything About You by THREE DAYS GRACE	-0.00003	n/a	n/a
.	.	.	.
.	.	.	.
.	.	.	.
534. You've Got To Hide Your Love by EDDIE VEDDER	0.00128	0.04166	168

Note that for some songs, like #2, the computation of $(B^2–4AC)^{0.5}$ yields a complex root (not a real number), so external-influence and total potential users cannot be computed.

Then, we run three more regressions to test whether internal-influence, external-influence, and total number of potential users are significantly linked to song characteristics, namely artist's past hit songs and whether they appear in the Spitzer files. We expect songs by artists with more past hit songs or identified in the Spitzer files to show both *greater* external-influence and *more* potential users.

$$\text{Internal-influence} = \delta_0 + \delta_1\text{Artist\_past\_songs} + \delta_2\text{Spitzer} + e_b \quad (16)$$
$$\text{External-influence} = \chi_0 + \chi_1\text{Artist\_past\_songs} + \chi_2\text{Spitzer} + e_a \quad (17)$$
$$\text{Total potential users} = \eta_0 + \eta_1\text{Artist\_past\_songs} + \eta_2\text{Spitzer} + e_N \quad (18)$$

As shown in table 2 below, the diffusion curves showed mostly external-influence (0.346) with no significant internal-influence. As expected, more radio stations played songs by artists that had more hit singles in the top 100 in the past year (8.4 radio stations per top 100 single on average).[7] Likewise, almost 17 more radio stations played songs identified in the Spitzer files compared to other songs on average. Otherwise, Spitzer and artist's past songs had no significant effects on either internal-influence or external-influence.

Table 2.
Ordinary least squares (OLS) regression models predicting 3 song diffusion curve parameters (external-influence, internal-influence, and total number of potential users).

	3 OLS Regression models predicting 3 diffusion curve parameters		
Variable	Internal-influence	External-influence	Total potential users
Constant	-0.002	0.346**	180.0***
	(0.004)	(0.103)	(5.5)
Artist_past_songs	0.0002	0.027	+8.4***
	(0.0007)	(0.084)	(1.5)
Spitzer	0.003	0.272	+16.7*
	(0.009)	(0.309)	(7.1)

Multi-level Diffusion Curves

Our new method uses a multi-level diffusion curve (MDC) rather than 534 single level diffusion curves to (a) model explanatory variables at all levels, (b) model the diffusion of multiple songs simultaneously, and (c) obtain more precise estimates. First, we can add explanatory variables (X_i) directly into the diffusion curve regression as follows:

$$N_{t+1} - N_t = [A_+\Sigma\alpha_i X_i]+[B+\Sigma\beta_i X_i]N_t+[C+\Sigma\gamma_i X_i]N_t^2+e_t \quad (19)$$

With a multilevel model, we can model both song and time variables simultaneously, yielding the following equation.

$$N_{(t+1)s} - N_{ts} = (A_{00}+\Sigma\boldsymbol{\alpha}_{0x}\mathbf{X}_{0s}+\Sigma\boldsymbol{\varphi}_{zs}\mathbf{Z}_{ts}) + (B_{1s}+\Sigma\boldsymbol{\beta}_{0x}\mathbf{X}_{0s}+\Sigma\boldsymbol{\kappa}_{zs}\mathbf{Z}_{ts})N_{ts} + (C_{2s}+\Sigma\boldsymbol{\gamma}_{0x}\mathbf{X}_{0s}+\Sigma\boldsymbol{\lambda}_{zs}\mathbf{Z}_{ts})N_{ts}^2 + e_{ts}+f_{0s} \quad (20)$$

N_{ts} is the number of radio stations that have broadcast song s by week t. Similarly, $N_{(t+1)s}$ is the number of radio stations that have broadcast song s by week t+1. A_{00} is the grand mean intercept, while B_{1s} and C_{2s} are regression coefficients of N_{ts} and N_{ts}^2 respectively. $\mathbf{X}_{0s}$ is a vector of *x* song-level explanatory variables while $\mathbf{Z}_{ts}$ is a vector of *z* time-level

[7] Artist past songs was measured as the number of songs the artist had in the "Billboard Hot 100" chart. To avoid endogeneity, it is lagged one year.

explanatory variables. The following are vectors of regression coefficients: α_{0x}, φ_{zs}, β_{0x}, κ_{zs}, γ_{0x}, and λ_{zs}. The error terms (residuals) at the time and song levels are e_{ts} and f_{0s}, respectively. Furthermore, B_{1s} can be modeled as an overall regression coefficient and its degree of variation across different songs (also known as random level variation, $B_{1s} = B_{10} + f_{1s}$). Likewise, C_{2s} can be modeled as $C_{2s} = C_{20} + f_{2s}$, and any of the following vectors can have random level variation: β_{0x}, κ_{zs}, γ_{0x}, and λ_{zs}.

Unlike Mansfield's (1961) method which only allows explanatory variables at the song level (or more generally, the level of the entity being diffused), MDCs can also model explanatory variables at many levels, including the time level. Moreover, MDC can model interactions between song properties and time properties, or more generally, any cross-level interactions.

An MDC analyzes the 534 songs in one model. Hence, an MDC saves time by running only 1 regression rather than 534 regressions (one for each song) as in Mansfield's (1961) method. Also, as MDC allows lower level units (weekly adds, in this case) to have as few as one data point, songs with less than 3 weeks of data were included. Likewise, songs that yielded individual diffusion curves without real root solutions to the quadratic equation can likewise be included. Thus, MDC uses all available information, unlike the single-level, two-stage regression model. Moreover, using the full information of 534 songs simultaneously yields more precise estimates than 534 piecemeal regressions on subsets of the data.

We modeled songs' diffusion curves with the following multi-level specifications, using MLn software (Goldstein 1995, Rasbash and Woodhouse 1995). Ordinary least-squares regressions tend to underestimate the standard errors of regression coefficients. In contrast, multi-level models separate unexplained error into time (level 1) and song (level 2) components, thereby removing the correlation among error terms resulting from the nested data (time nested within songs).

We begin with a variance components model to test if the variances are significant at each level.

$$N_{(t+1)s} - N_{ts} = A_{00} + e_{ts} + f_{0s} \quad (21)$$

If f_{0s} differs significantly from zero, then the diffusion curves differed significantly across songs. The results showed significant variance at both the week level (97%) and the song level (3%). Hence, the songs' diffusion patterns differed substantially.

We also tested the effect of song-level characteristics, specifically whether Spitzer songs differed from non-Spitzer songs, controlling for artists' past popularity. Furthermore, we can also model time-level explanatory variables such as Holiday season. As record labels hold major artist releases for the last quarter of the year, we expect that the holiday season would be positively linked to total potential users.

$$\begin{aligned} N_{(t+1)s} - N_{ts} = &[A_{00} + \alpha_1 \text{Spitzer}_s + \alpha_{2s}\text{Artist\_past\_songs}_s + \varphi_{ts}\text{Holiday}_{ts}] \\ &+ [B_{1s} + \beta_1 \text{Spitzer}_s + \beta_2 \text{Artist\_past\_songs}_s + \kappa_{ts}\text{Holiday}_{ts}]N_{ts} \\ &+ [C_{2s} + \gamma_1 \text{Spitzer}_s + \gamma_2 \text{Artist\_past\_songs}_s + \lambda_{ts}\text{Holiday}_{ts}]N_{ts}^2 + e_{ts} + f_{0s} \quad (22) \end{aligned}$$

Table 3 Multilevel regression results predicting the number of radio stations newly adding each song per week.

Predictor	Regression	
Constant	6.001	***
	0.345	

Top 100 hits in last year	3.904	***
	0.341	
Holiday season	-2.693	***
	0.545	
Spitzer	1.458	**
	0.543	
Cumulative adds	0.043	***
	0.004	
Top 100 hits in last year * Cumulative adds	-0.015	***
	0.003	
Holiday season * Cumulative adds	0.020	***
	0.006	
Spitzer * Cumulative adds	-0.048	***
	0.005	
Cumulative adds^2	-0.00022	***
	0.00001	
Top 100 hits in last year * Cumulative adds^2	0.000003	
	0.000008	
Holiday season* Cumulative adds^2	-0.00002	
	0.00002	
Spitzer* Cumulative adds^2	0.00017	***
	0.00001	
Variance explained at the song level	< 0.001	
Variance explained at the week level	0.124	
Total variance explained	0.120	

Extending the formulas for internal-influence, external-influence, and number of potential users (9, 10, and 12) to the multilevel model, we obtain the following equations. (For the total potential users to be a positive number, the ± from the quadratic formula must be a subtraction [–], thus the computations yield unique solutions.)

$$b = -[C_{2s}+\Sigma\gamma_{0x}\mathbf{X}_{0s}+\Sigma\lambda_{zs}\mathbf{Z}_{ts}] \quad (23)$$

$$a = 2[A_{00}+\Sigma\alpha_{0x}\mathbf{X}_{0s}+\Sigma\varphi_{zs}\mathbf{Z}_{ts}][C_{2s}+\Sigma\gamma_{0x}\mathbf{X}_{0s}+\Sigma\lambda_{zs}\mathbf{Z}_{ts}]/[-(B_{1s}+\Sigma\beta_{0x}\mathbf{X}_{0s}+\Sigma\kappa_{zs}\mathbf{Z}_{ts}) -([B_{1s}+\Sigma\beta_{0x}\mathbf{X}_{0s}+\Sigma\kappa_{zs}\mathbf{Z}_{ts}]^2-4[A_{00}+\Sigma\alpha_{0x}\mathbf{X}_{0s}+\Sigma\varphi_{zs}\mathbf{Z}_{ts}][C_{2s}+\Sigma\gamma_{0x}\mathbf{X}_{0s}+\Sigma\lambda_{zs}\mathbf{Z}_{ts}])^{0.5}] \quad (24)$$

$$\underline{N} = [-(B_{1s}+\Sigma\beta_{0x}\mathbf{X}_{0s}+\Sigma\kappa_{zs}\mathbf{Z}_{ts}) - ([B_{1s}+\Sigma\beta_{0x}\mathbf{X}_{0s}+\Sigma\kappa_{zs}\mathbf{Z}_{ts}]^2 - 4[A_{00}+\Sigma\alpha_{0x}\mathbf{X}_{0s}+\Sigma\varphi_{zs}\mathbf{Z}_{ts}][C_{2s}+\Sigma\gamma_{0x}\mathbf{X}_{0s}+\Sigma\lambda_{zs}\mathbf{Z}_{ts}])^{0.5}] / 2[C_{2s}+\Sigma\gamma_{0x}\mathbf{X}_{0s}+\Sigma\lambda_{zs}\mathbf{Z}_{ts}] \quad (25)$$

Next, we compute the impact of each explanatory variable on internal-influence, external-influence, and total potential users (Chiu and Khoo 2005). Consider a computation of the effect of a discrete variable X (e.g., Spitzer with values 0 or 1). For other explanatory variables (artist's past popularity and Holiday season), we set their values to their mean value (μ) for continuous variables (artist's past songs = 0.354) and to their median value (Mdn) for discrete variables (Holiday = 0). For internal-influence in Spitzer (=1) vs. non-Spitzer songs (=0) for example, we compute the following:

$$b_{Spitzer=1} - b_{Spitzer=0} = -(C_{2s} + \gamma_1 * (1)_{Spitzer=1} + \gamma_2 * \mu_{Artist\_past\_songs} + \lambda * Mdn_{Holiday}) - -(C_{2s} + \gamma_1 * (0)_{Spitzer=0} + \gamma_2 * \mu_{Artist\_past\_songs} + \lambda * Mdn_{Holiday}) \quad (27)$$

The term $\gamma_1*(0)$ equals zero, and the following terms cancel out: C_{2s}, $\gamma_2 * \mu_{Artist\_past\_songs}$, and $\lambda * Mdn_{Holiday}$. Thus, only $-\gamma_1*(1)_{Spitzer=1}$ remains, yielding the result that Spitzer songs tend to have 0.000167 less internal-influence than non-Spitzer songs ($-\gamma_1 = -0.00017$). Likewise, the computation of internal-influence during the Holiday season yields only the term, $-\lambda*(1)_{Holiday=1}$. Hence, internal-influence during the holiday season is + 0.00002 more than otherwise ($-\lambda = -[-0.0000237] = +0.0000237$). For continuous variables, we compute the expected effect on internal-influence of a 10% increase in the explanatory variable to facilitate reader understanding, namely $b_{x=(1.10*\mu)} - b_{x=\mu}$. For artists' past sales, we compute the following.

$$b_{Artist\_past\_songs=(1.10*\mu)} - b_{Artist\_past\_songs=\mu} = -(C_{2s} + \gamma_1 * Mdn_{Spitzer} + \gamma_2 * 110\% * \mu_{Artist\_past\_songs} + \lambda * Mdn_{Holiday}) - -(C_{2s} + \gamma_1 * Mdn_{Spitzer} + \gamma_2 * \mu_{Artist\_past\_songs} + \lambda * Mdn_{Holiday}) \quad (28)$$

As before, the other terms cancel, leaving $-\gamma_2 * 110\% * \mu_{Artist\_past\_songs} + \gamma_2 * \mu_{Artist\_past\_songs}$ or $-\gamma_2 * 10\% * \mu_{Artist\_past\_songs}$. As $\mu_{Artist\_past\_songs}$ is not significant, artist's past songs have no significant effect on internal-influence. Similarly, we compute the expected effect of these explanatory variables on external-influence and total potential users (see Table 4 and full computations in a spreadsheet at http://www.sscnet.ucla.edu/issr/da/datapickup/payola.zip).

Table 4. Multilevel model estimates of each explanatory variable's link to external-influence, internal-influence, and total potential users

	Multi-level Diffusion Curve Parameters		
Predictors	Internal-influence	External-influence	Total potential users
No predictors	0.00015	0.023	308
Artist's past Top 100 hits (+10%)	0	+ 0.001	0
Holiday season	+ 0.00002	– 0.010	+ 14
Spitzer	– 0.00017	+ 0.001	+ 41

The MDC results were similar to the earlier results in the following three ways. First, external-influence is much larger than internal-influence on song diffusion across radio stations. Second, artist's past songs did not affect internal-influence. Third, more radio stations tended to add songs identified in the Spitzer files than other songs, though the MDC estimates a much larger Spitzer effect of +41 radio station adds rather than +17 in the earlier analysis.

The MDC results differed substantially regarding the other estimated effects. According to the OLS results, more radio stations played songs by artists that had more hit singles in the top 100 in the past year (8.4 radio stations per top 100 single on average). However, this result was not significant according to the MDC results.

Moreover, both artist's past songs and Spitzer file association were linked to higher external-influence according to the MDC analysis. Songs identified in the Spitzer file also showed lower internal-influence.

Lastly, the MDC tested the effect of time, specifically radio station adds during the holiday season. As expected, radio stations tended to add more of these popular songs during the holiday season, 14 on average. Furthermore, there was significantly less external-influence, and a bit less internal-influence during the holiday season.

To test for the robustness of these results, we also did a) MDC analyses on the data set without the 55 songs removed in the earlier data set, b) MDC analyses on the first 95% of radio station adds per song, c) MDC analyses on the first 95% of radio station adds per song without the 55 songs, and d) OLS analyses on the first 95% of radio station adds per song. All MDC results were similar, and all OLS results were similar. Results are available upon request from the authors.

Discussion and Conclusion

In this study we developed a technique for modeling diffusion of multiple innovations. Compared to older techniques (Mansfield 1961, Mahajan and Peterson 1985, Valente 1993), this approach is more statistically efficient. More importantly, it allows testing of a larger range of hypotheses. This latter feature in particular should provide wide utility in diffusion studies as it allows simultaneous estimation of parameters at the levels of the innovation, the time, and the interactions between them.

As we tested for payola with music data to demonstrate our method, we simplified it accordingly in three ways: fixed $\underline{N}$, symmetric internal-influence curve, and independent innovations. First, we assume that the number of radio stations that might potentially add a song to its playlist, $\underline{N}$, is fixed throughout the innovation's diffusion.[8] One can relax this assumption and allow the number of potential adopters to vary over time as actors at-risk of adopting the innovation enter or exit the system. For instance, a firm (system) can hire more engineers (actors) who are then at risk to use calculators (innovation) (Randles 1983) or the world (system) can have newly independent countries (actors) who are at risk of joining the United Nations (innovation) (Mahajan and Peterson 1978). A related assumption is that $\underline{N}$ is fixed because the system has discrete boundaries. The usual way in which this assumption is relaxed is to add physical space as a dimension of diffusion (Mahajan and Peterson 1979). In addition to viewing space as kilometers between two locations, one can view distance metaphorically, as in the Blau space between actors, a gradient of cross-elasticity of demand between goods, or the path lengths between social network cliques. For instance, people in an area could join a riot and then that riot could spread into adjacent areas (Grannovetter 1978). Likewise, in radio it is common for a song to become popular in one format (e.g. alternative rock) and then crossover to another (e.g. Top 40).

Another assumption is that we use a linear form of the second term in equation 5. This assumes that an internal-influence curve would appear symmetrical, with the inflection point occurring at about half of $\underline{N}$. Meanwhile, diffusion in some systems

[8] In fact stations do enter Mediabase during the study, both because the station "flips" to playing a new kind of music and because Mediabase continually expands the scope of its coverage. We consider a station to be left-censored relative to a particular song if it enters Mediabase after that song has begun its diffusion. Since such left-censorship is relatively rare, we drop such cases from the analysis.

follow the Gompertz (1825) mortality function, where the term is not $\underline{N}$-N_t, but $ln(\underline{N})$-$ln(N_t)$. This produces an inflection point at about a third of $\underline{N}$.

We modeled songs (innovations) as independent of one another. However, innovations can substitute for one another if an actor has scarce resources (including space) or uses them for similar purposes (Mansfield 1961). On the other hand, innovations can complement one another if using one innovation lowers costs for using the next one, as with a learning curve (Randles 1983).

Fortunately, methods for relaxing all of these assumptions are well-documented (Randles 1983, Mahajan and Peterson 1985). Thus, our model can be extended to include them.

Future research might extend our model to the unaddressed issue of cross-classified data. Modeling cross-classification can estimate how diffusion patterns are related not only to traits of innovation, but also to traits of actors and even interactions between actor and innovation traits. For instance, imagine that one had data on individuals and on news stories. One can use MDC to correlate traits of the news items, such as volume of media coverage and salaciousness, to *a*, *b*, and $\underline{N}$. Ideally, one could simultaneously correlate them with actors' media exposure and interact this actor level trait with the innovation's volume of media coverage. Likewise, one could show not only which record labels (an innovation trait) *pay* bribes, but which radio chains (an actor trait) *take* bribes. Such an extension of the technique is beyond the scope of this paper but it presents a powerful possibility.

As to the specific case of payola, we showed that documented instances of payola had diffusion patterns with greater external-influence after controlling for other factors such as artist's past songs and holiday sales period. This implies that when one does not have documentation of payola, one can infer its probable existence by running an MDC using the data set of Spitzer songs and a new set of five or more songs from a given record company to be tested (*test songs*; see Tabachnick & Fidell [2006] regarding the statistical benefits of 5 or more data points in a comparison group). The specification is identical to the MDC specification above except that the Spitzer variable is replaced by a new variable *Test-songs*. A significant negative effect of the variable *Test-songs* on the external-influence parameter suggests that the test songs show significantly less payola than the Spitzer songs. A non-significant or positive result suggests substantial payola.

By its nature, payola is unlikely to be extensively documented, let alone publicly available. Furthermore, aggressive prosecutors come along only intermittently and when they do, their revelations about payola necessarily (and intentionally) have reflexivity with the object of their inquiry. In contrast, statistical analysis of readily available diffusion data offers an inexpensive alternative. The commercially available Mediabase, Nielsen/BDS (Broadcast Data Systems), and ASCAP/Mediaguide datasets all offer detailed and reliable data on the airplay of American radio stations. Comparable datasets exist for radio in other countries. By examining these data, one can estimate the prevalence of payola across time and across different parts of the music industry.

Regulators, prosecutors, and other interested parties can apply this method as a policy tool for gathering *prima facie* evidence of legal violations. Attorney General Spitzer extracted draconian consent decrees from the record labels and radio chains, and the Federal Communications Commission is negotiating its own consent decrees. However, these decrees cannot enforce themselves. Indeed, if the law were selfenforcing, payola would have ceased after Congress banned the practice in 1960. Although the state seemingly has substantial subpoena power to discover payola, this power is limited both by law and by practical considerations. Legally, subpoenas cannot be used for fishing expeditions. Instead, a subpoena requires probable cause, wherein the state has a reasonable suspicion that a specific crime has occurred. Practically, interpreting the documents produced by a subpoena is too labor-intensive to be taken on lightly, and one cannot easily tell if the subject is withholding evidence.

The technique described in this paper provides an efficient, non-invasive mechanism through which the state can estimate where and when payola has occurred. This technique requires no subpoenas and relatively little labor. One social scientist and a commercial database subscription are sufficient to monitor the entire radio industry. Sets of songs flagged by such monitoring as having a suspiciously high level of unaccounted external-influence could then be referred for more extensive traditional investigation. Such a regime would solve the key policy problem of payola, how to detect it efficiently.

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Appendix A: Summary statistics and ancillary results

Table of summary statistics

Variable	Mean	S. D.	Min	Median	Max
Song code	272	154	1	272	534
Artist code	198	117	1	189	420
Station code	431	248	1	433	852
Number of radio stations newly adding each song per week	6	10	1	2	200
Cumulative adds	158	110	1	143	610
Top 100 hits in last year by artist	0.374	0.863	0	0	6
Holiday season	0.225	0.417	0	0	1
Spitzer file	0.310	0.462	0	0	1

Correlation-variance-covariance matrix

	Variable	1	2	3	4	5
1	Number of radio stations newly adding each per song per week	**96.22**	-125	-0.04	0.54	-0.11
2	Cumulative adds	-0.12	**12004**	1.75	17.75	1.98
3	Holiday season	-0.01	0.04	**0.17**	0.05	-0.02
4	Top 100 hits in last year per artist	0.06	0.19	0.13	**0.74**	-0.04
5	Spitzer file	-0.02	0.04	-0.10	-0.09	**0.21**

Appendix B: Associated Data, Code, and Documents

http://www.sscnet.ucla.edu/issr/da/datapickup/payola.zip

File	Description
EMI.EV.PDF	Original evidentiary documents from the office of the NY Attorney General - EMI
ENTERCOM.EV.PDF	Original evidentiary documents from the office of the NY Attorney General - Entercom
SONY.EV.PDF	Original evidentiary documents from the office of the NY Attorney General - Sony
UNIVERSAL.EV.PDF	Original evidentiary documents from the office of the NY Attorney General - Universal
WARNER.EV.PDF	Original evidentiary documents from the office of the NY Attorney General - Warner
SPITZER.MDB	Raw data based on the evidentiary documents listed above
SPITZER.PDF	Codebook for SPITZER.MDB
PAYOLA_DATA.TXT	Cumulative adoption histories for every song mentioned in SPITZER.MDB
PAYOLA_DATA.PDF	Codebook for PAYOLA_DATA.TXT
PAYOLA_MLN.TXT	MLn program for use with PAYOLA_DATA.TXT data
MUSIC.CORRUPT.XLS	Spreadsheet with automatic computations for Payola regressions. You will need to enter the multilevel diffusion curve regression coefficients and the mean or median of the predictors.