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Abstract

The odds of success in creative industries like the book, music or movie industry are often said to be particularly low. A 1763 rule by Denis Diderot, for example, says that only one out of ten published books is a commercial success. Yet, representative evidence on new-product success rates and their development over time is scarce. Furthermore, the standard approach to use sales as success measure can be misleading from the producer's perspective. This paper presents a novel approach to empirically identify producer success by incorporating the standard terms of contract between creator and producer into a parsimonious model of information diffusion (word-of-mouth). The model is applied to a random sample of novels. Parametric and semiparametric estimates imply a success rate between 10 and 15% for this market. Set against Diderot's rule, these results suggest that new-product success in the book industry has been fairly constant over time.

Keywords: New-product success; word-of-mouth; creative industries; technological change.

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1 New-product success in creative industries

The commercial success of a new creative good such as a theatrical movie, a music record or a novel is extremely difficult to foresee. According to screenwriter William Goldman (1983), not even industry experts are able to predict a particular movie's box office performance. As a result, box office 'flops' are an empirical regularity. Similarly, the market for music albums has been said to be dominated by a "stiff ratio" – the share of loss-making albums – of around 90% (Caves, 2000, p. 79; Denisoff and Schurk, 1986, p. 4). The title of this paper refers to an old quantification of new-product success in the book industry: in 1763, Denis Diderot (1713-1784) – French philosopher, writer and editor-in-chief of one of the world's first encyclopedias – estimates in an article on book publishing that at most one out of ten published books is a success, while four recover costs in the long run, and five end up with losses.[1]

Rules of this kind are often circulated in the respective industries.[2] The odds of success are clearly important for the economic agents in these industries, such as authors, actors, producers and publishers – but why should anyone with a more general research perspective care? First of all, these rules of thumb suggest that patterns of new-product success resemble each other across different creative industries, but differ from the 80/20 rule commonly claimed for other, more 'industrial' industries.[3] If there is stronger empirical support for such a structural difference, this will have implications for industrial policy. And the perspective of producers is crucial in these industries, as they decide which creative project will be realized and brought to the market, and which not.

Another open question is whether patterns of new-product success may change over time, in particular as information technologies change. Hendricks and Sorensen (2009) find that the release of a new music album significantly increases sales of the artist's previous album, which implies that incomplete information and consumer learning are major determinants of success in this industry. Hendricks and Sorensen (2009) show that

[1] "*Ajoutez que, de compte fait, sur dix entreprises, il y en a une, et c'est beaucoup, qui réussit, quatre dont on recouvre ses frais à la longue, et cinq où l'on reste en perte*" (Diderot, 1763/2003, p. 61). See Turnovsky (2003) for a review of the general reception of Diderot's article.

[2] Diderot's rule is cited, for example, by Escarpit (1969, p. 123), Tietzel (1995, p. 38) and von Lucius (2005, p. 66).

[3] For example, the Food Marketing Institute (2002) reports failure rate estimates for new grocery products between 25% and 80%. To the best of my knowledge, there are no estimates for other markets. The vast management literature on the subject of course focuses on the determinants of new product success, not on the aggregate success rate (see Henard and Szymanski, 2001, for a meta analysis).

if consumers were more fully informed, the distribution of sales across titles would be substantially less skewed. The authors conclude that with the rise of the internet, consumers will overcome “information bottlenecks” of the analog world, and the distribution of sales and profits will become more equal. In contrast, the results presented in this paper suggest that it is unlikely that new-product success in creative industries changes significantly with changes in information technology. Similarly, Prince and Simon (to appear) find that although the internet has increased new-product diffusion by improving shopping convenience and product research, it has not increased consumer awareness for new products. In other words, the internet facilitates assessment and purchase of products of which consumers are already aware, but it does lead consumers to discover significantly more or other new products.

The odds of new-product success in creative industries are rarely subject to a direct empirical evaluation, except for the movie industry, which is well-studied empirically (see Elberse, Eliashberg and Leenders, 2006, for a recent review of the literature). With respect to new-product success, De Vany and Walls (2004) find that in the U.S. market, 6.3% of all movies earn 80% of all profits. The reason for the lack of direct results for other industries, next to the difficulty of obtaining a representative set of products, is that profits are unobservable. The data available to researchers usually contain product sales, but accounting data such as costs or profits are typically unobservable or unreliable. Therefore, studies revert to sales or bestseller status as measure of a product’s success, and concentrate on studying the distribution of sales. For example, Sorensen (2007) and Gaffeo, Scorcu and Vici (2008) show that the distribution of sales across book titles is highly unequal (skewed) in the U.S. and Italian book industry.

Yet, the concentration on sales as profit measure can misrepresent the perspective of producers, because potent creators (ie. ‘star’ actors or authors) often demand a large share of the revenues that can be expected from the presence of predetermined success factors such as the star herself. For example, Elberse (2007) finds that the involvement of star actors increases expected revenue of movie producers (film studios), but it does not increase their company valuation (expected profits). In other words, the fraction of new products that were profitable for the producer does not equal the fraction of its new products whose sales exceeded some threshold.

The first contribution of this paper is a novel approach to empirically identify new-product success, which combines the standard terms of contract between creator and producer with a parsimonious model of new-product diffusion. The resulting empirical identification strategy does not rely on a product's absolute level of sales, but on sales dynamics, and is based on the common observation that word-of-mouth – or, more generally, social influence – is a crucial success factor.[4] Recent experimental evidence by Salganik, Dodds and Watts (2006) shows that new-product success is basically unpredictable when consumption is subject to word-of-mouth. Participants in their study were offered to sample and then download previously unknown music. In some experiment groups, participants also received 'top downloads' information about the number of a song's previous downloads. In a significant number of cases, the same songs that were sampled but rarely downloaded in a group where participants did not receive 'top downloads' information became 'top downloads' in groups where participants did receive this information. *Vice versa*, songs that were popular in groups with 'top downloads' information were unpopular in groups without this information. Salganik, Dodds and Watts (2006) conclude that "experts fail to predict successes not because they are incompetent [...] but because when individual decisions are subject to social influence, markets do not simply aggregate pre-existing individual preferences."

In this paper, I show that measures of word-of-mouth approximate producer success better than nominal sales because the effects of word-of-mouth are hard to appropriate by creators in *ex ante* bargaining. In that case, the products that are profitable for the producer are those products that received unpredictable positive word-of-mouth. The theoretical model directly leads to a parametric approach to identify the occurrence and effect of word-of-mouth in week-to-week variation in unit sales. In order to allow for more general models of word-of-mouth, I also propose a semiparametric method of identification.

The second contribution of this paper is an empirical application to a representative sample of novels released on the German book market (section 3). Results indicate that between 10 and 15% of titles enjoy positive word-of-mouth. On average, titles that are estimated to enjoy positive word-of-mouth perform better in terms of total sales, however,

[4]In the context of this paper, 'word-of-mouth' is a catch-all phrase for the diffusion of consumer awareness for a product and information about its quality. This includes person-to-person communication, but also online and offline product reviews (Chevalier and Mayzlin, 2006; Sorensen and Rasmussen, 2004) and less direct forms of communication such as blogs, bestseller lists and *Oprah's Book Club*.

some of these titles have relatively low sales whereas some of the sample's best sellers are not estimated to enjoy positive word-of-mouth. It is therefore possible that a success measure based on word-of-mouth leads to a different result than a standard measure based on nominal sales.

Moreover, my estimates of word-of-mouth and new-product success in the book market are in line with Diderot's rule of thumb. As such, they suggest that, in spite of changes in information and communication technology since 1763 – amongst other revolutions – the odds of success in the book market have stayed largely the same. In the conclusion, I therefore extrapolate that the internet revolution will not make a significant difference for new-product success in creative industries, but I suggest that the internet will significantly change their channels and costs of production and distribution.

2 Identifying word-of-mouth and new-product success

This paper's strategy to empirically identify new-product success is based on a parsimonious formal model of new-product diffusion with word-of-mouth. The model features two ingredients that are essential for word-of-mouth to have an effect on sales: heterogeneous buyers and intertemporal dynamics. In contrast, most studies in the extensive theoretical and empirical literature on new-product diffusion follow Bass (1969) in assuming that consumers are homogeneous regarding their propensity to buy and differ only in the timing of their purchase[5]. Yet, in a model with homogeneous buyers, word-of-mouth among these buyers can only affect the distribution of sales over time, not their overall level. To have an effect on overall sales, word-of-mouth needs to take place between consumers that are heterogeneous in their propensity to buy.

I consider the simplest case of heterogeneity: a two-segment structure, where the population of M potential buyers of a newly released creative good – henceforth "title" – consists of two types: N_b buffs and N_c casuals (title subscripts omitted).[6] Buffs buy the title in any case. Casuals only buy if they are exposed to positive word-of-mouth. If there

[5]See Van den Bulte and Joshi (2007) for a review. Variants and extensions of the Bass model have also been used in a related literature on the diffusion of technological and organizational innovations across firms (Clerides and Kassinis, 2009).

[6]Caves (2000, p. 173) observes that the "distribution of consumers between 'buffs' and 'casuals' strongly influences the organization of an art realm".

is no positive word-of-mouth about a certain title, its long-run sales are restricted to N_b. The case of negative (sales-destructive) word-of-mouth is discussed in section 2.3.

Heterogeneity-driven word-of-mouth has implications for the *ex ante* as well as the *ex post* view on title performance. First, it affects *ex ante* bargaining over contract terms between creator (henceforth "author") and producer (henceforth "publisher"). Second, the heterogeneity implies that *ex post* studies of aggregate product-level sales need to address an identification problem: the extent of word-of-mouth needs to be inferred by decomposing observed sales into unobserved sales to buffs and casuals. In section 2.2, I therefore consider a parametric specification for intertemporal sales dynamics that can be used to identify the effect of word-of-mouth. In section 2.3, I discuss semiparametric identification in the context of more general models.

2.1 *Ex ante* bargaining and Diderot's rule

The typical contract between author and publisher grants the publisher the exclusive right to market the author's title. This publishing contract consists of a royalty scheme through which publisher and author share revenues from sold copies. Royalty schemes are a commonplace in creative industries, where the creator of a good typically lacks the funds to produce and market it, so that the producer takes over the investment risk in return for a share of the revenues.[7]

The advance. An additional – and in our context more important – aspect of author-publisher contracts is the fact that authors (or their agents) require a nonrefundable advance payment on the expected royalties before a title is released. The advance is often interpreted as a device to increase the publisher's incentives to market a title, which relates to one of the problems associated with the difficulty of profit-sharing (Caves, 2003), but the advance may serve other means as well.[8] Hansmann and Kraakman (1992) consider the context of an early contracting stage, before the author has written the book, and study a 'hands-tying' contract where the advance helps publishers to commit to producing the title without detailed knowledge of its contents. Here, it is simply taken as

[7] Horvitz (1966) and a subsequent literature discuss in more detail why the seemingly more natural alternative of profit-sharing is rarely observed in academic (textbook) publishing. Dana and Spier (2001) show that revenue sharing is valuable in manufacturer-retailer contracts, when demand uncertainty realizes only after inventory decisions have been made.

[8] For example, the advance insures the author against publisher insolvency, and the publisher may save on transaction costs after release, when a potentially large number of small royalty payments can be accounted against the advance.

given that each contract between author and publisher includes a nonrefundable advance royalty that is contracted upon under common knowledge of some forecast for a title's sales.

To be more precise, let r be the author's revenue share ($0<r\leq 1$) and A the advance on this share. Assuming fixed production costs of C and normalizing the title's wholesale price to one, the publisher's expected gross profits at the time of bargaining are

$$E[Q] - A - rE[\max\{0; Q - A/r\}] - C, \quad (1)$$

where $E[Q]$ are expected sales. Since A is nonrefundable, it implicitly defines a threshold value for sales (A/r) below which the author's factual *ex post* revenue share exceeds r. For any value of r, the author may use A to appropriate the remaining expected publisher profits. In practice, royalty rates indeed vary little across different contracts, whereas advance payments tend to vary strongly, even in relation to the number of copies finally sold (Caves, 2000, pp. 56ff). Book authors are frequently represented by literary agents who receive up to 20% of their client's remuneration and who thus have a direct incentive to achieve a high advance. In fact, agents often attempt to maximize the author's share of expected profits by auctioning publishing rights.[9]

The combination of royalty and advance implies that publisher profits are not monotone increasing in sales Q, but rather in their relation to expectations $E[Q]$.[10] In particular, this is true for titles whose authors have a strong bargaining position and are thus able to pocket much of the expected profits – presumably titles with high $E[Q]$. In the auction case with sufficiently many competing publishers, A will be close to $E[Q]$-C, such that the winning publisher's profits are close to zero in expected terms and positive *ex post* only if sales exceed their expectation.

From the publisher perspective, title success therefore depends on the accuracy of sales predictions. In a recent interview, Jonathan Galassi, the president of New York publisher *Farrar, Straus, and Giroux* nicely illustrates this point: "With regard to big advances, I'll tell you a dirty little secret. I think that very often the big advances you pay, at least for

[9] An auction is the optimal selling format from the author viewpoint (Bulow and Klemperer, 1996) and has a long tradition in the book industry: see Moldovanu and Tietzel (1998) for an analysis of 'Goethe's second-price auction' and Hansmann and Kraakman (1992) and De Vany and Walls (2004) for further anecdotal evidence.

[10] For authors, in contrast, total sales remain important *ex post* because they are associated with auxiliary revenues, for example from live performances or movie deals.

a company like ours, don't end up having the result you want. Sometimes you just have to pay them. But the real successes, which make the difference in our business, don't come from the books for which we pay big money. When we pay a big advance our job is to earn back what we gave the author so that we come out clean – basically break even or make a small profit. Whereas a book where we start much lower, and go a big distance, is much more mutually profitable." (Galassi and Ferrari-Adler, 2009)

Forecasting sales. The accuracy of sales predictions, in turn, is related to word-of-mouth. Suppose a title's potential market has the two-segment buyer structure discussed above. Since buffs buy the title in any case but casuals buy only if there is positive word-of-mouth, expected sales consist of

$$E[Q] = E[N_b] + Pr(word)E[N_c|word], \tag{2}$$

where $Pr(word)$ is the *ex ante* probability that a title receives positive word-of-mouth and $E[N_c|word]$ are expected sales to casuals in that case. The key question is whether it is possible, at the time of bargaining, to predict sales in all consumer segments. Some predetermined observable characteristics – like sales of previous titles by the author or the size of the author's fan club – are certainly informative regarding expected sales to buffs (N_b). Author-publisher bargaining is thus likely to operate under common knowledge of $E[N_b]$. In contrast, the findings by Salganik, Dodds and Watts (2006) and Hendricks and Sorensen (2009) indicate that predetermined characteristics are unlikely to contain information on the title-specific propensity to receive word-of-mouth ($Pr(word)$) and the corresponding additional sales ($E[N_c|word]$). In that case, parties can at best work with market-level statistics or general principles such as Diderot's rule.

For example, suppose the average probability for the occurrence of word-of-mouth ($Pr(word)$) is δ and the average value for the resulting additional sales $E[N_c|word]$ is k times N_b. The maximum advance a publisher is willing to pay is then $\bar{A} = E[N_b](1 + \delta k) - C$. It follows immediately that, with titles whose authors have strong bargaining power (hence $A \rightarrow \bar{A}$), publishers end up making profits only in case of word-of-mouth, that is, only with probability δ. With titles whose authors have weak bargaining power – presumably titles with low $E[N_b]$ – publishers may bargain down the advance payment.

For these titles, however, production costs are relatively more important, which can also lead to negative *ex post* profits in case there is no word-of-mouth.[11]

Empirical implication. In either case, given that data on advances, royalty rates and production costs are typically not available or unreliable, differences in *ex ante* expectations and advance payments across titles cannot be accounted for empirically. In consequence, observed total sales are not an appropriate success measure from the publisher perspective. But we can utilize the fact that the more appropriate success measure, the difference between *ex ante* expectations and *ex post* sales, is particularly affected by the *ex post* extent of word-of-mouth. We can thus empirically estimate new-product success by estimating the distribution of positive word-of-mouth across titles. The corresponding interpretation of Diderot's rule, for example, holds that $\delta=\frac{1}{10}$: one out of ten titles enjoys positive word-of-mouth.

An implementation of this empirical approach requires (*i*) a method to identify the presence of positive word-of-mouth in sales and (*ii*) data on a representative sample of titles. With respect to (*i*), the following model of new-product diffusion illustrates that – with reasonable assumptions on how sales to buffs and eventually casuals distribute over time – it is possible to not only identify the existence of positive word-of-mouth but also to quantify its effect on a title's overall sales (that is, to estimate N_c).[12] In section 2.3, I discuss more general models and semiparametric identification.

2.2 Intertemporal sales dynamics

As a matter of notation, it is more convenient to consider the total number of potential buyers of a title $M = N_b + N_c$ and its share of buffs $\theta = \frac{N_b}{M}$. Time-invariant predetermined variables that may affect N_b and thus M, such as a title's characteristics and price, can be omitted in this section.[13] Operating within a continuous-time framework, denote by $F_b(t)$ the c.d.f. of a title's sales to buffs, that is, cumulative sales to this group at time t divided

[11]If the negotiated advance payment is $\rho\bar{A}$, where $0<\rho\leq 1$, publisher profits are negative *ex post* if there is no word-of-mouth and $C > E[N_b](1 - \frac{\rho}{1-\rho}\delta k)$.

[12]Moul (2007), who quantifies the average effect of word-of-mouth in motion picture revenues, also identifies word-of-mouth through intertemporal dynamics of weekly unit sales. However, the specific demand model underlying his analysis (nested logit) is very different from the new-product diffusion model presented here, variants of which are widely applied in the marketing literature.

[13]In most European countries, book prices are by law subject to resale price maintenance and thus invariant over time. Even in the unregulated U.S. market, intertemporal price variation is virtually inexistent (Clerides, 2002).

by its population (θM). Similarly, $F_c(t)$ is the c.d.f. of sales to casuals and $f_b(t)$ and $f_c(t)$ are the corresponding densities.[14]

Buffs buy the title in any case, however, not necessarily in its release week. For example, some may want to first finish the book they are currently reading. A standard assumption is that in every period the title is bought by a fraction p of those buffs who have not bought earlier. In continuous terms, this is a constant hazard rate: $p = \frac{f_b(t)}{1-F_b(t)}$. Since $F_b(0)$=0, we can solve for $F_b = 1 - \exp(-pt)$ and the cumulative number of sales to buffs at time t is

$$n_b(t) = \theta M - \theta M \exp(-pt). \tag{3}$$

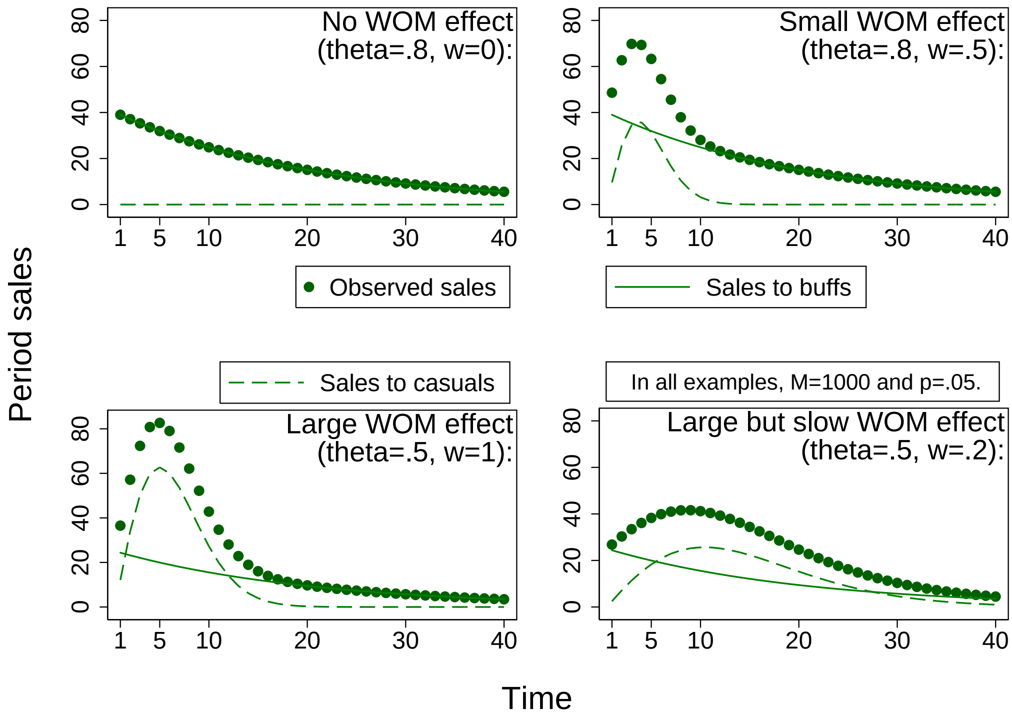
Sales to buffs in the period $(t-1, t)$ are $n_b(t) - n_b(t-1)$ and follow the steady decay pattern typically observed, for example, for blockbuster movies. In terms of the model, aggregate sales exhibit steady decay in two cases: if the number of casuals is zero (θ=1), or if there are casuals ($\theta > 1$) but there is no word-of-mouth from buffs. In both cases, overall sales are limited to N_b and sales dynamics are determined by equation 3. The upper left title in figure 1 provides an example for sales dynamics without word-of-mouth. An important implication for empirical work is that in this case, θ and M are not separately identified. In other words, it is impossible to say how much a title would have sold if it had received some word-of-mouth. As I discuss below, a related identification problem is associated with negative word-of-mouth.

Casuals. As long as θ<1 the title under consideration has the potential to benefit from word-of-mouth. In particular, an independent buyer may recommend the product to a non-negative number w ($\geq$0) of casuals each period following her purchase. Parameter w can be interpreted as a population average: For example, w=.5 means that one out of two buffs recommends the title to a casual each period after her purchase.[15] The contacted casuals then go ahead and buy the recommended title, unless they have not already done so in response to an earlier recommendation. Since the probability that a casual exposed to word-of-mouth at time t has not been contacted and therefore has not bought earlier is $1 - F_c(t)$, the cumulative number of sales-effective recommendations at

[14]The following specification was developed independently by Van den Bulte and Joshi (2007) and myself. In Beck (2007), I study the estimation properties of the model with a Monte Carlo simulation and present detailed estimation results for four example titles. In Van den Bulte and Joshi (2007), this model is a special case of a more general class of models (discussed in more detail in section 2.3 below).

[15]A simplifying assumption is that casuals do not recommend the title to other people (see section 2.3 below for a discussion).

Figure 1: Example sales patterns



time t is $1 - F_c(t)$ multiplied by w and $n_b(t)$. Divided by the overall number of casuals, $(1-\theta)M$, this amounts to the density $f_c(t)$ and rearranging yields the relationship

$$\frac{f_c(t)}{1 - F_c(t)} = qF_b(t), \tag{4}$$

where $F_b(t) = \frac{n_b(t)}{\theta M}$ and $q = w\frac{\theta}{1-\theta}$ is a convenient reparametrization. Using equation 3 and the fact that $F_c(0)$=0, this differential equation solves for

$$F_c(t) = 1 - e^{\frac{q}{p}(1-e^{-pt}-pt)}. \tag{5}$$

Hence, cumulative sales to casuals are $n_c(t) = (1-\theta)MF_c(t)$, and total cumulative sales at time t are the sum of $n_b(t)$ and $n_c(t)$:

$$N(t) = M(1 - \theta e^{-pt} - (1-\theta)e^{\frac{q}{p}(1-e^{-pt}-pt)}). \tag{6}$$

Period sales within the interval $(t,t-1)$ are then described by $N(t) - N(t-1)$. Figure 1 plots the corresponding sales pattern for four different value combinations of parameters θ and w. Most notably, sales without word-of-mouth follow a convex pattern, whereas with word-of-mouth they are concave (hump-shaped) in early sales weeks: due to an increasing number of buff buyers engaging in word-of-mouth, sales to casuals rise initially. The size and width of the resulting sales hump depends on the intensity of word-of-mouth and on the relative number of casuals.

2.3 Generalizations

Equation 6 provides a functional form that can be used to structurally identify the extent of word-of-mouth in title-specific time series of sales. As usual in structural modeling, the corresponding results depend on the viability of the model. It is therefore important to discuss the potential limitations of the above model.

First, it only considers positive word-of-mouth, although anecdotal evidence from the movie industry suggests that negative word-of-mouth can also be important. In terms of the model, negative word-of-mouth would not only imply that w=0, but in addition that buffs engage in sales-destructive communication among each other. Negative word-of-mouth aggravates the identification problem already present when w=0; for example, among buff buyers it implies that their overall number (θM) is subject to decay over time: first-week buff buyers dissuade other buffs from their initially planned purchase. As evident from equation 3, it is impossible to distinguish this effect from the hazard rate p. For example, consider the upper left title in figure 1, whose observed sales decline steadily after release. Based on such data, it is impossible to say whether the particular pattern is driven by negative word-of-mouth (decreasing θM over time) or merely by the decay parameter p. This is unproblematic in the context of this paper, which focuses on identifying positive word-of-mouth. However, if we wanted to identify negative word-of-mouth among buffs separately from the usual intertemporal sales decay, we would need to place more restrictions on parameter p, for example by assuming it to be equal across titles.

A second, more important restriction in the above model is that casuals care exclusively for recommendations from buffs. In general, however, positive word-of-mouth within segments – for example among casuals – may also be sales-effective. Van den Bulte and Joshi (2007) analyze a more general class of models, which allows for positive word-of-mouth within both segments. These more general cases have the property that period sales exhibit a 'dip' or are convex for early sales periods, when decreasing sales to buffs are not yet over-compensated by increasing sales due to word-of-mouth. In other words, a hump-shaped sales curve driven by word-of-mouth can have more than one stationary point and only one of these is the global maximum. Van den Bulte and Joshi (2007) present evidence on sales of music CDs that seem to exhibit such a 'dip' in early sales weeks. Since models of new-product diffusion are inherently nonlinear, model complexity increases exponentially for these more general cases. Indeed, estimation based on standard methods can be troublesome, which complicates comparison between model variants. Nevertheless, all cases share the property that word-of-mouth leads to a concave (hump-shaped) pattern around the global maximum of a title's sales curve. The semiparametric identification of word-of-mouth proposed in the next section relies on this property.

Alternative explanations for hump-shaped sales patterns. A related literature studies the diffusion of new technologies across firms, typically over a longer time period. Next to imitation effects, which are similar to effects of word-of-mouth in the diffusion of consumer goods, this literature generally explains a hump-shaped pattern in adoptions by decreasing costs or increasing benefits of adoption over time (Hall and Khan, 2003; Clerides and Kassinis, 2009). For a new creative good, however, both material product characteristics and price are constant within its short selling period. This is certainly the case in the data studied here, as prices in the German book market are governed by a law on retail price maintenance that prevents retailer discounts. Therefore, the only possible kind of increase in benefit is one associated with immaterial characteristics: for example, consumers may change their perception of the intellectual value of a title. This view is consistent with the occurrence of positive word-of-mouth.

Other, 'behavioral' explanations for hump-shaped sales often assume some form of suboptimal behavior by producers or retailers, which is outside the scope of this paper. For example, a publisher may gradually increase marketing efforts for some titles, although the logic of bestseller lists and return of investment implies that all marketing should be concentrated at the release date. At least in the book industry, in any case, traditional instruments such as advertising seem to have modest effects. Instead, industry sources emphasize the effects of public performances by a title's author, which are often out of direct publisher control.[16]

2.4 Parametric identification

The standard approach to estimating parametric models of new-product diffusion with aggregate sales data is based on first differences of the cumulative sales function (Putsis and Srinivasan, 2000) :

$$S(t) = N(t;\phi) - N(t-1;\phi) + \varepsilon_t, \tag{7}$$

where $S(t)$ denotes observed sales of a given title during the period ($t-1$,t). $N(.)$ is the cumulative sales function defined by the particular model, ϕ is the set of model parameters and t=1,...,T. Here, $N(.)$ is defined by equation 6 and ϕ consists of M, θ, p and q. Assuming that the error term ε has the usual least squares properties, parameters may be estimated by nonlinear least squares (NLS). A grid search procedure yields proper initial values for iterative estimation. Through log-transformations, I impose that all parameters are non-negative and that $\theta, p \leq 1$.

Neither asymptotic nor small-sample properties of such estimators are known (Boswijk and Franses, 2005), but bias and consistency can be studied by means of a a Monte Carlo simulation. For the present model, NLS estimates are reliable if observations cover a sufficiently large part of a title's life cycle and are not too volatile. Furthermore, residual autocorrelation may be present: for example, a television appearance by a title's author may boost sales not only in that but also in the following weeks. The procedure to test and account for residual autocorrelation is straightforward (see Beck, 2007, for more details on these issues).

Applied to a title with hump-shaped sales, the model provides estimates for all four parameters and thus identifies both the existence of word-of-mouth (w) and its relative sales effect ($1-\theta$). Based on a representative sample of titles, this approach therefore yields an estimate of the distribution of positive word-of-mouth – the share of titles with a positive w – and thus yields a measure of new-product success in this market.

Yet, such a parametric approach is associated with two main problems. First, equation 3 indicates that the parameters of the model are not identified when sales of a ti-

[16]"Booksellers say author tours, Oprah most effective for marketing books", *Book Publishing Report*, vol. 24, iss. 38; "Suche nach Öffentlichkeit", *Handelsblatt*, iss. 54, 16 March 2006.

tle decrease steadily over time. Effectively, estimates for such titles tend to converge at boundary values ($\hat{p}$ or $\hat{\theta}$ equal to zero or one, $\hat{w}$ equal to zero). Results of this kind may indicate that the respective title did not enjoy positive word-of-mouth and hence that w=0, but they may also be driven by data volatility (Beck, 2007). Second, as discussed in the previous section, parametric estimates are meaningful only if the imposed model is a good approximation of the data generating process. If more general forms of word-of-mouth cannot be excluded or if data volatility complicates estimation, semiparametric methods provide useful alternatives to test for the existence of positive word-of-mouth.

2.5 Semiparametric identification

A more general empirical specification for intertemporal sales dynamics is

$$S(t) = g(t) + \varepsilon_t, \tag{8}$$

where $g(t)$ denotes the unknown function according to which period sales distribute over time. Various methods are available to semiparametrically estimate $g(t)$ in order to obtain a smoothed time series $\hat{S}(t)$. In principle, these methods can be viewed as variants of kernel density estimation that differ mainly in the employed kernel and the degree of smoothing. Results are typically invariant to the researcher's choice of kernel but highly sensitive to the chosen bandwidth (Cameron and Trivedi, 2005). Further, a crucial distinction is between global estimators that search for a function that fits best over all available data, and local estimators that smooth over a moving data window (Ruppert, Wand and Carroll, 2003). Estimators also differ in their treatment of extreme observations ('outliers').

For the purposes of this paper, the locally weighted regression approach (*loess*, following Cleveland, 1979) seems most appropriate. First, as a local estimator it does not exhibit irregularities at the beginning or end of the sample that have been found with global estimators. This is important for the present application because sales humps driven by word-of-mouth tend to occur in early sales weeks. Second, the *loess* approach has a high degree of automation, which facilitates application to a large number of titles: only one smoothing parameter has to be chosen, and procedures exist to automate even this decision (I will use the improved Akaike information criterion developed by Hurvich, Simonoff and Tsai, 1998)). Finally, by iterative reweighting of observations the *loess* estimate is robust to extreme observations, which due to events like a television appearances of authors are likely to occur in sales data of creative goods.

3 Application to a representative sample of novels

The data used in this study is a sample of 229 novels randomly drawn from the set of all novels released 2003 as hardcover in Germany. The data come from a marketing research firm that aggregates scanner data from over 750 physical points of sale and all main internet retailers in Germany. In the appendix, I discuss data characteristics and sampling procedure in more detail.

I focus on novels because this segment is most important for the book trade – both in economic and cultural terms – and on hardcover editions because only newly released titles are of interest. German paperback editions of a title are delayed by one to two years.[17] Therefore, the sales data analyzed in this paper cover all sales of the respective new product and are not affected by other competing editions of the same title. The data proprietor was obliged to give me anonymized data, where all title-, author- and publisher-specific information had been removed, leaving as sample variables a title and publisher code, sales (by week) and price (constant). The release date of each title is inferred from the sales data (see the appendix for more details). The sample period ends in summer 2004, providing between 41 and 81 weekly sales observations per title.

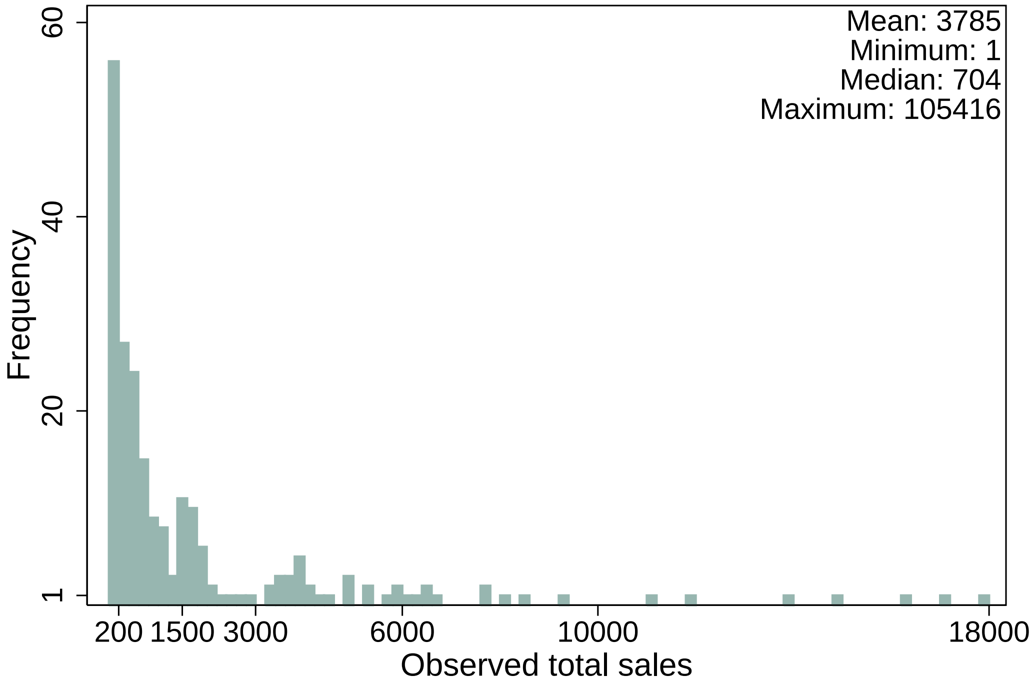
3.1 Sample characteristics

Figure 2 presents a histogram of total sales observed across titles. It does not account for the fact that titles are observed for differently long time periods, however, this turns out to be inessential: most sales take place within the first 26 weeks after release, which are observed for all titles.[18] The result is a well-known picture: most titles have very low overall sales – about 43% of titles sell less than 500 copies – and only few titles get to five- or six-digit sales figures. In effect the distribution of total sales is skewed: whereas

[17] This release strategy is a textbook example of intertemporal price discrimination (Clerides, 2002).

[18] Figure 6 in the appendix gives standard kernel density estimates for the distribution of cumulated sales: one including the first 26 sales weeks only and one including all observed weeks for each title. The distribution for sales including all observed weeks is quite similar and only slightly broader than the one including the first 26 weeks only.

Figure 2: Distribution of sales across titles



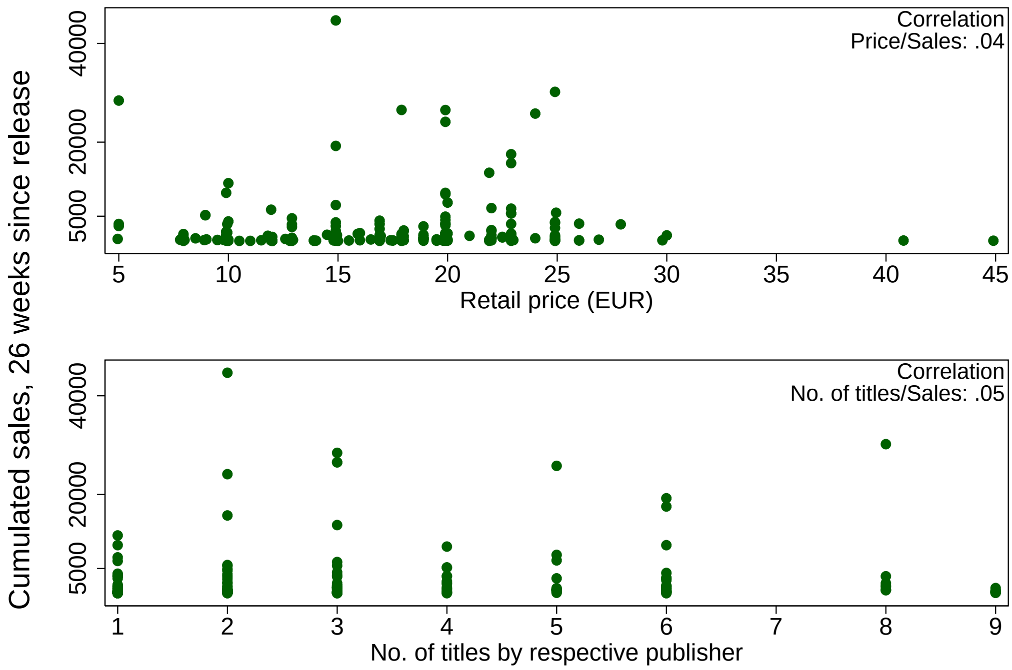
Note: graph omits 12 titles with observed total sales of over 20000 copies.

the best sellers drive the sample mean up to 3785 copies, the median title sells 704 copies only. Sorensen (2007) presents a similar graph based on U.S. data.

The data lack detailed information on title characteristics, but one might expect a title's retail price to proxy for characteristics like author reputation or the number of pages. Yet, in aggregate terms there does not seem to be a systematic relationship between a title's sales and its price: figure 3 relates cumulated sales after 26 weeks to price by title and gives the correlation coefficient, which is close to zero. The second panel in figure 3 relates sales by title to the number of titles a publisher has in the sample, a measure of firm size constructed from the publisher code. For the median title the measure is 1, but a number of publishers have multiple titles in the sample. There seems to be no correlation between this measure of publisher size and title sales.

The primary information contained in the sample are title-specific dynamics that underly week-to-week variation in sales. To illustrate both the variety of patterns observed in the sample as well as some of the estimation issues, figure 4 presents four example titles. Three observations can be made:

Figure 3: No evident relation between sales and price or publisher size



Note: graph omits one title with 26−week cumulated sales of 91939 copies and a price of 19.

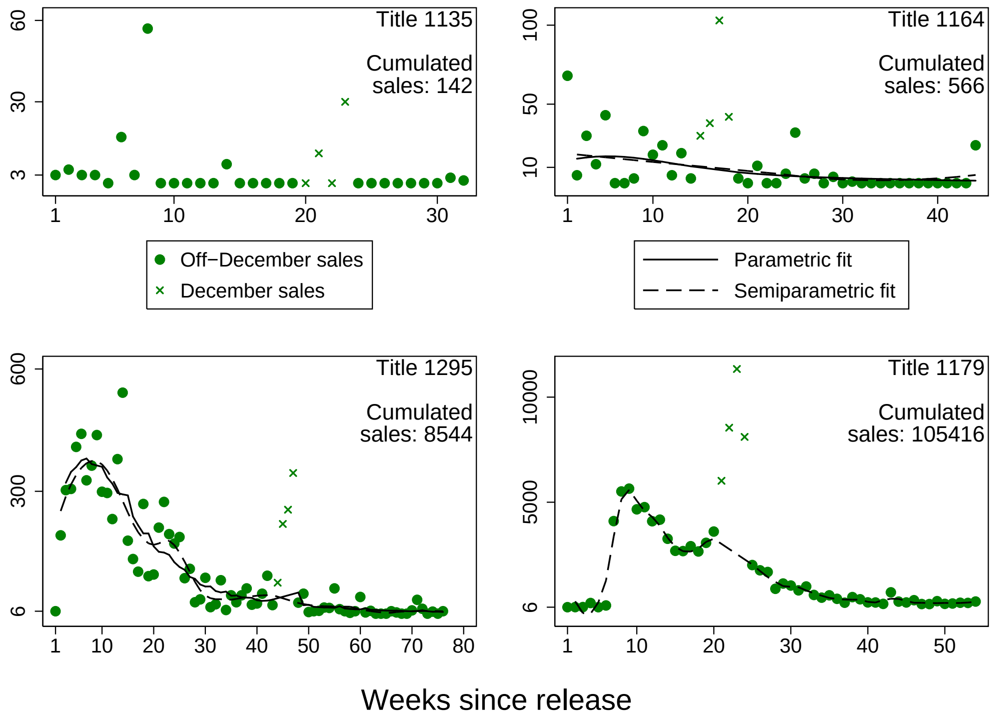
First, an evident pattern in all four examples is that December observations tend to depart quite starkly from whatever trend sales follow before and after December.[19] Obviously, books are popular Christmas presents, which introduces an additional identification problem for December observations. It is possible to estimate a separate Christmas effect for each title (Beck, 2007), but for the purpose of this paper, it suffices to merely acknowledge that this Christmas effect may lead December observations to deviate positively from a title's sales pattern before and after December. In practical terms, this amounts to placing zero weight to December observations in estimation of the word-of-mouth effect.[20]

Second, a significant share of the sampled titles, like title 1135 in the upper left panel of figure 4, has low overall sales and therefore zero sales in many weeks. For such a title, neither econometric method will yield useful results based on week-to-week variation.

[19]No other significant seasonal variation seems to be present. In a panel regression specification following Sorensen (2007), where $S_{i\tau} = (\alpha_i + \alpha_\tau + \beta t_{i\tau})S_{i\tau-1} + \varepsilon_{i\tau}$, τ denotes calendar weeks and $t_{i\tau}$ denotes title i's weeks since release at week τ, all off-December week fixed effects α_τ are insignificant.

[20]More details on estimation and interpretation of the Christmas effect can be found in section A.2 of the appendix. There, I also present regression results which indicate, on the one hand, that additional Christmas-driven sales do not have significant second-order effects on post-Christmas sales, and on the other hand, that any potential effect of strategic pre-Christmas release timing by publishers seems to be of minor importance.

Figure 4: Example titles



Altogether, 51 titles (22.2% of the sample) have less than 13 positive off-December sales observations before they reach 95% of cumulative sales. I assume that these titles, whose cumulative sales range between 1 and 796 with an average of 116, have not received positive word-of-mouth; I do not attempt to estimate any other parameter econometrically for these titles.

Third, for a number of titles, hump-shaped sales patterns such as those in the lower two panels of figure 4 suggest the existence of word-of-mouth effects. For other titles, such as title 1164 in in the upper right panel, sales variance is relatively high and it is difficult to infer a particular pattern merely by visual inspection. Therefore, figure 4 already includes predicted values from parametric and semiparametric estimations. These predictions turn out similar for titles 1164 (upper right) and 1295 (lower left): the smoothed series of title 1164 decrease quite constantly over time, while both methods indicate an early hump in sales for title 1295. In contrast, sales of title 1179 – which has the highest overall sales in the sample – remain at low levels initially and are hump-shaped only in later weeks. This is a case where parametric estimation is troublesome because, in the underlying model of positive word-of-mouth, the sales curve increases right from the start

Table 1: Distribution of parametric estimates*

	Mean	Minimum	Median	Maximum
Directly estimated:				
$M_i/N_i(T)$	1.1	.901	1.08	1.56
p_i	.103	.0118	.0541	.894
θ_i	.552	.0121	.606	.882
q_i	.914	.0213	.177	22
Indirectly estimated:				
w_i	.529	.0121	.172	10.3

*Summary statistics for 59 title-specific NLS results, based on equation 7 including time dummies for December observations (see section A.2 in the appendix).
For 12 of these titles, estimates base on an adapted version of equation 7 that includes AR(1) errors.

and has at most one stationary point. Therefore, in cases with multiple stationary points such as title 1179, NLS estimation based on equation 6 exhibits converges problems or converges only at boundary estimates for p and θ. Locally weighted regression, instead, is more adaptive to multiple stationary points and can thus identify patterns consistent with more general models of new-product diffusion.

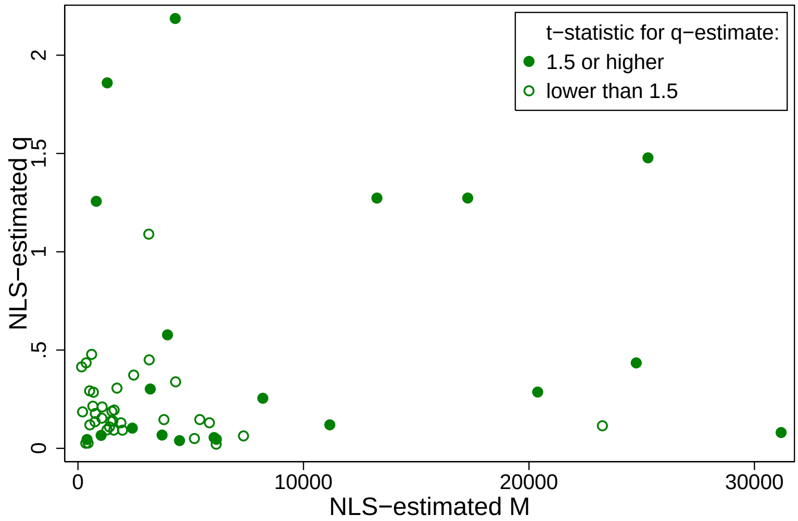
3.2 Estimation results

I apply the parametric and semiparametric estimators to all titles in the sample that have at least 13 positive sales observations before they reach 95% of observed cumulative sales (178 titles). Sales data for a title's release week are omitted from all estimations because they are not comparable to sales data for the following weeks: In contrast to theatrical movies, new books do not have a particular weekday for release. One title may be shipped on a Monday and another on a Friday, leaving only one or two sales days for the latter title's first calendar week.

Parametric results. As discussed earlier, parametric estimation based on equation 6 yields degenerate results for titles with steadily declining sales and does not converge for titles whose sales pattern requires a more general diffusion model.[21] Parametric estimation converges and yields nondegenerate results for 59 titles in the sample.

[21] I classify converged estimates as degenerate if they fulfill at least one of the following conditions: (*i*) $\hat{p}$ is smaller than .01 and not significantly different from zero, (*ii*) $\hat{\theta}$ is smaller than .01 or larger than .99 and not significantly different from zero or one (all with 95% confidence).

Figure 5: Correlation of word-of-mouth intensity and overall sales



Note: graph omits two titles with q−estimates larger than 10 (one insignificant, both M−estimates below 6000) and two titles with M−estimates larger than 32000 (q−estimates significant and below one).

The parametric test for the presence of positive word-of-mouth in sales of title i corresponds to a test for the significance of coefficient estimate $\hat{q}_i$. Within the set of nondegenerate results, $\hat{q}$ is significantly different from zero with 95% confidence for 23 titles. In other words, the parametrically estimated share of titles that received positive word-of-mouth is about 10%. Table 1 summarizes the corresponding coefficient estimates. To facilitate comparison across titles, the estimated total number of buyers $\hat{M}_i$ is summarized relative to observed total sales $N_i(T)$.[22]

The estimated hazard rate for sales to buffs ($\hat{p}_i$) is .1 on average, however, this average seems to be driven by some titles with high estimates. Mean and median estimates for the share of buff buyers are closer to each other (.55 and .61, respectively) and indicate that buff buyers tend to make up for the majority of sales also for titles with positive word-of-mouth.

To assess the relationship between word-of-mouth and total sales, figure 5 provides more details on the bivariate distribution of q- and M-estimates across titles. Most q-estimates are below .5 and whereas the few larger estimates are almost all significant, a good share of the lower estimates is significant as well. Altogether, across titles that seem to have enjoyed some word-of-mouth there is no evident relationship between its intensity (as measured by q) and overall sales (as measured by M).

[22]Since $\hat{M}_i$ does not include Christmas sales, it can be lower than $N_i(T)$ for titles with a large Christmas share.

Table 2: Distribution of total sales across titles with and without word-of-mouth

	No. of titles	Observed total sales Mean	Min.	Median	Max.	Price Mean	PubSize* Mean
Full sample	229	3785.0	1	704	105416	17.40	3.1
Estimation sample	178	4836.2	87	1250.5	105416	17.71	3.4
Parametric test for convex sales (95% confidence):							
not rejected	155	3743.6	87	1022	105416	17.66	3.3
rejected	23	12199.6	354	5911	43200	18.11	3.9
Semiparametric test for (locally) convex sales (95% confidence):							
not rejected	144	3561.6	87	1139.5	43200	17.83	3.3
rejected	34	10234.4	218	1983.5	105416	17.21	3.8

*Number of sampled titles published by the respective publisher.

Semiparametric results. The semiparametric test for the existence of word-of-mouth is directly based on the estimated shape of the sales curve. It draws on the theoretical result that positive word-of-mouth leads to a concave sales pattern around a title's peak sales. Loosely speaking, it is a simple test whether there is a sales peak after week 2. More technically, the semiparametric test corresponding to a test for q=0 in the parametric case is a test for convexity of the sales pattern around peak (maximum) sales. In particular, I reject local convexity if *loess*-predicted peak sales are significantly greater than predicted sales in week 2; that is, if the 95% confidence intervals around these two predictions do not overlap.

For example, the *loess* fit for sales of title 1164 in figure 4 is steadily decreasing. In such a case, the test is trivial because peak sales and sales in week 2 coincide, as well as their predicted values and confidence intervals, and convexity cannot be rejected. For titles 1295 and 1179 in figure 4, this test rejects convexity and thus indicates the existence of positive word-of-mouth. Altogether, the semiparametric test rejects convexity for 34 titles with 95% and hence suggests that less than 15% of the sampled titles received positive word-of-mouth.

Table 2 compares the distribution of total sales across the identified subsamples of titles with and without indication of word-of-mouth. For both methods of identification, subsample averages of observed total sales are significantly different (t-test, 99% confidence). On average, titles with signs of positive word-of-mouth perform better in terms of total sales, however, some of these titles have relatively low sales whereas some of the sample's best sellers are not estimated to enjoy positive word-of-mouth. The two success measures nominal sales and word-of-mouth can therefore lead to contrasting findings. In other words, a success measure based on word of mouth can lead to a different result than a measure based on sales alone, although the two measures are somewhat correlated.

Table 2 also summarizes retail prices (in Euro) and a measure of publisher size (the number of sampled titles published by the respective publisher) for each subsample. For both methods of identification, both average retail prices and publisher size do not differ significantly across titles with and without identified positive word-of-mouth (t-test, 95% confidence). These results suggest that predetermined title or publisher characteristics are of little help in predicting the occurrence of word-of-mouth.

4 Conclusion

In this paper, I propose a novel approach to study new-product success in creative industries. The empirical strategy to identify a profitable product is based on the standard terms of contract between creator (author) and producer (publisher), combined with a parsimonious model of new-product diffusion. In this context, measures of positive word-of-mouth are better indicators of publisher profits than measures based on absolute sales, because prominent authors can appropriate a large share of a product's expected revenues in *ex ante* bargaining. The existence and extent of positive word-of-mouth can be identified from a products's intertemporal variation in sales by either parametric or semiparametric estimation methods.

In an application to a random sample of novels, estimation results indicate that between 10 and 15% of titles enjoy positive word-of-mouth. Estimates of positive word-of-mouth are imperfectly correlated with a title's total sales and are not correlated with predetermined title characteristics such as a title's retail price. These findings support the view that the title-specific extent of word-of-mouth is extremely difficult to foresee and that choice of measure is important in studying new-product success.

The results are in line with Diderot's (1763) rule of thumb that one out of ten published books is a commercial success. If Diderot's rule is an appropriate description of market conditions in 1763, then changes in information technology since then do not seem to have much affected the odds of success in the book industry. I therefore suspect that current and future technological changes such as the internet revolution will not significantly improve its new-product success rate.

It is likely, however, that new technologies decrease costs of production and distribution. Even with constant or slightly decreasing sales by product, this will have a positive effect on the number of new books and thus variety in the market as predicted by Anderson (2006) and Hendricks and Sorensen (2009), because the investment requirements to produce a book decrease.

In the medium and long term, new technologies may also change the relationship between creators and producers. One possibility is that creators simply turn to producing and marketing their product themselves, as it becomes easier and less expensive to do so. For example, the number of self-published authors, who typically produce their books by print-on-demand, has risen over the last years. Another possibility is that creators and producers work more closely and concentrate on developing the content together, leaving physical production and distribution to service providers. In either case, the terms of contract and the distribution of revenues and profits across the value chain are likely to change.

A Appendix

A.1 Data characteristics

The data used in this paper is a sample of novels released 2003 as hardcover in Germany. This is a representative sample that I drew myself on location at the data provider (*Media Control GfK International*) from the set of all hardcover novels released in 2003. Sampling was based on a computer-generated list of random numbers. *Media Control GfK International* aggregates scanner data from over 750 points of sale (bookshops, department stores) as well as all main internet retailers in Germany. Not sampled are direct sales from publishers to consumers, book club sales and mail order sales. Supermarket sales are also not sampled, but they represent a negligible portion of German book sales. Altogether the sampled retail channels account for about 66% of total book sales in Germany. Yet, for the particular segment studied here (novels in hardcover), sales coverage of sampled channels is likely to be much higher. First, publisher direct sales are not very important for popular publications such as novels; direct sales usually concern professional publications. Second, book clubs can be regarded as a secondary market that only becomes important for a title after its diffusion in the primary market (which is studied here). Furthermore, no particular estimation bias arises from this type of sampling. By law, book prices are the same for all retail channels.[23] In theory, buffs may be more inclined to order directly from publishers because they do not need retailer advice; in practice, however, title availability is high and ordering processes are quicker (typically overnight) at stationary bookshops and online retailers. Direct orders from publishers are thus unattractive for non-professional buyers.

The raw data indicate negative sales – books returned by consumers after purchase – for 18 weekly observations. A good share of these take place in January and thus seem to be mis-given Christmas presents. In estimations, I replace sales with value zero in these observations. In addition, data for some titles appear to contain advance orders erroneously booked as sales: sales of 1, 2 or 3 copies followed by a number of zero-sales, long before sales actually take off with two- and three-digit weekly sales.[24] I therefore apply an automatic procedure to identify the most evident cases, namely those in which a

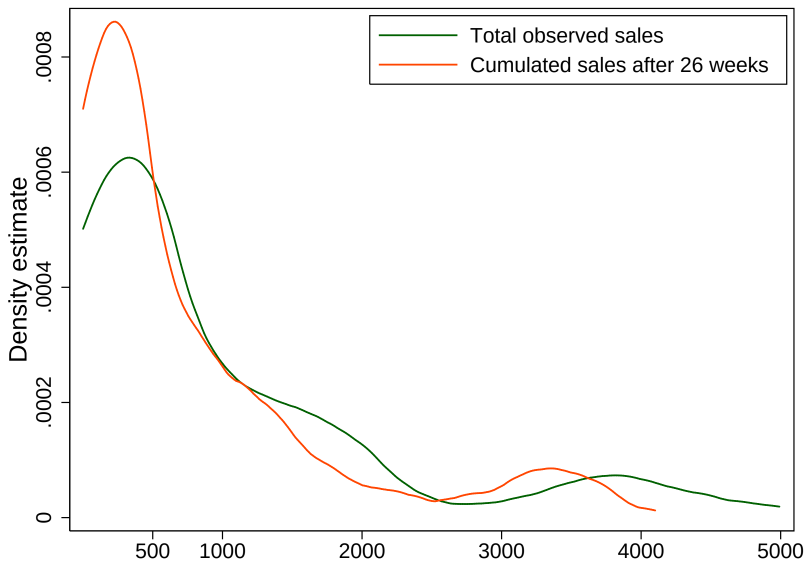
[23]In many European countries including Germany, book prices are by law subject to resale price maintenance; that is, retailers must not offer discounts from the publisher's list price.

[24]In fact, each observation of sales of 1, 2 or 3 may arise from just one pre-ordered copy because some points of sale from which the data were aggregated have a sample weight larger than one.

first sales observation of 1, 2 or 3 copies is below the respective title's average weekly sales (based on weeks with nonzero sales) and is followed by a zero-sale week. I assume that such an observation represents an advance order and add the amount to the following observation of positive sales, which I assume to be the effective release week. Since a few titles seem to exhibit multiple weeks with such advance orders, I repeat the procedure four times. In a similar exercise, I also interpret all first-week sales observations of sales of 1 to 3 copies as advance orders whenever they were below 10% of the title's average sales (based on weeks with nonzero sales). The main goal of these procedures is to identify a title's effective first sales week. They leave all other aspects of estimation essentially unaffected because first-week sales observations are omitted from estimations.

The initial sample consisted of 307 titles, but many of those were actually not sold before 2004 or very late in 2003. This is not unusual because a title's release year is determined with publication of the publisher's season catalogue, long before the start of the season. For many titles the production process is not yet finalized at that point. Therefore, a late start of observed sales is a sign of delayed release rather than weak demand. In order to ensure a sufficient number of observations per title, I restrict attention to the 229 titles in the sample that began selling before mid-October (week 43 of 2003).

Figure 6: Distribution of cumulated sales across titles



A.2 The Christmas effect

Christmas-driven purchases are usually concentrated on the December weeks (t_D; D=1,...4) and can boost a title's sales significantly. This raises three empirical points to discuss in this section: First, we have an additional identification problem because in each of the four December weeks, sales $S_i(t_D)$ now consist of three parts: Christmas-driven sales $s_i^x(t_D)$ in addition to the 'usual' model part $f(t)$ and the error term ε_{it_D}. Second, Christmas-driven sales may have second-order effects on sales after Christmas. Third, if Christmas sales are so important, publishers may engage in strategic release timing.

For the moment, suppose that $f(t)$ and $s_i^x(t_D)$ are independent (supportive evidence is presented below). For parametric identification of $f(t)$, I include time dummies for each December week, whose coefficients (λ_D) are assumed to be non-negative. With respect to estimation of model parameters, this amounts to placing zero weight on December observations only when they are above the title's specific trend. Predicted values from the original function to be fitted are then unresponsive to December spikes, and the λ-coefficients capture all sales in excess of those predicted by the otherwise best-fitting set of parameters. Provided $E[\varepsilon_{it_D}]$=0, the sum of these coefficients may then be interpreted as an estimate for a title's extra Christmas sales: $\tilde{S}_i^x = \sum_D s_i^x(t_D) = \sum_D \hat{\lambda}_D$.[25] On average, parametrically estimated extra Christmas sales $\tilde{S}_i^x$ represent about 10% of the average title's overall sales; for some titles, however, $\tilde{S}_i^x$ represents up to one third of overall sales.

If one is interested primarily in estimating $f(t)$, a simple solution to the Christmas identification problem is to place zero weight on December observations in estimation. I follow this approach for the semiparametric estimation results presented in this paper. The underlying assumption is again that $f(t)$ and extra Christmas sales ($s_i^x(t_D)$) are independent. This assumption would be violated, for example, if extra Christmas had a second-order effect on sales after Christmas - which brings us to the second point.

In order to assess the validity of this assumption, I first use the semiparametric model to obtain a title-specific estimate of extra Christmas sales ($\hat{S}_i^x$). Provided $E[\varepsilon_{it_D}]$=0 and given an estimated smooth function $f(t)$ for observed pre- and post-December sales, I impute December values $f(t_D)$ by interpolation. An estimate for extra Christmas sales in December week t_D is then the difference $S_i(t_D) - f(t_D)$ whenever it is positive, or

[25] Alternatively, one may specify a functional form for $s_i^x(t_D)$ and its relation to $f(t)$ and ε_{it}.

zero else. Yet, weekly sales are differently variant across titles (heteroskedastic), which affects this estimate of $s_i^x(t_D)$. As a more robust estimate that enables comparison across titles with different sales variances, I therefore use the upper limit of the prediction's confidence interval $f^{\bar{CI}}(t_D)$ in calculating extra Christmas sales:

$$\hat{S}_i^x = \sum_{t_D=1}^{4} (S_i(t_D) - f^{\bar{CI}}(t_D))\, \mathbb{1}(S_i(t_D) > f^{\bar{CI}}(t_D)).$$

Based on this estimate for S_i^x, I assess a potential relationship between a title's extra Christmas sales and its post-Christmas performance by running the following cross-title regression:

$$\frac{\mathbf{N_i^{2004}}}{\mathbf{N_i^{2003}} - \mathbf{\hat{S}_i^x}} = \overset{(1.16)}{\underset{(1.76)}{\mathbf{1.46}}} \quad \overset{(-.04)}{\underset{(-.02)}{-\mathbf{.03}}}\ \mathbf{T^{2003}} \quad \overset{(-.09)}{\underset{(+.33)}{+\,.12}} \frac{\mathbf{\hat{S}_i^x}}{\mathbf{N_i^{2003}} - \mathbf{\hat{S}_i^x}} \quad + \varepsilon_i,$$

$$\text{where} \quad i = 1, ..., 176 \ (R^2 = .25).$$

In this regression, N_i^{2004} denotes sold copies observed for title i's in the first half of 2004, N_i^{2003} denotes sold copies observed for title i's since its release in 2003, and T^{2003} denotes the number of weeks title i has been sold in 2003 (52 minus its 2003 release week). In other words, the regression relates a title's level of observed 2004 sales (relative to 2003 non-Christmas sales) to the number of weeks it has been for sale in 2003 as well as to the level of extra Christmas sales (relative to 2003 non-Christmas sales). Bracketed numbers indicate 95% confidence intervals for the estimates (centred).[26] The estimated coefficients indicate, for example for a title released in mid-2003 (hence T^{2003}=26), that on average 2004 sales represent about 68% of 2003 non-Christmas sales. The estimated effect of extra Christmas performance is modestly positive on average but not significantly different from zero (an increase in $\frac{S_i^x}{N_i^{2003} - S_i^x}$ by .25 – about one standard deviation – is associated with an increase in relative 2004 sales by about 3%-points on average.). Hence, additional Christmas-driven December sales do not seem to induce significant second-order sales effects in the new year.

[26]Confidence intervals do not account for the fact that $\hat{S}_i^x$ is itself the result of an estimation and are therefore too narrow. Furthermore, the above estimates exclude two titles that due to large sales shocks in 2004 have very large values of N_i^{2004}/N_i^{2003}. In a regression that includes these two titles, all coefficients are insignificant.

The third Christmas-related point that may affect estimation results is strategic release timing: do publishers strategically choose release times for titles that are expected to do well in the Christmas season? A simple approach to this question is to assess whether a title's extra Christmas sales are related to its release date (its distance to Christmas). Regressing extra Christmas sales, relative to overall non-Christmas sales (N_i), on release week (T^{2003}) gives the following result:

$$\frac{\mathbf{\hat{S}_i^x}}{\mathbf{N_i} - \mathbf{\hat{S}_i^x}} = \underset{(.40)}{\overset{(.24)}{\mathbf{.32}}} \quad \underset{(-.004)}{\overset{(-.009)}{\mathbf{\text{-}.006}}}\ \mathbf{T^{2003}} \quad + \varepsilon_i,$$

$$\text{where} \quad i = 1, ..., 178 \ (R^2 = .12).$$

These estimates indicate that the relationship between release timing and Christmas sales is indeed modestly positive: moving a title's release date one week closer to Christmas is associated with an estimated increase in the relative size of Christmas sales by .006%-points. Yet, it is unclear whether this effect is a strategic one. A confounding effect is that older titles are less attractive as Christmas presents because they have a higher probability that the donee already knows them. Given the relatively modest economic effect and the high variance in the data as indicated by a low R^2, I conclude that strategic release timing with respect to Christmas seems to be of minor importance.

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