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Replication

Revisiting firm-created word of mouth: High-value versus low-value seed selection

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ABSTRACT

A field test similar to Godes and Mayzlin's (2009) conceptually replicates the sales effect of word-of-mouth campaigns and empirically confirms Haenlein and Libai's (2013) findings that seeds with high value to the brand are preferred among noncustomers of the product because they show the largest effect on incremental sales. Seeds with low value to the brand, as in Godes and Mayzlin's study, may be preferred if marketers are limited to work with product customers only. Additionally, those peers that are unaware of the campaign product, but have bought the brand in the past are mainly responsible for incremental sales.

1. Introduction

Godes and Mayzlin (2009; henceforward G&M09) first identified the positive, incremental sales effect of firm-created word-of-mouth (WOM) campaigns or "seeding programs" (Haenlein & Libai, 2013; henceforward H&L13). In such campaigns, volunteer seeds receive product information and samples, then recommend the campaign product to their many peers (Berger & Schwartz, 2011). Selecting seeds is a critical strategy; using network assortativity concepts (Aral, 2011), G&M09 suggest selecting unaware noncustomers or less valuable customers of the campaign product—both called non-loyal consumers—as seeds, because they are more likely to know equally unaware and untapped peers. In a field test, G&M09 find a weakly significant incremental sales effect only for the WOM activity of non-loyal seeds. This idea is supported by Kumar, Petersen, and Leone (2007, 2010) who find that targeting customers with low referral value leads to higher incremental profits. In contrast, H&L13 suggest selecting seeds with high prior customer value to the brand, because more valuable seeds know more valuable peers. They confirm this notion in an agent-based simulation.

Faced with two seemingly conflicting seed selection strategies, we seek to conceptually replicate the G&M09 field test and re-investigate the incremental sales effect of a WOM campaign with seeds of higher or lower value to the brand. We use actual WOM campaign data and run a comparable sales regression model. The results may partly resolve the seemingly conflicting recommendations of G&M09 and H&L13. Their recommendations conflict, we argue, because these authors study different stages of the campaign product life cycle, with different availability of certain seed types.

Both G&M09 and H&L13 select seeds to reach peers unaware of the campaign product in order to generate incremental sales. But H&L13 consider a product innovation, so no seed is aware of or consumes the campaign product. Optimal seeding targets valuable consumers—necessarily based on prior brand consumption history—because these seeds likely know more valuable peers.

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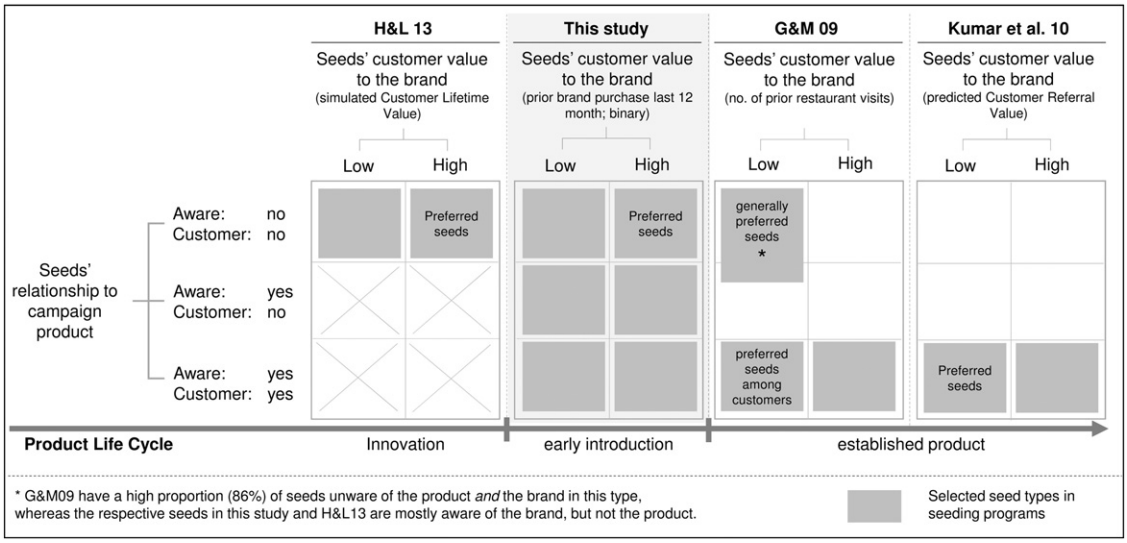

Fig. 1. Studied seed types in related literature.

Instead, G&M09 consider an established product with low awareness of product and brand. Similar to Kumar et al. (2007, 2010), they can select existing product customers, with higher or lower value to the brand—called loyal and less loyal customers. They assume that loyal customers have spread WOM previously, so peers are already aware of the product and have either adopted or not. Consequently, they favor selecting less loyal customers as seeds. Alternatively, G&M09 can draw from a group of product noncustomers (mostly unaware of product and brand), whom they consider comparable to less loyal customers. Integrating these considerations, Fig. 1 shows that seeds can be unaware noncustomers, aware noncustomers, or customers of the campaign product, while also differing in their prior customer value towards the brand. The current study extends the research stream to these six seed types. Furthermore, this study validates the network assortativity-based arguments of H&L13 and G&M09 by including data from WOM-receiving peers.

2. Field test design and models

Our WOM campaign selected 15,000 seeds from a WOM agency panel. It ran for eight weeks in a European market with no other marketing activity in parallel (see Table 1 for study settings and the respective settings in G&M09). The campaign featured a new soft drink by a well-known brand.[2] The recently introduced soft drink was available before the campaign but still low in product awareness, similar to G&M09. A key difference, however, is the high brand awareness in our study. While the unaware noncustomers in G&M09 include many seeds completely unaware of the product and brand, our respective seeds are mostly aware of the brand.

To determine seed type in our study, seeds stated whether they knew the campaign product (aware/unaware), and whether they bought this product before the campaign (customer/noncustomer). Furthermore, they stated whether they bought the brand in the last year (yes/no: high/low value customer), which is a different and weaker proxy measure of customer value compared to the Customer Lifetime Value simulated in H&L13, and also compared to the restaurant visits measured in G&M09.

Thus, our study differs from G&M09 regarding product category, product life cycle stage, brand awareness, and measures of customer value. It is, in the broadest sense, a conceptual replication.

We counted and aggregated WOM reports by seed type, week, and region to generate WOM activity variables for the model. The weeks and regions correspond to the 8 weeks and 11 sub-regions of sales data. Seeds could share survey cards among their peers (Carl, McGlinn, & Oles, 2007). We considered all peer survey counts as a measure of received WOM. By aggregating across self-reported peer type, week, and region, we generated the received WOM variables.

Similar to G&M09, our model structure is:

$$Sales_{it} = \sum_{c \in C} \omega_{it}^{c} \cdot WOM_{it}^{c} + \sum_{i=1}^{11} \mu_i + \sum_{t=1}^{8} \tau_t + \varepsilon_{it},$$

where $Sales_{it}$ is unit sales in region i in week t; WOM_{it}^{c} represents the WOM counts (seed or peer) in region i in week t, with c indicating the respective condition of the six seed/peer types; and μ_i accounts for differences between regions, τ_t for week effects, and ε_{it} is the normally distributed error term.

[2] At the request of the WOM agency and brand, we do not reveal specific names or precise revenues.

Table 1
WOM campaign field test settings.

Article	Product	Size	Data		
			Sales data	Seed data	Peer data
Godes and Mayzlin (2009), pp. 725–727	Food/drinks product; Brand: Rock Bottom Brewery. (Maximum 14% brand and product awareness among noncustomer seeds)	1000 seeds in 15 U.S. markets (unknown target population)	Sales ($); 15 markets × 12 weeks = 180 data points	Seed survey counts	–
This study	Soft drink product; Brand: Large soft drink brand (29% product awareness and 98% brand awareness among noncustomer seeds)	15,000 seeds in a European country (less than 0.1% of the target population)	Unit sales; 11 regions × 8 weeks = 88 data points	Seed survey counts	Peer survey counts

3. Results

Table 2 shows several models replicating the recommendations and arguments of G&M09. The Cohen's d effect sizes were calculated from the coefficient t-statistics (Ellis, 2010), to account for the smaller sample size and different degrees of freedom. Our models show the goodness of fit (R^2 and R^2 beyond the market fixed effects) comparable to G&M09. Variance inflation factors (all <6) indicate no problem with multicollinearity.

Table 2
Model results.

Seed/Peer type (Pr) = of product (Br) = to brand	Parameter	G&M09 Model 2 (p.729): Seed data	Model 1: Seed data	Model 2: Seed data	Model 3: Seed data full	Model 4: Peer data full
Noncustomers (Pr)	B (p)	192.00 **(.066)**	49.233 **(.069)**	52.798 **(.055)**		
	T	1.85	1.847	1.956		
	d	.300	.448	.478		
Customers (Pr)	B (p)	−55.16 (.58)	−2.344 (.971)			
	t	−.55	−.037			
	d	.089	.009			
Unaware noncustomers (Pr), low value (Br)	B (p)				−5.888 (.925)	−9.702 (.849)
	t				−.094	−.191
	d				.024	.048
Unaware noncustomers (Pr), high value (Br)	B (p)				98.496 **(.034)**	84.090 **(.055)**
	t				2.168	1.956
	d				.542	.489
Aware noncustomers (Pr), low value (Br)	B (p)				−70.404 (.588)	131.613 (.297)
	t				−.544	1.052
	d				.136	.263
Aware noncustomers (Pr), high value (Br)	B (p)				73.550 (.315)	−11.738 (.874)
	t				1.012	−.160
	d				.253	.040
(Aware) customers (Pr), low value (Br)	B (p)			197.976 (.402)	180.421 (.456)	−137.722 (.274)
	t			.843	.751	−1.104
	d			.206	.188	.276
(Aware) customers (Pr), high value (Br)	B (p)			−22.713 (.739)	−17.385(.807)	−6.735 (.923)
	t			−.335	−.245	−.097
	d			.082	.061	.024
N		180	88	88	88	88
R^2 total model		>.95	.925	.925	.928	.929
R^2 beyond market-fixed effects		.253	.226	.245	.318	.312
F		3.97	43.865	41.580	35.928	36.392
Pr > F		.000	.000	.000	.000	.000

Notes: Parameter estimates for regions and weeks are not shown, as in G&M09; the data are available as a web appendix. B = parameter estimates. d = Cohen's d. T = t-statistics. Any p-values below .10 are in bold. Cohen's d is calculated from the t-statistic (Ellis, 2010). R^2 statistics beyond market fixed effects are similar to G&M09 (footnote 10, p.728).

Model 1 replicates the main model and G&M09's results (their model 2, p. 729): Product noncustomer seeds show larger incremental sales effects than customer seeds. In Model 2, though not significant, product customer seeds of low value to the brand show larger effect sizes than customers of high value to the brand, in line with the arguments of both G&M09 and Kumar et al. (2007, 2010). Including all available seed types in Model 3 reveals instead that product unaware noncustomers of high value to the brand show the largest effect, consistent with H&L13. Model 4 supports this finding with the peer data: The product unaware noncustomer peers of high value to the brand drive incremental sales. These results integrate and empirically validate the assumptions of G&M09 and H&L13 about attempting to reach peers unaware of the product, as well as the more specific suggestion of H&L13 focused on peers with high potential value to the brand.

4. Discussion

Our study integrates seemingly conflicting findings of G&M09 and H&L13. We argue that these extant studies differ in their seed type recommendations because they considered different marketing access for working with certain seed types. If access is limited to existing product customers (e.g., marketers only have access to a customer database), marketers should consider seeding to customers of lower value—consistent with the argument in G&M09. In this scenario, these seeds are more likely linked to still untapped noncustomer peers than the alternative customer seeds of higher value, because the latter have already recommended the product.

If marketers can seed unaware noncustomers of a campaign product (e.g., when using agency panels), they should focus on seeds of high expected customer value (based on prior brand history), because these seeds are likely linked to similar untapped peers—consistent with the argument in H&L13. In our study, such product unaware noncustomer seeds and peers of high value to the brand mainly drive incremental sales.

Access to certain seed types can vary over product life cycles. For a product innovation, all seeds are still unaware noncustomers of the product and the most important issue for practical implementation deals with identifying customer value. All studies considered here differ in regard to the measure and definition of customer value to the brand, and none of these measures is applicable without prior brand history.

For an established product, access could extend to both existing customers and to noncustomers aware or unaware of the product or brand. G&M09 and our study show an incremental sales effect for seeding to noncustomers unaware of the product, irrespective of whether the seeds are aware of the brand (this study), or not (G&M09). Future work could focus on the different awareness levels of the brand in more detail.

Another question pertains to the case of a mature product with high product awareness and few untapped noncustomers remaining. Here, the arguments by both G&M09 and H&L13 would fail. We suggest that in this case, persuasion rather than awareness becomes important, and studying seeding at more mature stages would provide a fruitful avenue for further research.

We study a low awareness, low risk product, similar to G&M09 and H&L13. Within these bounds, we confirm the incremental sales effect of WOM campaigns. Using the WOM agency's proprietary information, we calculate a short-term revenue-to-cost ratio of 1.5, which corresponds to industry studies for similar campaigns. Thus, our study adds to the scientific body of research on WOM campaigns and seeks to answer practitioners' calls for more solid proof of the effects of WOM campaigns on sales.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ijresmar.2016.01.002.

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