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Charts and demand: Empirical generalizations on social influence

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ABSTRACT

Social influence on consumer behavior has long been a subject of academic research in various scientific fields. According to research by Salganik, Dodds, and Watts (2006), music demand is a function of social influence between consumers. Market concentration tends to increase when information on demand becomes publicly available. In addition, stochastic agglomeration caused by social influence decreases the predictability of market success. These heavily cited findings challenge traditional market research and provide important insights on the impact of social media and sales charts. We test the stability of their results by replicating the study on music demand in a slightly different setting. We further investigate the generalizability of findings by probing other product categories and different phases of purchase decisions, i.e., interest, consideration, and actual demand. Across all categories and across all dependent variables, we are able to replicate the direction of the effects. We do, however, consistently obtain smaller effect sizes than reported in the original paper.

Market research often relies on aggregated data provided by independent consumers. However, social influence and striving for conformity have an undeniable influence on individual behavior. The concept of social influence has been widely analyzed in different scientific fields and settings. Researchers employed individual-level experiments to demonstrate social influence of (reference) groups and conforming behavior (e.g., Asch, 1951; Bearden & Etzel, 1982; Burnkrant & Cousineau, 1975; Deutsch & Gerard, 1955). A large proportion of social influence research focuses on an aggregated macro perspective. Herding effects and information cascades are typically modeled theoretically, based on secondary or simulated data (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992, 1998; De Vany & Lee, 2001) and are rarely analyzed in laboratory settings (Anderson & Holt, 1997). The same holds true for social contagion and subsequently diffusion processes (Granovetter, 1973; Katz & Lazarsfeld, 1955; Rogers, 1962; Van den Bulte & Lilien, 2001).

In their seminal paper, Salganik et al. (2006) (SDW) demonstrate in a very controlled, yet realistic large-scale setting that the success of music products is not only a function of independent quality perceptions but also strongly driven by other consumers' choices. The authors report results from an experimental music website and show that public information on aggregate demand increases concentration of music markets. Furthermore, small and coincidental agglomerations of demand can attract cascades of customers and reduce predictability of market outcomes. These results are an important foundation for many recent marketing publications (e.g., Broekhuizen, Delre, & Torres, 2011; Chen, Wang, & Xie, 2011; Kuksov & Wang, 2013; Tucker & Zhang, 2011). They are also of timely interest for marketing practice since new social media and e-commerce sites often provide information on sales ranks for various product categories (e.g., amazon.com, iTunes). Despite this, we are not aware of any study replicating SDW's empirical findings. Consequently, there is a lack of information on the size and generalizability of the observed effects (Farley, Lehmann, & Sawyer, 1995).

We test the stability of SDW's results by employing a similar online music setting, for which we programmed separate online worlds to track and display previous respondents' decisions. While capturing actual demand is a natural objective of marketing, managers are often interested in and conduct research on earlier stages of the decision making process (e.g., De Bruyn & Lilien, 2008; Hauser, Toubia, Evgeniou, Befurt, & Dzyabura, 2010; Venkatesan, 1966). We therefore test the generalizability of social influence throughout the decision making process (general interest, consideration, and actual demand). In addition, we investigate whether the effect is generalizable across other cultural and non-cultural product domains by running experiments on movies and scarves. We chose a fashion product as a third category because the identity relevance of such publicly visible products can lead to reduced or even reversed effects (Berger & Heath, 2007; Kuksov & Wang, 2013).

We recruited 1143 participants using a commercial online panel and randomly assigned them to either an independent or a social influence condition (cf. SDW). Respondents consecutively chose products in three categories (music, movies, and scarves) where they were able to (1) listen to and obtain songs (actual demand), (2) indicate general interest in individual movies and (3) indicate which scarves they would consider in an actual purchase decision. In the social influence condition, participants received information on how many times a product

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Table 1
Market shares and Gini coefficients.

		Present study		SDW[a]	
		Independent	Social influence	Independent	Social influence
Music demand	Top 5 market shares (%)	4.44–4.84	4.55–7.37	3.5–3.6	13.0–20.0
	Bottom 5 market shares (%)	1.92–2.52	1.16–2.13	.5–.9	.5–1.0
	Gini coefficient	.147	.220	.2	.45–.55
	t-Test	p < .001		p < .001	
Movie interest	Top 5 market shares (%)	2.04–4.34	3.96–4.85	–	–
	Bottom 5 market shares (%)	2.42–2.74	2.44–2.74	–	–
	Gini coefficient	.088	.105	–	–
	t-Test	p < .001		–	
Scarf consideration	Top 5 market shares (%)	4.32–5.59	4.82–6.11	–	–
	Bottom 5 market shares (%)	1.82–2.48	1.74–2.22	–	–
	Gini coefficient	.155	.178	–	–
	t-Test	p < .001		–	

Note: Reported Gini coefficients for the independent condition are averages of Gini coefficients generated for each of 1000 splits of the independent group. The significance test was conducted by testing the difference between the independent Ginis and the social-influence Gini (present study) or a randomly drawn Gini of one of eight social-influence conditions ("worlds", SDW) against 0.
[a] SDW report their Gini coefficients and market shares graphically and do not differentiate market shares for different social-influence "worlds". For exact p-value and method also see SDW's supporting material.

was chosen by previous participants. In the independent condition no such information was provided (see Appendix A for details of the experimental design).

Across all categories and throughout all phases of the purchase decision process, our results confirm the findings of SDW. On an aggregate level, social influence results in herding effects which appear to dominate possible motivations to diverge. As a consequence, demand for popular songs, movies, and scarves increases whereas unpopular products become even less popular. To statistically test these relationships, we calculate Gini coefficients for each market condition[1] (cf. SDW). We employ bootstrapping to test for statistical significance and find significantly higher values for the social influence than the independent condition for music demand (.220 > .147, p < .001), movie interest (.105 > .088, p < .001), and consideration of scarves (.178 > .155, p < .001). Our findings indicate that the popularity of products is amplified by social information in the positive as in the negative. They also confirm the findings of SDW, who reported directionally similar but notably larger effects for music downloads (.45 to .55 > .2, p < .001) (Table 1).[2]

In line with SDW, we find that independent responses of customers are a better predictor of market success for independent than for social influence markets. The correlation between market shares of random samples of the independent condition is slightly but consistently higher than the correlation between the individual and the social influence condition for music (.771 > .767, p < .01), movies (.832 > .822, p < .001), and scarves (.946 > .933, p < .001). Specifically, popularity and sales ranks of products with intermediate sales are least predictable among the products in our sample. However, the top- and bottom-ten-percent of independent markets remain in the top- and bottom-ten-percent in the social influence markets. Thus, quality has an important impact on consumer decision making. However, for the top and bottom products the effect of quality on demand appears to be amplified by social influence. In terms of actual market share, the top ten products generally gain share through social influence as compared to the market shares in the independent market (on average 2% for music, 4% for movies, 8% for scarves) while the bottom ten loose market shares (−20% for music, −1% for movies, and −5% for scarves). For intermediate products, the direction of market share changes is unpredictable. For example, we observe decreases by up to 40% but also increases by up to 65% in the artificial music markets. This pattern is also reflected in larger differences in sales ranks for intermediate than for top and bottom ranking products. We do, however, note that throughout all categories, differences in market shares and sales ranks are smaller than the ones identified by SDW who show some market shares quintupling due to social influence.

Our findings have various implications for marketing managers and researchers. First, they suggest that companies across industries must expect shifts in market shares whenever social media sales ranks become popular. While traditionally sales charts were mostly available for cultural products (e.g., box office charts, bestseller lists, and "Billboard 100" charts) (Bradlow & Fader, 2001), sales ranks across product categories are now readily available online as a feature on most e-commerce sites (e.g., amazon.com, iTunes). As aggregate information on consumer behavior exerts social influence and modifies consumers' interest, consideration, and demand, this can result in market share gains or losses. If a company offers a high quality product which already has – or is anticipated to have – high market shares, sales channels which feature sales rank information are likely to result in higher sales. This research provides further evidence that quickly increasing a product's position in sales ranks can stimulate additional demand. Such tactics will be profitable whenever additional demand outweighs initial sales rank investments (Bikhchandani, Hirshleifer, & Welch, 1998). Second, firms are faced with lower predictive validity of traditional market research due to the stochastic nature of market share agglomerations. While market research will underestimate demand for popular and overestimate demand for unpopular products, no correction factors are conceivable for intermediate products. We note, however, that the effects we observe are consistently smaller than the ones reported by SDW. Third, our results are stable and significant, even though we have a smaller number of respondents and did not generate the same amount of worlds as in the original SDW paper. Apparently, steady states in social influence experiments can be reached with fewer respondents than previously reported by SDW. Therefore, effects of social influence can be assessed at lower costs than the original study of SDW suggests. Since the size of the effects varied across the product categories we have investigated, firms may be interested in testing the actual effect in their respective market. It appears this can be done at reasonable costs.

There are also limitations to this research. We note that market concentration and unpredictability are likely to be a positive function of product variety. We have kept the amount of alternatives constant at 30 per category to allow for a meaningful comparison. It would be interesting to test a possible minimum amount of variety for social influence

[1] The Gini coefficient ranks between 1 (total market concentration) and 0 (no market concentration). The Gini coefficient (G) is calculated based on the market shares (m_i) across all products (S): $= \sum_{i=1}^{S} \sum_{j=1}^{S} |m_i - m_j| / 2S \sum_{k=1}^{S} m_k$ (see Appendix A).

[2] Our market shares are less distinct and the market concentration as measured by the Gini coefficient is generally lower than SDW's (2006) because we used fewer products (30 instead of 48) and observed a higher number of average demand (2.64–7.47 compared to 1.4, see Appendix A).