

The Impact of Scarcity Messages on the Online Sales of Physical Information Goods

Stefan Cremer
University of Cologne
stefan.cremer@uni-koeln.de

Abstract

For physical consumer goods with no considerable information component, past research has identified scarcity, due to market conditions or as a producer strategy, as a driver of intention to purchase and willingness to pay. In contrast, information as the major value-creating component of physical information goods is inherently non-scarce. While anecdotal evidence suggests that intended or unintended scarcity can benefit sales of physical information goods, the underlying mechanisms have not been systematically investigated so far. To close this gap, this research develops a model based on an extensive literature review. The model is tested against evidence from e-commerce sales data of 34,748 information goods. We find that quantity-based scarcity overall decreases sales, but is associated with an increase in the quantity purchased among all purchasing customers. We discuss implications for theory development around the scarcification of information.

1. Introduction

Scarcity of goods has long been recognized as a fundamental principle of economic theory, driving the existence of markets, pricing, and revenues. As innovative, marginal-cost-reducing technologies emerge, scarcity has decreased for many types of goods [1], particularly for valuable and commoditized information, or short 'information goods'. Consumers may still value non-scarce goods, such as digital information goods, and consider them important, but they are often not willing to pay for them.

At the same time, and different from past predictions, physical information goods still play a surprisingly large role and are far away from having disappeared from today's markets. In 2014, the global print book market accounted for USD 102bn of revenue, which equals 70% of the total global book

market [2]. In the US home entertainment market, sales and rental of physical video formats (DVD and Blu-ray) amounted to revenues of USD 8bn in 2016, which is 44% of the overall market volume at that time [3].

Instead of causing disappearance of physical information good assortments, technology has largely increased their size due to lowered cost of offer. At the same time, inventory is commonly very low particularly for physical information goods in the long tail, as predicted by economic order quantity theory.

Even though low inventory may activate thinking patterns related to 'traditional scarcity', market transparency has become the really scarce resource – especially in information good markets. Many large Internet companies tailor their business model around making markets again transparent – or at least as transparent as it is favorable for them, inserting a blurring lens between the market participant and the market that distorts market information in a way that is conducive for their business model. Such a blurring lens may be the insertion of scarcity messages related to low inventory or close dispatch cutoff times, in the hope of activating the sales promoting thinking patterns associated with scarcity in traditional markets.

In the literature, the definition of scarcity has fulfilled the same paradigm shift from actual to perceived scarcity. In the simple and transparent markets of the past, scarcity was defined from a positivist perspective as the "presence of limited resources and competition on the demand side" [4, p. 453]. In these markets, participants directly observe relevant and non-ambiguous market information to make informed and rational decisions. The newer, interpretive view of scarcity [5, 6, 7, 8] redefines it as an attribute of goods linked to the *perception* of unavailability [4]. Research has shown that this perception of scarcity – beyond any objective unavailability – can be a main driver for willingness to pay and producer surplus [7, 9], and thus impact sales quantity for goods that are not completely inelastic in supply.

Even though scarcity messages are frequently applied in practice, it remains questionable if, how and

why scarcity messages (the operationalization of perceived scarcity; for an overview, see [6, 10]) work for physical information goods, especially in the presence of digital versions of the same information goods.

By our research, we aim to make a first step towards closing the identified gap, building on the following research question: How do scarcity messages impact the sales of physical information goods?

We subsequently focus on physical information goods, since quantity- and time-related scarcity messages only play a minor role for digital information goods (e.g., for a limited-edition e-book).

To answer the research question, we first conduct an extensive review of the relevant literature. We then develop a model on the impact of scarcity messages on physical information good sales and empirically test it against evidence from e-commerce sales data of 34,748 physical information goods (print books and movies distributed in physical formats).

Epistemologically, we position our research as post-positivistic.

With our work, we aim to contribute to the literature on information goods marketing, artificial scarcity, and the economics of information goods in general. For practice, we aim to offer a new avenue for escaping the price erosion trap and offer insights on how to artificially influence scarcity and scarcity perceptions of information goods.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 develops a model on the impact of scarcity messages on physical information goods sales. Section 4 describes the methods used for data collection and analysis. Section 5 presents the results. Section 6 discusses the results and concludes.

2. Literature background

2.1. Consumer choice in information good markets

On the highest level, consumer choice processes are a sequence of problem recognition, information search, evaluation of alternatives and purchase decision [11, p. 166]. To deal with the decision task and come to a purchase decision, consumers evaluate product information against their own knowledge and preferences [2]. In doing so, consumers often behave differently than rational choice theory would predict, since they are subject to bounded rationality [12]. The decision rules used in the shopping process are rather constructed on the spot than mechanistically derived from memory [12, 13]. Still, memory encoding, storage, and retrieval have been described as key

processes in developing the rules that guide the shopping process [14].

The product information relevant to purchase decisions can be of search attribute or experience attribute nature (depending on whether the information can be assessed before purchase or not [15]). For information goods, the information component is commonly considered an experience attribute [16]. Determining the hedonic or utilitarian value derived from consumption of the information is infeasible without consuming the information itself. Instead, however, consumers can evaluate search attributes such as price, sales rank, reviews, and summaries as heuristics for evaluating the good itself. For evaluation of information goods, prices are not a good information source as they are largely unrelated to quality or popularity and particularly rigid across titles and time (for an analytical explanation and empirical data, see [17]). Likewise, reviews are not necessarily a good information source particularly for hedonic information goods, as their product space is complex and high-dimensional, compared to other types of goods, which has been referred to as infinite variety [18].

2.2. The impact of scarcity and scarcity messages on sales

Instead, a growing body of literature suggests that scarcity and scarcity messages can serve as a search attribute that affects choice among goods. Scarcity is found to act like a frame for shopping processes, and impact choice particularly in their final stage [19]. Psychological research has further found that scarcity cues induce arousal and lead to reactance [20, 21, 22]. Scarcity alters and captures attention [23, 24] and thereby makes tradeoffs more accessible and gives rise to judgment polarization [25]. In social settings, scarcity can – in case of conspicuous consumption – serve the desire for uniqueness [10, 26, 27] and the desire for status [6, 28, 29, p. 481]. It can evoke feelings of envy and serve to express conformity with social groups [6], as well as represent and extend the self [11].

2.2.1. Scarcity and scarcity messages as a sales promoter. In line with framing theory and the theory of planned behavior, scarcity can act as a sales promoter particularly if the scarcity is framed positively and behavioral control is perceived as high (“it is still possible to get the good”).

Findings related to the positive framing of scarcity indicate that consumers may learn over time that scarce commodities are better than non-scarce [10, 30], in that they are of enhanced value – in the sense of subjective, not objective value [4] – in general [8, 26] or of higher

quality [4, 31, 32, 33]. Scarce goods are more popular than non-scarce ones [5, 32] and consumers perceive them as more attractive [34]. Consumers have also learned that scarcity may be connected with future price increases [6, 7, 26, 35] and transfer learnings about scarcity to unknown products [6, 36, 37].

2.2.2. Scarcity and scarcity messages as a sales hinderer. If scarcity is instead framed negatively, it can act as a sales hinderer (“it is possible that the product will be out of stock” – a ‘threat’ that would be less salient in case of absence of a scarcity message). A large body of out-of-stock research has demonstrated that customers react to stock-out-situations with negative emotions, reduced behavioral intent [38] purchase deferment, purchase cancellations or store switching [39]. Particularly the emergence of e-commerce has set a high reference point for expectations around availability and speed of delivery.

Despite this initial evidence about the effects of scarcity and scarcity messages in online contexts, the impact of scarcity messages on e-commerce sales of physical information goods has not been systematically investigated so far.

3. Hypotheses and research model

This section introduces a random effects variance model for predicting physical information good sales from quantity- and time-based scarcity.

In line with the literature, we differentiate between two major classes of scarcity: scarcity due to time restriction, and scarcity due to quantity restriction [10]. Depending on whether consumers frame scarcity positively or negatively, scarcity messages for physical information goods may either promote or hinder sales:

H1a/b. Current quantity-based scarcity positively / negatively impacts future physical information good sales.

H2a/b. Current time-based scarcity positively / negatively impacts future physical information good sales.

In terms of the relation between past demand and inventory, lower past demand for a focal product is associated with lower inventory. In line with conceptualizing low inventory as scarcity, we propose:

H3. Past demand negatively impacts current quantity- and time-based scarcity.

Similar to the inferences from scarcity on quality, past research has shown that consumers make inferences from scarcity on popularity of a product, and that these inferences can even be stronger than the inferences related to quality [40].

H4. Past demand positively impacts future physical information good sales.

H5. Current quantity- and time-based scarcity mediates the impact of past demand on future physical information good sales.

Major contingency factors of the effects of scarcity on sales are product quality, availability of a digital version, time on market and price. We first propose for their direct effects on sales:

H6. Quality positively impacts future physical information good sales.

H7. Availability of a digital version negatively impacts future physical information good sales.

H8. Time on market negatively impacts future physical information good sales.

H9. Price negatively impacts future physical information good sales.

With regard to quality, past research has suggested that, as a producer strategy, scarcity is only effective for high quality goods [41] and that it therefore is more frequently applied for higher quality goods [4]. Plus, in a naïve economics sense, consumers make inferences from scarcity to popularity and quality [6, 40], so positive ratings would support such inferences, making the scarcity signal more credible. We therefore propose:

H10. Quality positively moderates the impact of current scarcity on future physical information good sales.

With regard to time on market, scarcity effects may be particularly effective for novel goods. When a new product is introduced, the market has initially no information about the good’s quality, so introductory scarcity can serve as a replacement signal for quality [36]. We propose:

H11. Time on market positively moderates the impact of current scarcity on future physical information good sales.

When scarcity is present for a good, consumers take the price as a heuristic cue to make inferences about the good’s quality [7, 8]. Even for low priced products, scarcity can lead to an increased value perception [8]. We therefore propose:

H12. Price positively moderates the impact of current scarcity on future physical information good sales.

To control for the visitors and thus number of prospective buyers on an e-commerce platform at a certain time of the day, we propose:

H13. The higher the number of prospective buyers online, the more physical information goods are sold.

As sales are monitored indirectly through changes of inventory over time intervals, we control for marginal changes in the length of those intervals:

H14. The longer the observation time frame, the more physical information good sales are observed within that time frame.

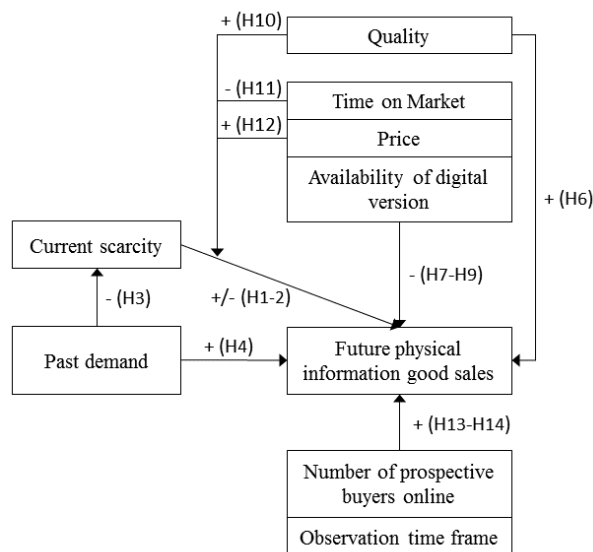


Figure 1. Research model

4. Methodology

4.1. Research design, method, and data source

To test the research model, we employ an observational, longitudinal study design. We choose to analyze real-world data, obtained from product pages of a large e-commerce platform for physical and digital goods. Real-world data constitute an appropriate data source for testing our model, as they allow for the high case numbers required to capture even small effects and are less subject to systematic biases typical in 'staged' experimental purchase situations.

The product pages of the focal e-commerce platform contain basic product information (such as price, quality rating, date of market launch, and sales rank). In addition, they display a quantity-based scarcity message ("Only n units left.") if stock is less or equal fifteen units. They further display a time-based scarcity message that points to the dispatch cutoff ("Order within the next n hours to get the article

tomorrow."). Hence, observing product pages in fixed time intervals allows for tracking sales while controlling for scarcity messages and product data.

4.2. Data collection

To prepare the data collection, we first had to determine a sample of physical information goods to track over time. We initially confined the sample to goods from the top-level categories 'books' and 'video' of the focal e-commerce website. From both categories, we obtained a list of 1,247,484 products after eliminating duplicates. The list can be considered as comprehensive with regard to the 'head' of the product assortment and marginally incomprehensive towards the end of the 'long tail'.

For continuous tracking product pages and the related sales, we then had to address three limitations: First, due to technical limitations, we could track a maximum of 40,000 products over time. Second, sales can only be tracked for goods with a maximum stock of fifteen units, as only for those inventory is displayed on the product page. Third, sales had to occur sufficiently frequent (e.g., excluding goods that are sold once in a month) to be able to observe a sufficient number of sales within a reasonable time frame.

To meet all three restrictions, we decided against a random sampling from the 1,247,484 products. Instead, we ordered the products by sales rank. We ran through the list, starting with the highest selling product and included a product into the sample if the product page displayed a quantity-based scarcity message ("Only n units left."). Thereby, we captured physical information goods (as there is no inventory for digital goods) with a maximum inventory of fifteen units. We stopped as we had obtained 40,000 products. The lowest ranked product of the sample had a sales rank that is associated with roughly one sale per day.

For this sample, we tracked product pages during fourteen consecutive days in January and February 2017. Every day, snapshots of product pages were recorded in two-hour intervals from 8 am to 12 pm, since sales commonly occur in this time period. The fixed interval was chosen to allow for comparability of changes between snapshots. Later analysis revealed that physical information goods that were 'scarce' during the initial sampling, were also frequently scarce (i.e. had an inventory of fifteen units or less) at later points in time.

4.3. Data preparation and analysis

In the next step, we compiled case data for the variables listed in Table 1 from the raw data. We

deleted cases with no information on inventory (inventory > 15 or stock-outs), as they do not allow for tracking sales. As we cannot reliably determine a drop of inventory to zero, we decided to further eliminate cases that had an inventory of two units or less at the beginning of the observation period. 99.9% of the cases report a sales quantity between zero and two, thus this elimination allows for a compromise between accuracy and comprehensiveness of the dataset. Even though observation time periods were rather constant (mean = 120.23 minutes, SD = 10.12 minutes), some cases had disproportionally high or low observation time periods due to technical reasons. We thus eliminated the 2% most extreme cases with regard to the observation time period. To control for the number of visitors who see a product page at a certain hour of the day, we added an index from a secondary data source [42] to every case. The index estimates the timely distribution of web visits during a day in the country of the e-commerce platform.

Table 1. Description of variables

Variable	Description	Range
<i>UnitsSold</i>	Sales quantity in time frame	0-14
<i>ScarcityQuantity</i>	Reverse score of inventory	0-12
<i>ScarcityTime</i>	Reverse score of minutes till cutoff	>0
<i>PastDemand</i>	Norm. reverse score of sales rank	0-1
<i>Quality</i>	Average consumer rating	1-5
<i>DaysOnMarket</i>	Days passed since market launch	>0
<i>Price</i>	Price in Euro	1-300
<i>HasDigitalVers</i>	Availability of digital version	0, 1
<i>ObservPeriod</i>	Minutes passed between the two snapshots for the focal case	84-160
<i>EstVisitors</i>	Index of the number of users surfing the Internet at an hour of the day	1.9-6.9

4.4. Data analysis

Due to the count data nature of the dependent variable, poisson regression analysis or negative binomial regression analysis are appropriate for testing the research model. As the dependent variable is overdispersed (variance exceeding mean), negative binomial regression analysis (with log link function) is the method of choice.

To account for the proposed mediating role of scarcity, we follow the step method for mediator analysis proposed by [43].

Since only 21% of all observations contain information on time-based scarcity, we decided to calculate a regression (model 1) on all cases, excluding the variables related to time-based scarcity, and a second model (model 2) on only those 21% of observations for all variables. We calculate a third regression model (model 3) on all cases that actually

observed a sale (6% of all observations), again excluding the variables related to time-based scarcity, to determine whether sales quantity in the case of a sale can be explained from quantity-based scarcity.

5. Results

5.1. Descriptive Statistics

The dataset covers data for 34,748 unique products (for 5,252 products, scarcity only occurred during the initial sampling, but was not observed during the two-week observation period). For these products, overall 2,536,753 two-hour time intervals were observed. Table 2 reports further descriptive statistics.

Table 2. Descriptive statistics

Variable	N	Min.	Max.	Mean	Std. Dev.
<i>UnitsSold</i>	2583474	0	14	.08	.36
<i>ScarcityQuantity</i>	2583474	0	12	6.85	3.40
<i>ScarcityTime</i>	965972	0	1353	849	418
<i>ObservPeriod</i>	2583474	84	160	120.23	10.12
<i>PastDemand</i>	2583474	0	1.00	.45	.26
<i>Quality</i>	2563753	1.0	5.0	4.43	.65
<i>DaysOnMarket</i>	2583474	4	79298	1839	2126
<i>Price</i>	2583474	1.30	299.99	18.43	15.15
<i>HasDigitalVers</i>	2583474	0	1	.30	.46

5.2. Correlation analysis

Table 3 reports Pearson correlation coefficients for the variables in the research model.

Table 3. Bivariate correlations

	<i>UnitsSold</i>	<i>ScarcityQuantity</i>	<i>ScarcityTime</i>	<i>ObservPeriod</i>	<i>PastDemand</i>	<i>Quality</i>	<i>DaysOnMarket</i>	<i>Price</i>	<i>HasDigitalVers</i>
<i>UnitsSold</i>	1								
<i>ScarcityQuantity</i>	.06	1							
<i>ScarcityTime</i>	-.02	-.01	1						
<i>ObservPeriod</i>	.02	.00	.01	1					
<i>PastDemand</i>	.08	-.16	.00	-.02	1				
<i>Quality</i>	.01	-.03	.00	.00	.01	1			
<i>DaysOnMarket</i>	-.02	.06	.00	.00	-.02	-.02	1		
<i>Price</i>	-.02	.06	.00	.00	-.03	.07	-.09	1	
<i>HasDigitalVers</i>	.00	-.08	.00	-.00	.03	-.07	-.10	.00	1

White/grey shading: significant at level .01 / not significant

5.3. Negative binomial regression analysis

We estimated three regressions models to predict physical information goods sales from the independent variables and moderators.

Table 4. Regression Analysis

Model Summaries			
	M1	M2	M3
Model effects	SQ*	SQ, ST*	SQ
Cases	all	ST ≤ 1440 min.	Units Sold ≥ 1
Observations	2,563,753	526,900	157,616
Unique products	34,748	32,453	30,649
Parameter Estimates (Exponentiated β; DV: UnitsSold)			
(Intercept)	.02700	.03766	1.03144
<i>Direct effect of mediators on DV</i>			
ScarcityQuantity	.94834	.93755	1.00374
ScarcityTime		.99968	
<i>Direct effects of IVs/Moderators on DV</i>			
PastDemand	3.23107	3.03550	1.06380
Quality	1.05958	1.04695	1.00345
DaysOnMarket	.99998	.99997	1.00000
Price	.99548	.99457	.99978
HasDigitalVers=0	1.11886	1.06711	1.04427
SQ_Quality	1.00106	1.00388	
ST_Quality		1.00001	
SQ_DaysOnMarket	1.00000	1.00000	
ST_DaysOnMarket		1.00000	
SQ_Price	.99967	.99964	
ST_Price		1.00000	
ObservPeriod	1.00680	1.00827	1.00055
EstVisitors	.96375	.93225	1.00386
<i>Direct effect of IV on Mediator</i>			
PastDemand	.72846	.72846	.72846
Model Fit			
Pearson Chi-Square / df	1.551	1.265	.236
Omnibus Test (p-value)	< .0001	< .0001	< .0001

* SQ = Quantity-based scarcity; ST = Time-based scarcity

** Estimated in separate analysis due to low number of cases for variable

White/light grey/grey shading: significant at level .01 / .05 / not significant

6. Discussion and conclusion

Findings across all models indicate a significant association of quantity-based scarcity (“only 3 units left”) and time-based scarcity (“order within the next two hours to get the good tomorrow”) with physical information good sales. Quantity-based scarcity overall is negatively associated with sales, but at the same time is related to an increase in the quantity purchased across actual purchases. With regard to the negative association of quantity-based scarcity and sales, the coefficient (exponentiated β) was estimated to .94834

in model 1, meaning that for the highest quantity-based scarcity level observed (an initial inventory of 3 units), compared to the lowest quantity-based scarcity level observed (an initial inventory of 15 units), .62 units less are sold on average in the subsequent two hours. Considering only the cases in which a sale occurred (model 3), a change from the lowest to the highest level of quantity-based scarcity is instead associated with .38 more units sold in the subsequent two hours.

The latter finding is consistent with the common scarcity literature [10, 44, 45]. The finding that quantity-based scarcity only increases purchase quantity across actual buyers confirms prior work that finds scarcity to be particularly effective at later stages of the shopping process [19, 46].

As further estimated in model 1, .12 more units are sold in the next two hours if no digital version of a physical information good is available. In that case, consumers cannot easily switch to a digital substitute when being confronted with potential future unavailability.

As expected, more physical information goods if quality is higher, goods are newer to the market, price is lower and past demand was higher.

Regarding the proposed moderating effects of quality, time on market and price, findings were as follows: Across models, quality was not found to significantly affect the association between scarcity and sales. For time on market, the moderating effect was significant, but far too small to affect the association between scarcity and sales. For price, the moderating effect was significant for both quantity- and time-based scarcity, but only had a considerable effect size in case of scarcity-based quantity (a one-unit increase in the product of scarcity-based quantity and price is associated with .0003 less units sold in the next two hours).

Overall, findings for moderators are not in line with past research that found scarcity to be more effective for higher quality goods [4, 41]. The finding for the moderator 'price' shows that the effect of scarcity on sales is least partly dependent on the good's price.

In summary, our findings confirm that consumers take scarcity-messages into consideration in their purchase behavior, that the observed effects are economically significant, and that the direction of the effect of scarcity message is contingent on the stage of the shopping process for quantity-based scarcity [19, 46]. Moreover, findings allow for rejecting the null hypothesis of the rational consumer who ignores scarcity messages, since direct effect sizes would have been zero in that case – particularly after controlling for the mediating effect of scarcity between past demand and future sales.

On a more general level, our analysis confirms the importance of the interpretive view of scarcity complementary to the traditional positivist view. In an information economy, scarcity is no longer a construct that describes excess demand towards limited supply, but describes much more the perception of unavailability.

6.2. Limitations and suggestions for future research

Our research approach and data source is associated with a few limitations that can be addressed by future research. First, our sample contains both hedonic and utilitarian information goods, while the effect of scarcity may depend on the good type. Future research should therefore control whether the good is consumed for hedonic or utilitarian purpose. Second, our data source does not allow to control for sociodemographic characteristics of the buyers or beliefs and intentions that are formed prior to a purchase or non-purchase decision. Future studies could incorporate those constructs into the proposed model and test it – preferably in an experimental setting – to triangulate our findings and further illuminate the underlying causes for the observed effects. Third, whereas we can only track the impact of changes in the *content* of the scarcity messages, future research should assess the impact on sales of displaying or not displaying a scarcity message per se for a focal product. Fourth, the approach taken and the data investigated in the focal work do not allow to further control for the stage of the shopping process. Fifth, we investigated a mass market where information goods are highly commoditized and easily substitutable. It remains open for investigation whether the effect of quantity-based scarcity as a sales promotor for goods works likewise for other channels (such as individual websites that only promote the focal good). Sixth, we operationalized and measured time-based scarcity as the time till the shipment cutoff point (this information is prominently shown on every product page of the focal platform). Future research should test whether other forms of time-based scarcity (e.g., “In addition to A, get B for free if you order through next Tuesday”) actually promote sales of information goods. Seventh, future work could condense the findings into decision models that help with determining the optimality of scarcity strategies.

7. References

- [1] Rifkin, J. 2014. The zero marginal cost society: The internet of things, the collaborative commons, and the eclipse of capitalism. New York: Palgrave Macmillan.
- [2] PwC. 2015. The global entertainment and media outlook 2015-2019, <https://www.pwc.com/ca/en/entertainment-media/publications/pwc-global-em-outlook-2015-2019-canadian-highlights-2015-09-en.pdf>.
- [3] DEG. 2017. US home entertainment market report, <http://www.nscreenmedia.com/us-home-entertainment-spending-q4-2016/>.
- [4] Mittone, L., and Savadori, L. 2009. The scarcity bias. *Applied Psychology* (58:3), 453-468.
- [5] Eisend, M. 2008. Explaining the impact of scarcity appeals in advertising: The mediating role of perceptions of susceptibility. *Journal of Advertising* (37:3), 33-40.
- [6] Gierl, H., and Huettl, V. 2010. Are scarce products always more attractive? The interaction of different types of scarcity signals with products' suitability for conspicuous consumption. *International Journal of Research in Marketing* (27:3), 225-235.
- [7] Lynn, M. 1992. Scarcity's enhancement of desirability: The role of naive economic theories. *Basic and Applied Social Psychology* (13:1), 67-78.
- [8] Suri, R., Kohli, C., and Monroe, K. 2007. The effects of perceived scarcity on consumers' processing of price information. *Journal of the Academy of Marketing Science* (35:1), 89-100.
- [9] Verhallen, T. 1982. Scarcity and consumer choice behavior. *Journal of Economic Psychology* (2:4), 299-322.
- [10] Gierl, H., Plantsch M., and Schweidler, J. 2008. Scarcity effects on sales volume in retail, *The International Review of Retail, Distribution and Consumer Research* (18:1), 45-61.
- [11] Belk, R. 1988. Possessions and the extended self. *Journal of Consumer Research* (15:2), 139-168.
- [12] Bettman, J., Luce, M., and Payne, J. 1998. Constructive consumer choice processes. *Journal of Consumer Research* (25:3), 187-217.
- [13] Kahneman, D., Ritov, I., Jacowitz, K., and Grant, P. (1993). Stated willingness to pay for public goods: A psychological perspective. *Psychological Science* (4:5), 310-315.
- [14] Puccinelli, N., Goodstein, R., Grewal, D., Price, R., Raghubir, P., and Stewart, D. 2009. Customer experience management in retailing: understanding the buying process. *Journal of Retailing* (85:1), 15-30.

- [15] Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research*, 19(4), 456-474.
- [16] Nelson, P. 1970. Information and consumer behavior. *Journal of Political Economy* (78:2), 311-329.
- [17] Clerides, S. 2002. Book value: intertemporal pricing and quality discrimination in the US market for books. *International Journal of Industrial Organization* 20, 10, 1385-1408.
- [18] Caves, C.M. 2000. *Creative industries: Contracts between art and commerce*. Harvard University Press, 1-18.
- [19] Mallalieu, L. 2006. Consumer perception of salesperson influence strategies: an examination of the influence of consumer goals. *Journal of Consumer Behaviour* (5:3), 257-268.
- [20] Brehm, J. 1966. *A theory of psychological reactance*. New York: Academic Press.
- [21] Brehm, J. 1972. Responses to loss of freedom: A theory of psychological reactance. Morristown: General Learning Press.
- [22] Clee, M., and Wicklund, R. 1980. Consumer behavior and psychological reactance. *Journal of Consumer Research* (6:4), 389-405.
- [23] Broadbent, D. 1971. *Decision and Stress*. London: Academic Press.
- [24] Kahneman, D. 1973. *Attention and Effort*. Englewood Cliffs, NJ: Prentice-Hall Press.
- [25] Paulus, L., Lim, T. 1994. Arousal and evaluative extremity in social judgments: A dynamic complexity model. *European Journal of Social Psychology* (24), 89-99.
- [26] Lynn, M. 1991. Scarcity effects on value: A quantitative review of the commodity theory literature. *Psychology & Marketing* (8:1), 43-57.
- [27] Snyder, C., and Fromkin, L. 1980. *Uniqueness: The Human Pursuit of Difference*. New York: Plenum Press.
- [28] Bhattacharya, C. 1998. When customers are members: Customer retention in paid membership contexts. *Journal of the Academy of Marketing Science* (26:1), 31-44.
- [29] Blumberg, P. 1973. The decline and fall of the status symbol: Some thoughts on status in a post-industrial society. *Social Problems* (21:4), 480-498.
- [30] Cialdini, R. 1993. *Influence: the psychology of persuasion*. New York: William Morrow.
- [31] Ditto, P., and Jemmott, J. 1989. From rarity to evaluative extremity: Effects of prevalence information on evaluations of positive and negative characteristics. *Journal of Personality and Social Psychology* (57:1), 16-26.
- [32] van Herpen, E., Pieters, R., Zeelenberg, M. 2009. When demand accelerates demand: Trailing the bandwagon. *Journal of Consumer Psychology* (19:3), 302-312.
- [33] Worchel, S., Lee, J., and Adewole, A. 1975. Effects of supply and demand on ratings of object value. *Journal of Personality and Social Psychology* (32:5), 906-914.
- [34] Szybillo, G. 1975. A situational influence on the relationship of a consumer attribute to new-product attractiveness. *Journal of Applied Psychology* (60:5), 652-655.
- [35] Lynn, M. 1989. Scarcity effects on desirability: Mediated by assumed expensiveness?. *Journal of Economic Psychology* (10:2), 257-274.
- [36] Stock, A., and Balachander, S. 2005. The making of a "hot product": A signaling explanation of marketers' scarcity strategy. *Management Science* (51:8), 1181-1192.
- [37] Swami, S., and Khairnar, P. 2006. Optimal normative policies for marketing of products with limited availability. *Annals of Operations Research* (143:1), 107-121.
- [38] Kim, M., & Lennon, S. J. 2011. Consumer response to online apparel stockouts. *Psychology & Marketing*, 28(2), 115-144.
- [39] Campo, K., Gijsbrechts, E., & Nisol, P. 2000. Towards understanding consumer response to stock-outs. *Journal of Retailing*, 76(2), 219-242.
- [40] Parker, J., and Lehmann, D. 2011. When shelf-based scarcity impacts consumer preferences. *Journal of Retailing* (87:2), 142-155.
- [41] Balachander, S., and Stock, A. 2009. Limited edition products: When and when not to offer them. *Marketing Science* (28:2), 336-355.
- [42] AT Internet Institute. 2009. Temporal distribution of website visits, <http://news.worldsites-schweiz.ch/prime-time-im-internet-tageszeiten-der-internetnutzung-in-europa.htm>.
- [43] James, L. R., & Brett, J. M. 1984. Mediators, moderators, and tests for mediation. *Journal of Applied Psychology*, 69(2), 307.
- [44] Inman, J., Dyer, J., and Jia, J. 1997. A generalized utility model of disappointment and regret effects on post-choice valuation. *Marketing Science* (16:2), 97-111.
- [45] Tereyağoglu, N., and Veeraraghavan, S. 2012. Selling to conspicuous consumers: Pricing, production, and sourcing decisions. *Management Science* (58:12), 2168-2189.
- [46] Yi, C., Jiang, Z., and Zhou, M. 2014. The effects of social popularity and deal scarcity at different stages of online shopping. *Proceedings of the International Conference on Information Systems (ICIS)*.