

Long tail in omnichannel retailing: A field study on showroom and sales distribution

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Abstract

We examine the unintended consequences of traditional brick-and-mortar store as a showroom emerging in the retail industry. Because showrooms are light on inventory, are used to display products, and focus on in-store customer experience, they are likely to exhibit high sales dispersion. We analyze data from a leading Italian retailer operating an omnichannel business model via online, catalog, and showroom channel. We show that the showroom channel exhibits the highest sales dispersion among the three channels. Our paper provides the first empirical evidence of an increasingly important retail phenomenon (showroom) and discusses several implications on returns management and last-mile delivery.

Keywords: Long tail, showroom, econometrics

Introduction

The retail sector is experiencing a significant change, driven by evolving customer expectations and increased accessibility to high-speed Internet. Big brands like Macy's, Walmart and J.C. Penney are closing down stores while traditional brick-and-mortar retailers are trying on showrooms as part of their omnichannel strategy to better engage consumers (Ewen, 2017). Although the rapid adoption of offline showrooms has triggered academic studies to evaluate the demand and operational benefits from the adoption of these showrooms (e.g. Bell et al., 2018), little research has documented the empirical impact on product sales concentration as a result of retailers operating the showroom channel relative to the other primary sales channels (i.e. online and catalog). The development stands in stark contrast to the several studies that have investigated the product sales concentration between online and catalog channel (Brynjolfsson et al., 2011), between online and offline channel (Elberse, 2008), Internet sales and returns concentration (Rabinovich et al., 2011), and the use of ship-to-store functionality that allows customers to ship products to their local stores (Gallino et al., 2017).

The understanding of product sales concentration in retail operations is important because it affects inventory management (Gallino et al., 2017), forecasting and product assortment decisions (Rabinovich et al., 2011), product returns management, and last-mile delivery performance. Moreover, extant studies have largely assumed that the identified sales concentration characteristics among channels are static. Our study extends this line of research to evaluate sales concentration of showroom vis-à-vis the online and catalog channel. We are primarily interested to empirically examine whether the showroom channel exhibits a less concentrated distribution of product sales.

To do so, we analyze sales data from a national leading Italian retailer operating an omnichannel business model via online, catalog, and showrooms. We show that the showroom channel exhibits the highest sales dispersion (or least concentrated distribution) among the three channels. Our paper provides the first empirical evidence of an increasingly important retail phenomenon (showroom) and discusses several implications on returns management and last-mile delivery.

Literature review

Sales dispersion for a given sales distribution can be defined as the “percent sales contribution to the total sales of the x percent of lowest-selling products” (Gallino et al., 2017). Research in operations management has investigated the product sales concentration between online and catalog channel (Brynjolfsson et al., 2011; Ma, 2016), between online and offline channel (Elberse, 2008), Internet sales and returns concentration (Rabinovich et al., 2011), and the impact to brick-and-mortar’s sales concentration from the use of ship-to-store functionality, allowing customers to ship products to their local stores (Gallino et al., 2017). Gallino et al. (2017) found that sales dispersion increases after a retail introduced the ship-to-store functionality. The literature has also documented the so-called “long-tail” phenomenon (high sales dispersion) in various industry, including clothing (Brynjolfsson et al., 2011), video rental (Elberse and Oberholzer-Gee, 2007), and furniture and housewares (Gallino et al., 2017). The literature has also identified interventions that offset the long-tail phenomenon, for instance, providing online search tools and recommendation systems (Brynjolfsson et al., 2011), sales channel’s information capabilities (Ma, 2016), or overly increasing the available product options (Tan et al., 2014).

Although these studies contributed to understanding sales dispersion characteristics among different sales channels, the interventions that offset sale dispersion, and the operational impact, little research has systematically compare the sales distribution of showrooms vis-à-vis the other primary channels (i.e. online and catalog) within an omnichannel setting. Recent studies on showrooms has only examined the demand and operational benefits of operating showrooms (Bell et al., 2013; Bell et al., 2018). For example, Bell et al. (2018) found that showrooms increase demand, and improve operational efficiency by increasing conversion and decreasing returns.

Data description

We collaborated with a leading national furniture retailer in the European Union for this study. For the purpose of confidentiality, we use the pseudonym “Omnichannel co.” to identify this retailer in this paper. Omnichannel co. has 35 stores around Italy and provided us with detailed order-level transactions between the period 01 January 2015 and 28 February 2017. Each showroom store has a warehouse located nearby responsible for order fulfilment. These warehouses are also responsible for fulfilling orders from the online and catalog channels. Omnichannel co. offers a two-day delivery guarantee policy for make-to-stock products. A key attribute of Omnichannel co.’s showroom strategy is

the unique in-store customer experience served by experienced sales assistants to support in-store customers with their purchasing process, including the provision of product information, and budgeting. These sales assistants are equipped with digital devices that provide customers with additional digital media to support their purchasing activities. For example, customers can better inspect products not displayed in the stores via high-definition and high-resolution photographs, as well as detailed product descriptions and customer reviews. For the retailer’s catalog channel, catalogs are distributed on a three-monthly basis via postal mails to all households in Italy. They are also available in the stores. Because of space and page limit (small booklet with about 150 pages), only limited photographs are selected to be displayed in the catalogs, and coupled with a brief product distribution. Omnichannel co. collects catalog orders by telephone.

Although the raw dataset comprises 4.67 million observations, we chose to focus on one catalog period to control for product availability, consistent with the approach adopted by Brynjolfsson et al. (2011). We have chosen the catalog period commencing January to March 2016 and used the January to March 2015 as robustness check, in which we obtained qualitatively similar results (results are available upon request). From our chosen catalog period, we obtained 447,828 observations with 21 product categories after excluding error outliers and duplicated entries.

Econometric approach and findings

Table 1 and 2 provide the summary statistics for the three channels included in our study, and the distribution of the product categories. We first calculate the aggregate sales for each of the 429 products in each channel between January and March 2015. We then use the Lorenz curve and Gini coefficient, commonly followed in the long-tail literature to evaluate the concentration of product sales in each channel (e.g. Gallino et al., 2017; Brynjolfsson et al., 2011; Rabinovich et al., 2011).

Table 1 – Summary of channel distribution

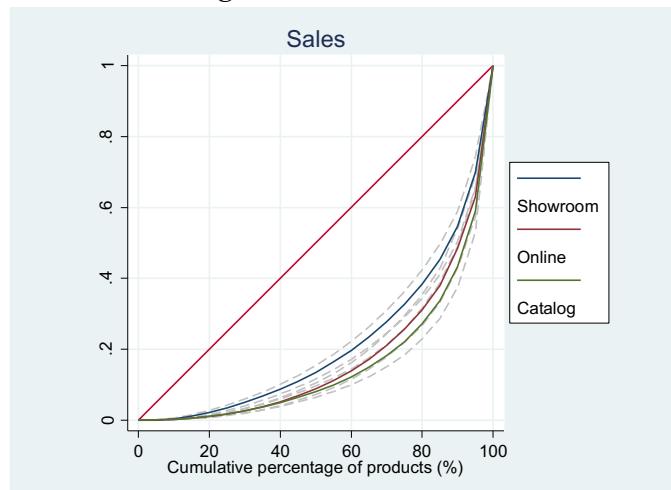
	Frequency	Percent (%)	Cumulative Percent (%)
Online	16,307	3.6	3.6
Showroom	397,937	88.9	92.5
Catalog	33,584	7.5	100
Total observations	447,828	100	

From Figure 1, the showroom channel’s Lorenz curve lies above that of online and catalog channel’s, implying that the showroom channel exhibits less concentration of product sales. Moreover, the Gini coefficient for the showroom channel (0.574) is lower than both the online (0.655) and catalog channel (0.687). The intuition is that the more dispersed a sales distribution, the thicker its tail and so the higher the contribution from the lowest-selling products.

Table 2 – Summary of product category distribution

Category	Frequency	Percent (%)	Cumulative Percent (%)
Bed	46,982	10.5	10.5
Bedroom	24,221	5.4	15.9
Bedside	12,797	2.9	18.8
Bedsprings	21,776	4.9	23.6
Bookcase	11,930	2.7	26.3
Bridge	936	0.2	26.5
Bureau	14,749	3.3	29.8
Chair	48,146	10.8	40.5
Chest	9,314	2.1	42.6
Column	7,145	1.6	44.2
Couch	61,688	13.8	58.0
Dresser	27,310	6.1	64.1
Flap	3,618	0.8	64.9
Living room	4,105	0.9	65.8
Mattress	82,491	18.4	84.2
Mirror	10,302	2.3	86.5
Pillow	551	0.1	86.7
Showcase	1,047	0.2	86.9
Sink	2,289	0.5	87.4
Table	30,518	6.8	94.2
Wardrobe	25,913	5.8	100.0
Total	44,7828	100.0	

Figure 1 – Lorenz curve



Since the Lorenz curve and Gini coefficient do not allow us to conclude whether the difference among the channels are statistically significant, we fit sales and sales rank data via a log-linear model to compare the sales rank coefficient when using data from the three channels.

$$\ln(\text{Sales}_j + 1) = \beta_0 + \beta_1 \ln(\text{Sales Rank}_j) + \varepsilon_j \quad (\text{Model 1-3})$$

β_1 measures how quickly product j 's demand in a particular channel falls as the sales rank increases. If the showroom channel exhibits a longer tail, then β_1 would be less negative (i.e. lower in absolute value) in the showroom channel vis-à-vis the other channels. Indeed, from Table 3, the β_1 coefficient is -1.156, -1.207, and -1.287 for the showroom, online and catalog sales channel, respectively. As per the approach employed by Brynjolfsson et al. (2011), we pooled the three channels data into a single data set and perform a single regression and varying the baseline channel in order to evaluate whether the β_1 coefficients of the three channels are significantly different from each other (Model 4A-4C). Using this approach, we found that the showroom channel exhibits the least concentration of product sales followed by catalog and online. That is, in our context, the online channel shows the most concentrated distribution of product sales among the three channels. All standard errors are clustered at the product level.

$$\ln(\text{Sales}_j + 1) = \beta_0 + \beta_1 \ln(\text{Sales Rank}_j) + \beta_2 \text{Online}_j + \beta_3 \text{Catalog}_j + \beta_4 \ln(\text{Sales Rank}_j) \times \text{Online}_j + \beta_5 \ln(\text{Sales Rank}_j) \times \text{Catalog}_j + \varepsilon_j \quad (\text{Model 4A-4C})$$

Table 3 – Regression results

Sales	Model 1: Showroom data	Model 2: Online data	Model 3: Catalog data	Model 4A: Pooled data, OLS	Model 4B: Pooled data, OLS	Model 4C: Pooled data, OLS
Constant	11.901 *** (0.476)	8.956*** (0.268)	9.923*** (0.284)	11.901*** (0.476)	8.9575*** (0.268)	9.9233*** (0.284)
Sales Rank	-1.156*** (0.096)	-1.207*** (0.053)	-1.287*** (0.054)	-1.156*** (0.096)	-1.2071*** (0.053)	-1.2868*** (0.055)
Online				-2.944*** (0.5192)		-0.9658*** (0.141)
Online × Sales Rank				-0.0515 (0.1050)		0.0798* (0.030)
Catalog				-1.978*** (0.4331)	0.9658*** (0.141)	
Catalog × Sales Rank				-0.131 (0.0865)	-0.0798* (0.030)	
Showroom					2.9437*** (0.519)	1.9778*** (0.433)
Showroom × Sales Rank					0.0515 (0.105)	0.1312 (0.086)
Adj. R ²	0.6506	0.8526	0.8591	0.8956	0.8956	0.8956
Sample Size	429	429	429	1,287	1,287	1,287

Note: Std. errors in parentheses.

* P<0.05, ** p<0.01, *** p<0.001

We check for the robustness of the results reported in Table 3 by using quantile regression (Model 5A-5C). Quantile regression relates the conditional median of the dependent variable to the independent variables and is more robust to outliers than the linear regression approach. As Table 4 shows, the sales rank coefficient in Model 5A (showroom) remains the least negative among the three channels, consistent with our estimates reported in Table 3. We further check the robustness of our results by randomly

selecting a product category (in this case, sofa) and repeat the analyses for the results reported in Table 4 and 5. In addition, we repeat the analyses by using the entire sample across the period of our observation. These results are reported in *Appendix A* and *B*, respectively.

Table 4 – Quantile regression results

Sales	Model 5A: Pooled data, OLS	Model 5B: Pooled data, OLS	Model 5C: Pooled data, OLS
Constant	11.440*** (0.1004)	9.2893*** (0.1004)	10.0301*** (0.1004)
Sales Rank	-1.005*** (0.0194)	-1.227*** (0.019)	-1.2623*** (0.019)
Online	-2.150*** (0.1420)		-0.7408*** (0.142)
Online × Sales Rank	-0.2217*** (0.0275)		0.0354 (0.027)
Catalog	-1.409*** (0.0616)	2.1504*** (0.142)	
Catalog × Sales Rank	-0.247*** (0.0121)	0.2217*** (0.027)	
Showroom		0.7408*** (0.027)	1.4096*** (0.142)
Showroom × Sales Rank		-0.0354 (0.027)	0.2575*** (0.0275)
Adj. R ²	0.7797	0.7797	0.7797
Sample Size	1,287	1,287	1,287

Note: Std. errors in parentheses.

* P<0.05, ** p<0.01, *** p<0.001

Of course, one might argue that consumers who purchase through the showroom channel could exhibit systematic difference from consumer who purchase through the online and catalog channel. Therefore, consumer selection effect might our estimation results. To account for this possibility, we use a propensity score matching method (Rosenbaum and Rubin, 1983) to control for the potential consumer selection effect.

We define “niche” products as the bottom 50% of products that are purchased least frequently by ranking products by their aggregate sales. Table 5 compares the units sales and price across the two types of products: top 50% and bottom 50% across the three channels. We find that the average unit sales and average price for the bottom 50% and across all three channels are statistically lower than the top 50% products.

Table 5 – Niche products

		Avg. unit sales	Avg. price
Showroom	Top 50%	2,330.1 (212.12)	247.1 (12.52)
	Bottom 50%	257.7 (10.40)	326.0 (14.54)
Online	Top 50%	102.7 (9.99)	224.3 (10.76)
	Bottom 50%	7.28 (0.35)	348.8 (15.20)
Catalog	Top 50%	205.3 (20.90)	228.8 (11.31)
	Bottom 50%	13.6 (0.61)	344.4 (14.97)

Note: Std. errors in parentheses.

* P<0.05, ** p<0.01, *** p<0.001

We match the observations in our data using demographic and socioeconomic variables collected from the 2011 Italy Census¹ at the zip code level. We use the propensity score matching approach suggested by Rosenbaum and Rubin (1983) to match the showroom observations with online observations, and separately with catalog observations at the order level based on observable characteristics of the consumers who made the purchase. We chose to match the observations based on six variables commonly used in the literature: *population*, *average age of consumer*, *percentage female*, *percentage with university education*, *average household size*, and *status of the building the consumers live in*. Prior to the matching, we find statistically difference between the online and the showroom sample in all the matching variables except *population*. Similarly, all variables are statistically different between the showroom and catalog samples (see Table 6). As we observe in Table 6, the variables are all statistically insignificant in both the matched showroom sample for online and matched showroom sample for catalog after the matching procedure.

Table 6 – Niche products

Matching variables	Online	Showroom	Catalog	Matched showroom sample for online	Matched showroom sample for catalog
Population	403,069.7 (7,338.07)	413,684.7 (1,881.82) [O-S: 0.177]	377,712.8 (4,934.88) [S-C: 0.000***] [O-C: 0.004**]	411,653.7 (1,472.56) [O-S: 0.177]	371,387.4 (1,292.38) [S-C: 0.947]
Avg. age	45.70051 (0.02147)	45.11 (0.00569) [O-S: 0.000***]	45.58 (0.01631) [S-C: 0.000***] [O-C: 0.000***]	45.75 (0.0569) [O-S: 0.345]	45.60 (0.0341) [S-C: 0.474]
Percent female	0.519 (0.00011)	0.518 (0.00003) [O-S: 0.000***]	0.519 (0.00008) [S-C: 0.000***] [O-C: 0.559]	0.519 (0.00002) [O-S: 0.643]	0.520 (0.0238) [S-C: 0.826]
Percent with university education	0.156 (0.00061)	0.151 (0.00014) [O-S: 0.000***]	0.153 (0.00041) [S-C: 0.000***] [O-C: 0.001**]	0.155 (0.014) [O-S: 0.627]	0.154 (0.023) [S-C: 0.492]
Avg. household size	2.336 (0.00222)	2.388 (0.00059) [O-S: 0.000***]	2.360 (0.00172) [S-C: 0.000***] [O-C: 0.000***]	2.337 (0.007) [O-S: 0.837]	2.365 (0.028) [S-C: 0.754]
Building status	0.356 (0.00141)	0.344 (0.00036) [O-S: 0.000***]	0.337 (0.00100) [S-C: 0.000***] [O-C: 0.000***]	0.353 (0.005) [O-S: 0.329]	0.336 (0.003) [S-C: 0.182]
# of Obs.	11,492	195,273	23,300	11,492	23,300

Note: Std. errors in parentheses.

t-statistic comparing mean differences in brackets. For example, “O-S” compares the mean difference between the online and showroom channel, while “S-C” compares the mean difference between the showroom and catalog channel for the associated matching variable.

* P<0.05, ** p<0.01, *** p<0.001

Overall, our results in Table 7 are consistent with the results we reported in Table 3 and 4. The percentage of unit sales generated by niche products (i.e. bottom 50%) remains statistically higher in the matched showroom sample than in the online and

¹ We obtain the 2011 Italy Census from the Italian Institute of Statistics: <http://www.istat.it>.

catalog sample: 14.03% vs. 9.1%, and 14.03% vs. 7.87%, respectively. We also vary the definition of niche products using bottom 40% and bottom 60% and we obtain consistent results. Henceforth, we conclude that the difference in sales distribution we identified in this study among the showroom, online, and catalog channel persists, even after accounting for potential consumer selection effects.

Table 7 – Results using matched samples for percentage of unit sales

	Online	Showroom	Catalog
Bottom 40%	0.0541 (0.00199)	0.0908 (0.00058) [O-S: 0.000***]	0.0498 (0.00133) [S-C: 0.000***] [O-C: 0.069]
Bottom 50%	0.0909 (0.00253)	0.1403 (0.0007) [O-S: 0.000***]	0.0787 (0.00165) [S-C: 0.000***] [O-C: 0.000***]
Bottom 60%	0.1422 (0.00306)	0.2004 (0.0008) [O-S: 0.000***]	0.1239 (0.00203) [S-C: 0.000***] [O-C: 0.000***]
# of Obs.	11,492	195,273	23,300

Note: Std. errors in parentheses.

t-statistic comparing mean differences in brackets. For example, “O-S” compares the mean difference between the online and showroom channel, while “S-C” compares the mean difference between the showroom and catalog channel.

* P<0.05, ** p<0.01, *** p<0.001

Implications and future research

Implications for practice and theory

Our analysis regarding the sales dispersion exhibited by showrooms has important implications given the rapid adoptions of this emerging channel among retailers in the retail industry. While using showrooms allow retailers to downsize their footprint per store, allowing these retailers to redistribute their capital to expand the density of their store networks, and gains efficiency from inventory aggregation, our findings caution retailers in their showroom operations given the higher sales dispersion. Our findings present the first empirical evidence that support the existence of the long tail in the showroom channel, and through our systematic and robust comparisons, show that the showroom has the highest sales dispersion among the three primary channels (showroom, online, and catalog) in a typical omnichannel business model.

Conclusions and extensions

Our study on product sales concentration of showroom vis-à-vis the online and catalog channel shows that the showroom channel exhibits the least concentrated distribution of product sales distribution among the three channels, followed by the catalog channel and online channel.

In our extensions to this base finding, we extend and contribute to the sales dispersion and showroom literature by identifying three new mechanisms that offset the sales distribution of showroom, namely – distance separating consumers and the nearest showroom, store size, and promotions. Specifically, distance separating consumers from the nearest showroom moderates showroom channel’s sales distribution; as distance increases, product sales becomes more concentrated. We also expect products ordered via the showroom channel to associate with longer home delivery lead-time. This is because, the inventories of low-selling SKUs are typically aggregated and centralized at selective

warehouses and therefore tend to be more removed from the consumers locations. In instances where the products are fulfilled directly from the suppliers, the overall delivery lead-times are likely to be higher. Moreover, we evaluate the operational impact of sales distribution on product returns. We expect showroom channel to have the lowest rate of product returns among the three channels during our period of observation. However, we hypothesize that store size moderates this relationship. Smaller stores tend to generate higher (probability of) product returns vis-à-vis larger stores. Overall, we expect our findings to have important implications on store location decisions, returns management, and last-mile delivery operations.

References

- Bell, D., Gallino, S., Moreno A. (2013), Inventory showrooms and customer migration in omnichannel retail: The effect of product information. Working paper, The Wharton School, University of Pennsylvania, Philadelphia.
- Bell D.R., Gallino S. and Moreno A. (2018), Offline Showrooms in Omnichannel Retail: Demand and Operational Benefits. *Management Science*, Vol. 64 No. 4, pp. 1629-1651.
- Brynjolfsson, E., Hu, Y.J., Smith, M.D. (2003), Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science*, Vol. 49 No. 11, pp. 1580-1596.
- Brynjolfsson E., Hu Y. and Simester D. (2011), Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales. *Management Science*, Vol. 57, pp. 1373-1386.
- Elberse, A., Oberholzer-Gee, F. (2007), Superstars and underdogs: An examination of the long tail phenomenon in video sales. Working Paper 07-015, Harvard Business School, Boston.
- Elberse, A. (2008), Should you invest in the long tail? *Harvard business review*, Vol. 86, No. 7-8, pp. 88.
- Ewen, L. 2017, *Why retailers are trying on showrooms [online]*. RetailDIVE. Available at: <https://www.retaildive.com/news/why-retailers-are-trying-on-showrooms/439990> (Accessed 10 January 2018).
- Gallino S., Moreno A. and Stamatopoulos I. (2017), Channel Integration, Sales Dispersion, and Inventory Management. *Management Science*, Vol. 63 No. 9, pp. 2813-2831.
- Ma, J. (2016), Does Greater Online Assortment Pay? An Empirical Study Using Matched Online and Catalog Shoppers. *Journal of Retailing*, Vol. 92 No. 3, pp. 373-382.
- Rabinovich E., Sinha, R. and Laseter T. (2011), Unlimited shelf space in Internet supply chains: Treasure trove or wasteland? *Journal of Operations Management*, Vol. 29, pp. 305-317.
- Rosenbaum, P., Rubin, D. (1983), The central role of the propensity score in observational studies for causal effects. *Biometrika*, Vol. 70 No. 1, pp. 41-55.
- Tan, T., Netessine, S., Hitt, L. (2014), An empirical study of the impact of product variety on demand concentration. Working paper, Southern Methodist University, Dallas.
- Zentner, A., Smith, M., Kaya, C. (2013), How video rental patterns change as consumers move online. *Management Science*, Vol. 59 No. 11, pp. 2622-2634.

Appendix

A. Estimation results for Sofa category

Table A1 – Regression results for sofa category

Sales	Model 1: Showroom data	Model 2: Online data	Model 3: Catalog data	Model 4A: Pooled data, OLS	Model 4B: Pooled data, OLS	Model 4C: Pooled data, OLS	Model 5A: Pooled data, OLS	Model 5B: Pooled data, OLS	Model 5C: Pooled data, OLS
Constant	9.7498*** (0.310)	7.4959*** (0.157)	8.170*** (0.165)	9.7498*** (0.222)	7.4959*** (0.222)	8.1702*** (0.222)	9.2511*** (0.181)	7.5245*** (0.181)	7.8017*** (0.181)
Sales Rank	-1.1589*** (0.087)	-1.372*** (0.044)	-1.4197*** (0.046)	-1.1589*** (0.062)	-1.3721*** (0.062)	-1.4297*** (0.062)	-0.9261*** (0.051)	-1.3468*** (0.051)	-1.3094*** (0.051)
Online				2.2539*** (0.314)		-0.6744* (0.314)	-1.7267*** (0.256)		-0.2772 (0.2559)
Online × Sales Rank				-0.2132* (0.088)		0.05759 (0.088)	-0.4206*** (0.072)		-0.0374 (0.072)
Catalog × Sales Rank				-1.579*** (0.314)	2.2539* (0.088)		-1.4495*** (0.256)	1.7267*** (0.256)	
Showroom					0.6744* (0.033)	1.5796*** (0.314)		0.2772 (0.256)	1.4495*** (0.256)
Showroom × Sales Rank					-0.0576 (0.088)	0.2708** (0.088)		0.0374 (0.0716)	0.3833*** (0.072)
Adj. R ²	0.6845	0.9221	0.9214	0.9229	0.9229	0.9229	0.7904	0.7904	0.7904
Sample Size	83	83	83	249	249	249	249	249	249

Note: Std. errors in parentheses.

* P<0.05, ** p<0.01, *** p<0.001

B. Estimation results for entire period of observations (January 2015 to February 2017)

Table B1 – Regression results for entire period of observations

Sales	Model 1: Showroom data	Model 2: Online data	Model 3: Catalog data	Model 4A: Pooled data, OLS	Model 4B: Pooled data, OLS	Model 4C: Pooled data, OLS	Model 5A: Pooled data, OLS	Model 5B: Pooled data, OLS	Model 5C: Pooled data, OLS
Constant	16.818*** (0.885)	13.359*** (0.644)	14.426*** (0.708)	16.811*** (0.886)	13.3594*** (0.645)	14.4217*** (0.708)	16.907*** (0.236)	15.0485*** (0.237)	15.4598*** (0.237)
Sales Rank	-1.727*** (0.147)	-1.696*** (0.110)	-1.749*** (0.708)	-1.726*** (0.147)	-1.6962*** (0.110)	-1.7495*** (0.121)	-1.653*** (0.040)	-1.9415*** (0.040)	-1.8698*** (0.040)
Online				-3.451*** (0.631)		-1.0623*** (0.124)	-1.858*** (0.334)		-0.4113 (0.335)
Online × Sales Rank				0.031 (0.104)		0.0533* (0.022)	-0.288*** (0.057)		-0.0717 (0.057)
Catalog × Sales Rank				-2.389** (0.578)	3.4515*** (0.631)		-1.447*** (0.057)	1.8585*** (0.335)	
Showroom									
Showroom × Sales Rank					1.0632*** (0.124)	2.3892** (0.578)		0.4113 (0.335)	1.4472*** (0.335)
					-0.0533* (0.022)	0.0227 (0.094)		0.0717 (0.057)	0.2168*** (0.057)
Adj. R ²	0.6486	0.8086	0.7871	0.8277	0.8277	0.8277	0.6361	0.6361	0.6361
Sample Size	867	867	867	2,601	2,601	2,601	2,601	2,601	2,601

Note: Std. errors in parentheses.

* P<0.05, ** p<0.01, *** p<0.001