Regressions Report

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April 2024

Abstract

In this report, I will present the results of the regressions using the original IV as well as the lag-term IV.

1 SCAN*PRO

In this section, I will go over the reviewer's suggestions and provide some own thinking, as well as related regression results.

1.1 Log-log Model and Related Literatures

The SCAN*PRO model, first proposed in [Wittink et al., 1988], interprets how promotion can influence market sales. The name of 'SCAN*PRO' is based on scanner and promotion: using the data collected by scanner in the retailing stores to understand the mechanism of promotion. The original version has the form:

$$\begin{aligned} q_{kjt} = & \left[\prod_{r=1}^{n}\left[\frac{p_{krt}}{\overline{p}_{kr}}\right]^{\beta rj}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lkn}}\right]\left[\prod_{t=1}^{T}\delta_{ji}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{u_{kjt}} \\ & k = 1,\ldots,K,\ t = 1,\ldots,T \end{aligned} \tag{1}$$

q_{kjt} is the unit sales at store k for brand j at week t, $\frac{p_{krt}}{\overline{p}_{kr}}$ is called the price index for brand r at store k in week t, where p_{krt} is the price at time t and $\bar{p}_{kr}$ is the median price for brand r at store k (regular price without promotion). Note that even when estimating the sales of brand j, the equation produces the terms for all brands (see the subscript r). This is the 'cross-brand' effect: the price of other brands can affect the own-brand sales.

Within the first product, there are several interaction terms D_{lkrt}, which are dummy variables indicating whether the type l non-price advertising was launched at store k for brand r in week t, the corresponding parameter γ_{lrj} can be interpreted as the **interaction** effects between the price and non-price advertising.

The last two variables, X_t, Z_k, are time and store-level fixed effects, and u_{kjt} is the error term. The equation seems complicated, but if we take a log transform on both sides, we can get:

$$\log q_{kjt} = \sum_{i=1}^{n}(\log p_{krt} - \log \bar{p_{kr}}) \cdot \beta_{rj} \cdot \sum_{l=1}^{3}\log\gamma_{lkj}D_{lkrt} + Fixed\_Effects + u_{kjt} \tag{2}$$

This is called **log-log** model because the variables of both sides have been log-transformed, and the parameter β_{rj} can be explained as the **elasticity** of the price change of brand r on the demand of brand j.

[Leeflang et al., 2002] reviewed some extended SCAN*PRO models based on the original one. Some extend the original to the product level instead of the brand level due to improved data granularity. However, among all the extensions, none of them include the interactions between the promotion of two products (brands); the only interaction term mentioned in their article is the interaction between price index (promotion) and non-price advertisement. My intuition about this phenomenon is: if one wants to capture the cross-brand effects, the size of the parameter estimated is $O(n^2)$, where n is the number of brands; but if one wants to capture the interaction effects between all decision variables, the size becomes $O(n^3)$, without enough observed data ($t \gg n^2$), the equation can not be specified.

Comment:

1. Equation 1 is called multiplicative model, also known as **gross** sales model. There is another stream of model: the **net** model, which doesn't adopt the log transform and is easier for demand decomposition (see an example of [Van Heerde et al., 2004]). The reviewer suggests we should adopt this model (log-log), I think it's a great idea.
2. The reviewer mentioned that we should include the interaction term between different channels. This idea can be applied in our study since the size of parameters is only $o(n^2)$ even after we include the channel-interaction term. However, it brings some difficulties in the following optimization stage.

Note that there are some differences between our study and the prior study on promotion. In the study on promotion, the price can be considered as the decision variable. Our model is not designed for dynamic pricing, meaning the price can be assumed exogenous in the decision process.

1.2 Implications on Our Study

First, when controlling the effect of price, we can use a price index similar to the SCAN*PRO model: $p_{i,t}/\bar{p}_i$, where $\bar{p}_i$ is the regular price for product i (the mean price across all periods).

Second, we can use the log term on both sides when building the model (multiplicative model). The dependent variable should be demand rather than revenue (this won't affect the complexity of the optimization.)

Third, the interaction effects across different channels should be helpful, but we shouldn't make it nested with the price index. (This may affect the complexity of the optimization)

The refined model is given by:

$$\begin{aligned}\ln q_i^t =& \alpha_{i,0} + \sum_{j\in\mathcal{J}} \alpha_{i,j} \ln s_{i,j}^t + \sum_{j,j'\in\mathcal{J},j>j'} \delta_{j,j'} \ln s_{i,j}^t \cdot \ln s_{i,j'}^t + \\ & \sum_{j\in\mathcal{J}} \left(\alpha_{i,j}^{pre}\delta_{pre}^t + \alpha_{i,j}^{pro}\delta_{pro}^t + \alpha_{i,j}^{pos}\delta_{pos}^t\right) \ln s_{i,j}^t + \\ & \sum_{j\in\mathcal{J}} \left(\beta_{i,j}^{\ell 1} \ln s_{i,j}^{t-1} + \beta_{i,j}^{\ell 2} \ln s_{i,j}^{t-2} + \beta_{i,j}^{\ell 3} \ln s_{i,j}^{t-3}\right) + \Theta_i \cdot \Omega_i^t + \epsilon_i^t,\end{aligned} \tag{3}$$

where Ω_i^t contains the price index $\ln p_{i,t}/\ln \bar{p}_i$ and other control variables. I use three identification techniques: OLS, Lagged term as IV (2SLS-L), non-competitor activity as IV (2SLS-N), and two different products as the focal products: M8 and JW.

2 The Main Results

The base model:

$$\begin{aligned} r_i^t = \alpha_{i,0} + \sum_{j\in J} \alpha_{i,j} s_{i,j}^t + \sum_{j\in J} \hat{\alpha}_{i,j} (s_{i,j}^t)^2 + \sum_{j\in J} \left(\alpha_{i,j}^{pre}\delta_{pre}^t + \alpha_{i,j}^{pro}\delta_{pro}^t + \alpha_{i,j}^{pos}\delta_{pos}^t\right) s_{i,j}^t + \\ \Theta_i \cdot \Omega_i^t + \epsilon_i, \quad i \in \mathcal{I}, \end{aligned} \tag{4}$$

The results are given in table 6 and 7.

The cross-period model:

$$\begin{aligned} r_i^t = \alpha_{i,0} + \sum_{j\in\mathcal{J}} \alpha_{i,j} s_{i,j}^t + \sum_{j\in\mathcal{J}} \hat{\alpha}_{i,j} (s_{i,j}^t)^2 + \sum_{j\in\mathcal{J}} \left(\alpha_{i,j}^{pre}\delta_{pre}^t + \alpha_{i,j}^{pro}\delta_{pro}^t + \alpha_{i,j}^{pos}\delta_{pos}^t\right) s_{i,j}^t + \\ \sum_{j\in\mathcal{J}} \left(\beta_{i,j}^{\ell 1} s_{i,j}^{\iota-1} + \beta_{i,j}^{\ell 2} s_{i,j}^{\iota-2} + \beta_{i,j}^{\ell 3} s_{i,j}^{\iota-3}\right) + \Theta_i \cdot \Omega_i^t + \epsilon_i, \quad i \in \mathcal{I}. \end{aligned} \tag{5}$$

The cross-product model:

$$
\begin{aligned}
r_i^t = \alpha_{i,0} + \sum_{j\in\mathcal{J}} \alpha_{i,j} s_{i,j}^t + \sum_{j\in\mathcal{J}} \hat{\alpha}_{i,j} (s_{i,j}^t)^2 + \sum_{j\in\mathcal{J}} \left(\alpha_{i,j}^{pre}\delta_{pre}^t + \alpha_{i,j}^{pro}\delta_{pro}^t + \alpha_{i,j}^{pos}\delta_{pos}^t\right) s_{i,j}^t + \\
\sum_{k\in\mathcal{I}\setminus\{i\}} \sum_{j\in\mathcal{J}} \gamma_{k,j} s_{k,j}^t + \Theta_i \cdot \Omega_i^t + \epsilon_i, \quad i \in \mathcal{I}.
\end{aligned}
\tag{6}
$$

The cross-period and cross-product model:

$$
\begin{aligned}
r_i^t = \alpha_{i,0} + \sum_{j\in\mathcal{J}} \alpha_{i,j} s_{i,j}^t + \sum_{j\in\mathcal{J}} \hat{\alpha}_{i,j} (s_{i,j}^t)^2 + \sum_{j\in\mathcal{J}} \left(\alpha_{i,j}^{pre}\delta_{pre}^t + \alpha_{i,j}^{pro}\delta_{pro}^t + \alpha_{i,j}^{pos}\delta_{pos}^t\right) s_{i,j}^t + \\
\sum_{j\in\mathcal{J}} \left(\beta_{i,j}^{\ell 1} s_{i,j}^{t-1} + \beta_{i,j}^{\ell 2} s_{i,j}^{t-2} + \beta_{i,j}^{\ell 3} s_{i,j}^{t-3}\right) + \sum_{k\in\mathcal{I}\setminus\{i\}} \sum_{j\in\mathcal{J}} \gamma_{k,j} s_{k,j}^t + \Theta_i \cdot \Omega_i^t + \epsilon_i, \quad i \in \mathcal{I}.
\end{aligned}
\tag{7}
$$

There are four classic papers that address the endogeneity issue of estimating the demands using IV ([Berry et al., 1995], [Hausman, 1996], [Nevo, 2000], [Nevo, 2001]). I selected several representative articles that cite these classic articles and were published in the top business journals. Then, I sorted out the instrumental variables they used.

I also came up with some potential IVs that may be applicable to our research.

Table 1: Potential Instrumental Variables and Rationales

Instrumental Variable	**Rationale**
One-week lagged advertising expenditures	The lagged advertisement in the future are correlated with the advertisement at the current, but it doesn't correlate to the error term. It may be difficult to use this IV in the optimization scheme.
The unit cost of advertising on Tmall	This is a cost-related variable.
The advertisement cost of the same product on different platforms, such as JD.com	This is a cost-related variable. After controlling for the platforms (consumer demographics), platform-specific unobserved error terms are independent across the platforms. Hence, the advertisement activity of the same product by the same company will be correlated because of the common marginal costs.
The advertisement cost of the same category by the same company on different platforms	This is a cost-related variable. The rationale is the same as above.
The company's average advertisement behavior in the same category (excluding the focal one) on other platforms.	The rationale is similar to the above.
The cost of the products (such as ingredients prices)	This is a cost-related variable.
low-cost products' market share in the same category	This serves as a proxy for competition level, and the competition level would influence the consumer demands through the pricing and advertising;
The marketing variables of the same products in other channels.	Shocks in costs that cause exogenous variation in other marketing channels will cause similar exogenous variation in the focal channels.

Table 6: The base model for product JW

	(1) JW-OLS	(2) JW-2SLS-L	(3) JW-2SLS-N	(4) JW-2SLS-C
S_banner	-0.0533			
	(-0.78)			
S_recommender	0.143			
	(1.82)			
S_product	-0.0387***			
	(-6.26)			
S_store	0.530*			
	(2.53)			
S_banner_squared	0.0000153**			
	(3.27)			
S_recommender_squared	-0.00000971*			
	(-2.03)			
S_product_squared	0.000000558***			
	(8.96)			
S_store_squared	-0.000109***			
	(-3.99)			
Pre_S_banner	-0.288	0.559	0.139	-0.737
	(-0.64)	(0.47)	(0.32)	(-1.52)
Pre_S_recommender	0.0577	-1.227	-0.289	0.356
	(0.29)	(-1.50)	(-1.07)	(1.38)
Pre_S_product	-0.0262	-0.0788	0.0392	0.00145
	(-1.09)	(-1.43)	(0.76)	(0.05)
Pre_S_store	-0.357	-6.525**	1.662**	1.172
	(-0.54)	(-2.96)	(2.73)	(1.04)
Pro_S_banner	0.960*	-2.576	1.407	0.153
	(2.01)	(-1.76)	(1.82)	(0.29)
Pro_S_recommender	-0.876***	5.191***	-0.432	-0.270
	(-3.33)	(5.44)	(-0.90)	(-0.75)
Pro_S_product	0.00185	-0.182**	-0.00613	0.0890*
	(0.07)	(-2.60)	(-0.12)	(2.24)
Pro_S_store	-0.559	-4.000	0.278	-0.758
	(-0.73)	(-1.67)	(0.36)	(-0.60)
Pos_S_banner	-0.876**	2.889*	-1.173	-0.540
	(-2.84)	(2.35)	(-1.59)	(-1.16)
Pos_S_recommender	0.373	-4.861***	0.374	0.444
	(1.02)	(-6.49)	(0.82)	(1.25)
Pos_S_product	0.0653***	0.175**	0.0313	-0.0161

	(3.84)	(3.23)	(0.62)	(-0.50)
Pos_S_store	-0.182	4.122*	-0.827	-0.521
	(-0.34)	(2.41)	(-1.34)	(-0.67)
Pro	1750.6	12512.9	-1647.2	238.7
	(0.82)	(1.82)	(-0.67)	(0.08)
Pre	1917.9	20663.9***	-6510.0*	-2704.0
	(0.97)	(3.38)	(-2.56)	(-1.04)
Pos	-1406.5	-15486.8**	2130.9	1238.8
	(-0.96)	(-3.04)	(1.14)	(0.64)
Price	-352.5***	-281.6**	-349.6***	-390.1***
	(-13.04)	(-3.29)	(-9.29)	(-12.69)
Price2	1.260***	1.080**	1.193***	1.422***
	(10.76)	(3.14)	(6.89)	(10.14)
GiftV	-21.16**	-31.58	-19.35	-33.12***
	(-3.05)	(-1.52)	(-0.52)	(-3.57)
GiftQ	0.0176***	0.0633**	0.0211	0.0248***
	(3.52)	(2.70)	(1.95)	(4.15)
S_banner_hat		-0.00516	-0.306	-0.214
		(-0.01)	(-0.71)	(-0.93)
S_recommender_hat		-0.157	0.175	-0.0541
		(-0.61)	(0.55)	(-0.65)
S_product_hat		-0.00906	0.0267	-0.00380
		(-0.98)	(1.07)	(-0.84)
S_store_hat		0.0411	-0.538	-0.230
		(0.07)	(-0.19)	(-0.80)
S_banner_squared_hat		0.00000799	-0.00000598	0.0000167
		(0.21)	(-0.12)	(0.83)
S_recommender_squared_hat		0.0000112	0.0000174	0.00000787**
		(0.61)	(0.70)	(3.00)
S_product_squared_hat		0.000000302*	-1.86e-08	3.54e-08
		(2.51)	(-0.07)	(1.50)
S_store_squared_hat		-0.0000491	0.0000685	-0.00000222
		(-0.66)	(0.20)	(-0.06)
_cons	23642.6***	18354.9**	24323.2***	26777.5***
	(14.26)	(3.21)	(4.43)	(14.35)
N	496	493	496	493

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary of Relevant Papers for [Deng et al., 2023]

Paper	Setting	Dependent Variable (DV)	Endogenous Variable	Instrument Variable (IV)	Rationale for IV	Statistical Test and Robustness Checks
[Zhang et al., 2022]	They want to control the effects of the property price on the demand. Property price is endogenous because it correlates with random demand shocks in the current period, which also affect property demand.	Demand of property	Price of property	• the characteristics of competing properties; • cost-related variables such as residential utility fee.	• The characteristics of competing products are unlikely to correlate with unobserved demand shocks. However, they can influence the property markup and price through competition. • The cost-related variables can influence the price, but they are unlikely to be correlated with demand in the short-term lodging market.	No, because it's not the main effect to identify.
[Ghose and Han, 2014]	They want to identify the effect of the app's price on the demand, but it suffers from the endogeneity issue caused by unobserved app valuation.	market share	price	• the average price of same-category apps by the "same app developer" in the other app store; • the price of the same app by the "same app developer" in the other app store.	After controlling for app developers and consumer demographics, app-store specific valuations are independent across app stores. Hence, prices of same-category apps by the "same app developer" and prices of the same app by the "same app developer" in different app stores will be correlated because of the common marginal costs.	• Performed an F -test in the first-stage regression (> 10); • Hansen J-test could not reject the null hypothesis of valid overidentifying restrictions.

Table 3: Summary of Relevant Papers for [Deng et al., 2023]

Paper	Setting	Dependent Variable (DV)	Endogenous Variable	Instrument Variable (IV)	Rationale for IV	Statistical Test and Robustness Checks
[Liu et al., 2017]	This paper identifies the car's aesthetic design on demand, which needs to control the effect of price and advertisement on demand. However, these two control variables suffer from endogeneity issues because econometrically unobserved factors may affect a firm's price and advertising spending decisions.	demand of car 3	short-run pricing and advertising 3	• functions of car attributes • advertising cost (average unit cost across media)	The first IV follows BLP style. The advertising cost only affects the demand through the advertisement activity.	The first-stage regression results show that the instruments explain the variation in price and advertising well.
[Golara et al., 2021]	The authors aim to identify the effect of the dealer's service quality on the manufacturer's success. It has an endogeneity issue on the consumer ratings: manufacturers may be influencing their dealers according to characteristics of the corresponding market.	market share	consumer ratings	• average ratings of the dealers of the same make in other markets in the same state; • average ratings of the dealers of the same make in markets outside the focal state but in the same census division.	Dealer ratings in different markets should be correlated because they share the same manufacturer and follow its general guidelines. Consumers in one market are not usually influenced by the purchase decisions of consumers in other markets.	Sargan-Hansen test of overidentifying restrictions. The F-test from the first stage equation.

Table 4: Summary of Relevant Papers for [Deng et al., 2023]

Paper	Setting	Dependent Variable (DV)	Endogenous Variable	Instrument Variable (IV)	Rationale for IV	Statistical Test and Robustness Checks
[Gong et al., 2018]	The authors aim to identify the keyword's ambiguity on the CTR. The endogeneity issue arises because the position of ads is correlated with unobserved factors.	the click-through rate	the position of ads	the average position of ad a displayed for all keywords other than keyword k	Supply-side factors such as advertisers' willingness to bid and advertising budget are correlated across keywords and affect ad positions, thus the positions of the same ad across keywords should be correlated. However, these supply-side factors are unlikely to affect users' clickthrough behavior directly.	Not mentioned.
[Xu et al., 2021]	The authors want to predict the effect of comments information on the demand of the doctors. The endogeneity between overall rating and demand arises from omitted variables such as the underlying doctor quality.	the demand for doctors	underlying doctor quality	the average ratings of the same specialty physicians in all other markets.	Market-specific valuations are independent across markets after controlling for demographics (but can be correlated within the same market).	F-statistics for the joint significance of our IVs for the first-stage regression; Sargan test of overidentifying restrictions.
[Granados et al., 2018]	The authors want to identify the effects of opaque channel on the demands of online transparent channel and offline channel in the airline industry. They need to conquer the endogeneity of price.	the booking shares for different channels	price	• stage length; • hub; • low-cost carriers' market share; • one-week lagged price;	• The first two IVs are cost-related variables; • The low-cost carriers' market share is a proxy for competition level, hence, affects the demands through prices; • One-week lagged price significantly correlates with the current price, but not with the dependent variables.	First-stage F-test of weak identification; Sargan test of overidentification.

Table 5: Summary of Relevant Papers for [Deng et al., 2023]

Paper	Setting	Dependent Variable (DV)	Endogenous Variable	Instrument Variable (IV)	Rationale for IV	Statistical Test and Robustness Checks
[Dinner et al., 2014]	The authors want to identify the cross-effects of the advertisement of different channels on the sales. All advertising variables have endogeneity issues: for example, a manager may plan weekly advertising expenditures according to unobserved demand shocks known to her.	online sales	advertising expenditures	marketing variables from a similar but different market (advertising expenditures of lower-end retailers)	Shocks in costs that cause exogenous variation in marketing variables in one market will cause similar exogenous variation in the focal market	F-test for the first-stage regressions; Hausman–Wu estimand to test the existence of endogeneity; A Sargan test is used to test for overidentifying restrictions. They also use a different set of IVs based on costs of advertising (unit costs for television, magazine, newspaper, and online display for the retail industry) for robustness checks.

Table 7: The base model for product M8

	(1) M8-OLS	(2) M8-2SLS-L	(3) M8-2SLS-N	(4) M8-2SLS-C
S_banner	-0.0593			
	(-1.85)			
S_recommender	0.451***			
	(5.95)			
S_product	-0.0213			
	(-0.98)			
S_store	0.0939			
	(0.19)			
S_banner_squared	-0.00000220*			
	(-2.38)			
S_recommender_squared	-0.0000287***			
	(-6.55)			
S_product_squared	0.00000321***			
	(7.66)			
S_store_squared	0.0000325			
	(0.19)			
Pre_S_banner	0.0861	5.451*	-0.250*	-0.0714
	(0.40)	(2.16)	(-2.45)	(-0.54)
Pre_S_recommender	0.134	-6.681	1.531**	0.256
	(0.26)	(-1.59)	(3.26)	(0.71)
Pre_S_product	0.151	0.363	-0.113	0.139
	(1.53)	(0.57)	(-1.38)	(1.80)
Pre_S_store	1.979	30.07***	-7.565**	1.564
	(1.45)	(5.12)	(-2.62)	(0.95)
Pro_S_banner	0.219	-0.186	0.302*	-0.151
	(0.94)	(-0.06)	(2.05)	(-0.95)
Pro_S_recommender	-0.133	3.814	-1.554**	-0.141
	(-0.25)	(0.83)	(-3.19)	(-0.36)
Pro_S_product	-0.0920	-1.069	0.191*	0.107
	(-1.14)	(-1.59)	(2.04)	(1.31)
Pro_S_store	-0.545	19.79***	3.120	-1.250
	(-0.38)	(3.44)	(1.15)	(-0.74)
Pos_S_banner	0.120	-2.479	-0.621***	-0.128
	(0.70)	(-1.29)	(-4.16)	(-0.88)
Pos_S_recommender	-0.685*	-2.647	1.265***	-0.162
	(-2.32)	(-1.08)	(4.58)	(-0.61)
Pos_S_product	0.100	1.722**	-0.104	0.0394

	(1.00)	(2.72)	(-1.47)	(0.54)
Pos_S_store	1.405	-19.92***	-0.207	2.155*
	(1.66)	(-5.16)	(-0.17)	(2.07)
Pro	109.9	-17995.4	-4757.3	669.4
	(0.06)	(-1.82)	(-1.56)	(0.30)
Pre	-2000.2	-38638.1***	9338.5**	-938.9
	(-1.09)	(-4.45)	(2.91)	(-0.47)
Pos	-1649.8	14313.5*	1403.1	-2840.8*
	(-1.41)	(2.00)	(0.91)	(-1.97)
Price	-607.4***	-943.9	-256.4*	-923.2***
	(-5.30)	(-1.32)	(-2.32)	(-7.36)
Price2	3.078***	5.081	0.929	4.831***
	(4.76)	(1.27)	(1.49)	(6.81)
GiftV	11.63	8.907	28.47*	5.551
	(1.11)	(0.16)	(2.34)	(0.52)
GiftQ	-0.0260*	0.0763	-0.0816***	-0.0304**
	(-2.16)	(1.69)	(-6.99)	(-2.65)
S_banner_hat		0.0432	-0.00126	-0.0371
		(0.27)	(-0.06)	(-1.07)
S_recommender_hat		-0.105	-0.331***	-0.0439
		(-0.44)	(-4.35)	(-0.73)
S_product_hat		-0.0948	0.119***	0.00301
		(-0.82)	(6.30)	(0.14)
S_store_hat		0.00582	-1.037	0.405
		(0.00)	(-0.79)	(0.74)
S_banner_squared_hat		0.000000977	-0.00000261***	8.40e-08
		(0.12)	(-4.86)	(0.24)
S_recommender_squared_hat		0.00000393	0.0000550***	0.00000376***
		(0.51)	(9.59)	(5.23)
S_product_squared_hat		-6.71e-09	-0.00000415***	0.000000115
		(-0.01)	(-7.87)	(1.46)
S_store_squared_hat		-0.0000609	0.000207	-0.0000842
		(-0.08)	(0.46)	(-0.44)
_cons	29771.4***	44292.4	16606.9***	43896.5***
	(5.89)	(1.38)	(3.35)	(7.96)
N	486	483	486	483

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

References

[Berry et al., 1995] Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica : journal of the Econometric Society*, 63(4):841–890.

[Deng et al., 2023] Deng, Q., Hu, K., and Lim, Y. F. (2023). Cross-Channel Marketing on E-commerce Marketplaces: Impact and Strategic Budget Allocation. *SSRN Electronic Journal*.

[Dinner et al., 2014] Dinner, I. M., Heerde Van, H. J., and Neslin, S. A. (2014). Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising. *Journal of marketing research*, 51(5):527–545.

[Ghose and Han, 2014] Ghose, A. and Han, S. P. (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science*, 60(6):1470–1488.

[Golara et al., 2021] Golara, S., Dooley, K. J., and Mousavi, N. (2021). Are Dealers Still Relevant? How Dealer Service Quality Impacts Manufacturer Success. *Production and Operations Management*, 30(10):3560–3578.

[Gong et al., 2018] Gong, J., Abhisek, V., University of California - Irvine, Li, B., and Carnegie Mellon University (2018). Examining the Impact of Keyword Ambiguity on Search Advertising Performance: A Topic Model Approach. *MIS Quarterly*, 42(3):805–829.

[Granados et al., 2018] Granados, N., Han, K., and Zhang, D. (2018). Demand and Revenue Impacts of an Opaque Channel: Evidence from the Airline Industry. *Production and Operations Management*, 27(11):2010–2024.

[Hausman, 1996] Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The Economics of New Goods*, pages 207–248. University of Chicago Press.

[Leeflang et al., 2002] Leeflang, P. S., Van Heerde, H. J., and Wittink, D. R. (2002). How Promotions Work: SCAN*PRO-Based Evolutionary Model Building. *SSRN Electronic Journal*.

[Liu et al., 2017] Liu, Y., Li, K. J., Chen, H. A., and Balachander, S. (2017). The Effects of Products' Aesthetic Design on Demand and Marketing-Mix Effectiveness: The Role of Segment Prototypicality and Brand Consistency. *Journal of Marketing*, 81(1):83–102.

[Nevo, 2000] Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, pages 395–421.

[Nevo, 2001] Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica : journal of the Econometric Society*, 69(2):307–342.

[Van Heerde et al., 2004] Van Heerde, H. J., Leeflang, P. S. H., and Wittink, D. R. (2004). Decomposing the Sales Promotion Bump with Store Data. *Marketing Science*, 23(3):317–334.

[Wittink et al., 1988] Wittink, D. R., Addona, M. J., Hawkes, W. J., and Porter, J. C. (1988). SCAN* PRO: The estimation, validation and use of promotional effects based on scanner data. *Internal Paper, Cornell University*.

[Xu et al., 2021] Xu, Y., Armony, M., and Ghose, A. (2021). The Interplay Between Online Reviews and Physician Demand: An Empirical Investigation. *Management Science*, 67(12):7344–7361.

[Zhang et al., 2022] Zhang, S., Lee, D., Singh, P. V., and Srinivasan, K. (2022). What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science*, 68(8):5644–5666.