



Mitigating the negative effect of intrabrand clustering: the role of interbrand clustering and firm size

Moeen Naseer Butt¹

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Abstract

Clustering—geographic concentrations of entities—has recently received more attention in marketing research and has been shown to affect multiple outcomes. This study investigates the impact of intrabrand clustering (clustering of same-brand outlets) on an outlet's quality performance. Further, it assesses the moderating effects of interbrand clustering (clustering of other-brand outlets) and firm size. An examination of approximately 21,000 food service establishments in New York State in 2019 finds that the impact of intrabrand clustering on an outlet's quality performance is context-dependent. Specifically, intrabrand clustering decreases, whereas interbrand clustering and firm size help to increase the outlet's performance. Additionally, this study finds that the role of firm size is more substantial than interbrand clustering in mitigating the adverse effects of intrabrand clustering on outlet quality performance.

Keywords Intrabrand clustering · Interbrand clustering · Firm size · Brand competition · Outlet performance · Quality violations

Introduction

Clustering—geographic concentrations of interconnected entities in a particular field (Porter 1998)—has recently gained more traction in the marketing and management literature. Some published papers show the effect of clustering or proximity on outlet sales revenue (Butt et al. 2018; Kalnins 2004; Pancras et al. 2012), nursing home quality (Lu and Wedig 2013), communication (Ganesan et al. 2005), and franchisor performance (Zheng et al. 2020). A close examination of that research stream shows that most of this published research focused on the clustering of same-brand outlets, i.e., *intrabrand clustering* (e.g., Butt et al. 2018; Kalnins 2004). Further, it provides mixed evidence with both positive and negative performance outcomes of clustering (e.g., Butt et al. 2018; Lu and Wedig 2013; Pancras et al. 2012).

The overwhelming focus on intrabrand clustering ignores the potential impact of other-brand outlets located nearby,

i.e., *interbrand clustering*. It is much more common to find same-brand outlets near other-brand outlets with similar offerings in our daily lives. For example, McDonald's restaurants will most likely be located next to Burger King, Wendy's, and KFC restaurants. The fact that outlets belonging to the same brand situate near other brands may significantly affect the outlets' performance.

Further, *firm size*—the number of outlets of a brand—may significantly affect outlet performance when clustered. A larger firm size generally means more resources, more significant experience advantage, and higher efficiency that may lead to a better quality of processes, products, and services at lower costs (Bachmann et al. 2021; Kalyanaram et al. 1995; Scherer and Ross 1990; Liu 1995; Wang 2010). An outlet associated with a larger-sized firm may thus perform differently when clustered than the one related to a smaller-sized firm.

Relying on clustering literature in marketing, management, and economics (Butt et al. 2018; Lu and Wedig 2013; Porter 1998) and brand competition literature in branding and brand management (Carpenter and Lehmann 1985; Depeyre et al. 2018; Faulkner et al. 2014; González-Benito et al. 2010), this study aims to assess the effect of intrabrand clustering on outlet quality performance measured in terms of quality violations. Further, it investigates the potential

✉ Moeen Naseer Butt
moeen.butt@lums.edu.pk

¹ Suleman Dawood School of Business, Lahore University of Management Sciences (LUMS), DHA, Lahore Cantt., Lahore 54792, Pakistan



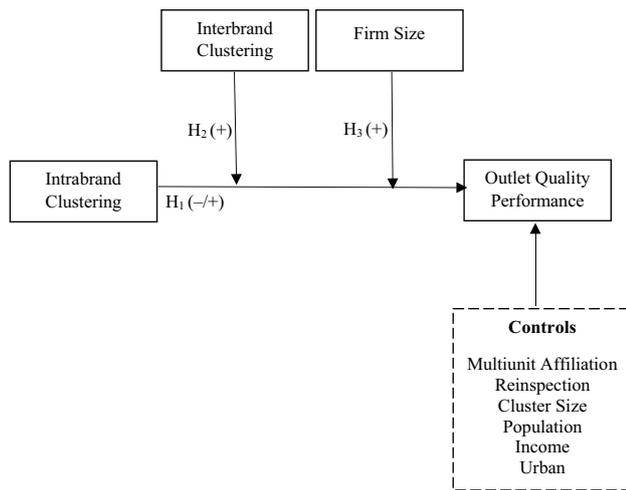


Fig. 1 Conceptual diagram

role of interbrand clustering and firm size as moderators that may impact the relationship between intrabrand clustering and outlet quality performance.

This study uses publicly available New York State Department of Health (NYSDOH) data. The NYSDOH records the inspection of every food service establishment located within the New York State boundary. The dataset comprises approximately 21,000 food service establishments operating across New York State in 2019. I supplement these data with population, income, and location information at the zip code-level collected from the US Census Bureau and USDA. Additionally, I use ArcGIS software to compute intrabrand and interbrand clustering variables within a specified radius.

In what follows, I present the conceptual framework and hypotheses sections. This follows by describing my research context, model specification, and results. I conclude with a discussion of the implications of my study for theory and practice, limitations, and some future research avenues.

Literature review

Figure 1 represents my conceptual diagram. My interest focuses on the potential impact of intrabrand clustering on outlet quality performance and how interbrand clustering and firm size might temper the relationship between intrabrand clustering and outlet quality performance.

According to Porter (1998), “clusters promote both competition and cooperation”.

Accordingly, prior work on clustering has emphasized its positive and negative outcomes. It has adopted several theoretical mechanisms to explain its impact, including knowledge sharing, monitoring efficiency, agglomeration

effects, brand awareness, and competition. Table 1 provides selected empirical papers related to clustering/proximity, and Fig. 2 shows the intrabrand and interbrand clustering instances individually in Panels 1 and 2 and together in Panel 3.

Prior research shows the advantage of clustering in disseminating knowledge among outlets sharing the same-brand name (Argote and Darr 2000; Bradach 1997; Butt 2017; Butt et al. 2018). Clustering allows the outlets’ operators to observe and meet each other more frequently and cost-effectively and, therefore, share knowledge without spending more time and effort (Argote and Miron-Spektor 2011; Ganesan et al. 2005). This knowledge transfer facilitation due to clustering likely improves outlets’ performance (Butt 2017; Butt et al. 2018; Kalnins and Mayer 2004).

Another theoretical mechanism links clustering of outlets with greater monitoring efficiency. As the proximity of outlets increases, it gets less time-consuming to monitor outlets owing to reduced travel time from one outlet to another. Therefore, the cost of monitoring per outlet within an area goes down significantly (Holmstrom and Milgrom 1991; Lafontaine and Slade 2007; Lu and Wedig 2013). This advanced efficiency to monitor better enables firms to expose violations and noncompliant behavior exhibited by the outlets (Brickley and Dark 1987; Lu and Wedig 2013), thereby increasing the performance.

As well, clustering is shown to create agglomeration effects in terms of heightened demand (Marshall 1920). The closely located outlets of different brands reduce customer search costs and give customers more variety and options, increasing the likelihood of their visits and purchases (Baum and Mezias 1992; Chung and Kalnins 2001). The heightened demand increases the overall market size for clustered outlets, positively affecting their performance.

Further, clustering of same-brand outlets can increase brand awareness and help forge positive brand associations with target customers (Avery et al. 2012). The clustered same-brand outlets are highly noticeable and provide more brand exposure to customers. Therefore, managers increasingly view stores as a form of promotion that has the potential to reach more customers with greater frequency and performs the same function as the brand’s billboard (Avery et al. 2012; Chang 2009).

Lastly, clustering yields some adverse outcomes too. It can harm outlet performance due to the intense competition (Porter 1998). Previous work supports the existence of more significant competition among clustered same-brand outlets (e.g., Butt et al. 2018; Kalnins 2004). The competition among closely located same-brand outlets likely results from the almost identical product and service offerings with little room for differentiation (Pancras et al. 2012), which



Table 1 Selected prior empirical studies on clustering/proximity

Study	Data	Interbrand clustering as a context-dependency studied	Firm size as a context-dependency studied	Outlet-level clustering studied	Outlet-level performance studied
Brickley and Dark (1987)	Franchised firms operating in multiple industries located in the USA	No	No	Yes	No
Kalnins and Mayer (2004)	Pizza restaurants located in Texas State	No	No	Yes	Yes
Kalnins (2004)	Franchised and company-owned lodging establishments in Texas State	No	No	Yes	Yes
Ganesan et al. (2005)	Firms belonging to the optics industry located in the USA	No	No	No	No
Pancras et al. (2012)	A franchised chain of fast-food restaurants located in a large metropolitan area in the USA	No	No	Yes	Yes
Lu and Wedig (2013)	For-profit nursing home chains located in the USA	No	No	Yes	Yes
Butt et al. (2018) ^a	A large franchised automotive service firm located in the USA	No	No	Yes	Yes
Guler (2018)	Starbucks stores located in the USA	No	No	Yes	Yes
Zheng et al. (2020)	Franchised systems located in the USA	No	No	No	No
This study	Food service establishments located in New York State	Yes	Yes	Yes	Yes

^aButt et al. (2018) included interbrand competition into their model as a control variable. Further, their measure of interbrand competition was at the aggregated county level, not at the individual outlet level

results in customers viewing them as close substitutes leading to sales cannibalization (Davis 2006; Kalnins 2004).

Competition is also an established topic in branding and brand management literature. Prior research has studied various aspects of brand competition, including the impact of brand name, multiple products, and advertising on intrabrand and interbrand competition (Carpenter and Lehmann 1985), the strength of cannibalization effects versus competitive effects on other brands (González-Benito et al. 2010; Lomax et al. 1997), patterns of brand competition in emerging markets such as China (Faulkner et al. 2014), the effects of brand competition and co-competition strategies on business performance (Depeyre et al. 2018), and brand competition leading to undifferentiation and commoditization (Nandan 2005).

My research contributes to the brand management literature by considering brand competition arising due to geographical proximity or clustering of same- and other-brand outlets. This study acknowledges the possibility of both positive and negative effects of clustering and relies on the competition literature (Chung and Kalnins 2001; González-Benito et al. 2010; Pancras et al. 2012), monitoring efficiency (Brickley and Dark 1987; Lu and Wedig 2013), and

agglomeration effects (Chung and Kalnins 2001; Marshall 1920) to describe relationships and state hypotheses.

Hypotheses

The main effect of intrabrand clustering

The proximity of same-brand outlets likely triggers intrabrand competition due to shared markets and customers. The same-brand outlets share similar traits; therefore, they have the potential to compete more intensely (Baum and Mezias 1992; Porter 1998). As closely located outlets of the same brand sell identical products to the same customer segments with little differentiation (Baum and Mezias 1992; González-Benito et al. 2010), customers are shared, and market size per outlet is reduced (Butt 2017; Lomax et al. 1997). Dealing with the increasing prospect of intrabrand competition, same-brand outlets are more likely to free-ride to take advantage of the common brand name (Rubin 1990) and shirk their quality obligations (Bergen et al. 1992; Lu and Wedig 2013). Therefore, I expect a negative association



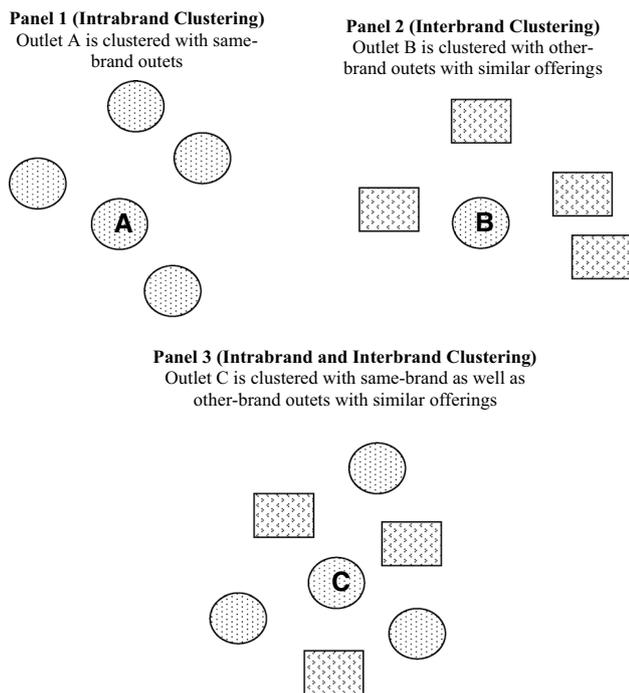


Fig. 2 Intrabrand and interbrand clustering

between intrabrand clustering and outlet quality performance. My baseline expectation is as follows:

H₁ The higher the intrabrand clustering, the lower the outlet quality performance.

As well, clustering of same-brand outlets increases monitoring efficiency due to reduced travel time of inspectors (Lu and Wedig 2013). The reduced travel time decreases the cost of monitoring per outlet (Lafontaine and Slade 2007), enabling firms to detect outlet quality violations (Brickley and Dark 1987; Lu and Wedig 2013). This credible threat of monitoring brought about by clustering likely deters outlets from shirking on quality aspects, increasing the quality performance of outlets. Therefore, my alternate expectation is as follows:

H_{1Alt} The higher the intrabrand clustering, the greater the outlet quality performance.

The moderating effect of interbrand clustering

A higher intensity of interbrand clustering may significantly affect the relationship between intrabrand clustering and outlet quality performance. Specifically, I argue that interbrand clustering mitigates the adverse effects of intrabrand clustering on outlet quality performance, hence helping the outlets perform better.

A higher intensity of other-brand outlets likely increases the market size owing to agglomeration effects¹—the external economies accruing from the collocation of different firms (Chung and Kalnins 2001; Liu et al. 2022; Marshall 1920). The presence of closely located outlets of different brands creates a destination marketplace for customers who want more variety in one place. It helps customers to evaluate the options presented by various brands situated close to each other, increasing the likelihood of their visits and purchases versus if the outlets had been located dispersedly (Chung and Kalnins 2001). This increase in market size and customer patronage may decrease the propensity of the outlet to free-ride and shirk on quality aspects, hence helping the outlet perform better.

In sum, in the presence of both intrabrand and interbrand clustering, there is an inflection point where the outlet decides whether it is better off free-riding to take advantage of a common brand or cleaning up its act. I argue that a higher intensity of interbrand clustering likely mitigates the adverse effects of intrabrand clustering and helps the outlet perform better thanks to the agglomeration effects.

About my alternate baseline hypothesis (H_{1Alt}), I expect that the agglomeration effect generated by interbrand clustering strengthens the positive association between intrabrand clustering and outlet quality performance. The increase in market size and customer patronage discourages outlets from shirking on quality obligations. This effect, combined with monitoring efficiency generated by intrabrand clustering, further bolsters the positive impact of interbrand clustering on outlet quality performance.

H₂ A higher interbrand clustering weakens (strengthens) the negative (positive) association between intrabrand clustering and outlet quality performance.

The moderating effect of firm size

Firm size of clustered outlets may significantly affect the relationship between intrabrand clustering and outlet quality performance. Specifically, a larger firm size could be instrumental in mitigating the harmful effects of intrabrand clustering in at least two ways. First, a larger firm size generally means more resources and a more significant experience advantage that may lead to a better quality of processes, products, and services (Bachmann et al. 2021; Kalyanaram et al. 1995; Scherer and Ross 1990). Second, the larger firm

¹ I acknowledge that interbrand clustering may also trigger competition and harm the outlet performance. In this paper, I base my argument on the widely accepted positive outcome of interbrand clustering—agglomeration effect in terms of heightened demand (e.g., Chung and Kalnins, 2001; Liu, Wei, and Gao, 2022; Marshall, 1920).



generates greater economies of scale, reducing the cost of doing business and increasing efficiency relative to competition (Kalyanaram et al. 1995; Liu 1995; Wang 2010).

When clustered with same-brand outlets, there is an inflection point where the outlet decides whether it is better off free-ride or perform well. I argue that a larger firm size deters the outlet from indulging in free-riding and shirking on quality aspects due to more resources, experience, and efficiency effects, even in the presence of high intensity of intrabrand clustering. Therefore, I expect that the larger firm size mitigates the adverse effects of intrabrand clustering and helps the clustered outlets perform better.

Alternatively (H_{1Alt}), I expect that the larger firm size of clustered outlets strengthens the positive association between intrabrand clustering and outlet quality performance due to greater resources, experience, and efficiency effects. A high level of intrabrand clustering serves as a credible threat of monitoring and discourages outlets from shirking on quality aspects. A larger firm size strengthens this effect and further prevents outlets from shirking.

H₃ A larger firm size weakens (strengthens) the negative (positive) association between intrabrand clustering and outlet quality performance.

Method

Empirical context and data collection

I investigate the performance consequences of intrabrand clustering in the context of food service establishments located in New York State. Food service establishments are mainly situated close to each other. Various brands compete directly with each other. Information on their precise locations and quality performance are publicly available, making this context suitable for studying the effects of intrabrand and interbrand clustering and firm size.

New York State is the 27th largest state by area in the USA, with a total area of 54,556 square miles. Further, it is ranked fourth in the US concerning population, with more than 20 million people (US Census Bureau). The GDP of New York State is the third-largest in the USA, behind California and Texas (Bureau of Economic Analysis).

New York State Department of Health (NYSDOH) inspects food service establishments to maintain food quality standards and reduce the incidence of foodborne illness. The food service establishments include full-service restaurants, quick-service restaurants, cafes, and snack bars. The mission statement of NYSDOH is “*To protect public health by assuring that food service establishments are operated in a manner that eliminates hazards through design and*

management, resulting in a decreased incidence of food-borne illness in our communities”.²

The data provided by NYSDOH are publicly available (<https://health.data.ny.gov/>). It includes approximately 21,000 food service establishments in New York State in 2019. Temporary food service establishments, such as mobile and vending machines, are excluded from this dataset.

This dataset comprises food service establishments' names and street addresses, inspection dates, inspection type (such as inspection or reinspection), and quality violations found during their inspections. The types of quality violations include food conditions (e.g., food found in rusty cans), food temperature (e.g., food not kept at recommended temperatures), food from unapproved sources, food contamination, plumbing and drainage issues, improper installation and maintenance of equipment, inaccessible handwashing facility, and inadequate lighting and ventilation. The quality violation details and descriptions are collected on inspection reports, including corrective actions for violations. Food service establishments are graded based on the observed number and types of violations.

I use the food service establishments' street-level addresses to compute intrabrand and interbrand clustering variables using ArcGIS 10.7.1 software. Further, to control market-specific effects, I supplement the NYSDOH data with the population, income, and location type data collected at the most fine-grained level—the zip code-level from US Census Bureau and USDA. Table 2 displays the list of all variables used in this study and their data sources.

Operationalizations

The unit of analysis in this study is the individual food service establishment (outlet) inspected in New York State in 2019. My objective is to relate intrabrand clustering with outlet quality performance and assess the moderating effects of interbrand clustering and firm size.

I measure the dependent variable, outlet quality performance ($QPER_i$), as the total count of quality violations committed by outlet i . Therefore, the lesser the number of violations, the greater the outlet quality performance. The number of quality violations determines inspection scores and restaurant letter grades that are displayed to consumers. Therefore, it is a crucial indicator of an outlet's quality performance (Ibanez and Toffel 2020).

I measure the intrabrand clustering ($INTRACL_i$) as the ratio of the number of same-brand outlets to the total number of outlets within a 5-mile radius of the outlet i . Similarly, I measure the interbrand clustering ($INTERCL_i$) as the ratio of

² <https://www.health.ny.gov/>.



Table 2 variables and data sources

Construct	Measure	Level of analysis	Notation	Data source
Outlet quality performance	The total number of quality violations of outlet i (lesser the number of quality violations, the greater the outlet quality performance)	Outlet	$QPER_i$	New York State Department of Health
Intrabrand clustering	The proportion of same-brand outlets located within the 5-miles radius of outlet i	Outlet	$INTRACL_i$	New York State Department of Health (computed using ArcGIS 10.7.1 software)
Interbrand clustering	The proportion of other-brand outlets located within the 5-miles radius of outlet i	Outlet	$INTERCL_i$	
Firm size	The total number of outlets of brand j of outlet i located in New York State	Firm	FS_{ij}	New York State Department of Health
Cluster size	The total number of same-brand and other-brand outlets within a 5-mile radius of outlet i	Outlet	CLS_i	New York State Department of Health (computed using ArcGIS 10.7.1 software)
Multiunit affiliation	The binary variable that equals 1 when outlet i is affiliated with a multiunit brand j , and 0 otherwise	Outlet	MUA_{ij}	New York State Department of Health
Reinspection	The binary variable that equals 1 when outlet i is reinspected, and 0 otherwise	Outlet	$REINSP_i$	
Population	The total population of zip code k	Zip code	POP_k	US Census Bureau
Income	The median family income of zip code k	Zip code	INC_k	
Urban	The binary variable that equals 1 when a zip code k falls in an urban area, and 0 otherwise	Zip code	URB_k	Economic Research Service, USDA

the number of other-brand outlets to the total number of outlets within a 5-mile radius of outlet i . I compute intrabrand and interbrand clustering measures using the Point Distance module of ArcGIS 10.7.1 software. The Point Distance module determines the distance of a point (location) to all nearby points (locations) within a specified search radius. Here, it calculates the distance of an outlet from proximally located same-brand and other-brand outlets within a 5-mile radius. The Point Distance module provided a table with a considerable amount of data that included the distance in miles of each of 21,000 outlets from all other outlets in my dataset. I counted the number of same-brand, other-brand, and total outlets within a 5-mile radius of each outlet from this table to compute my clustering variables. Considering prior research, I use a 5-mile radius as a suitable distance (e.g., Guler 2018).

I measure firm size (FS_{ij}) as the total number of outlets of brand j , the outlet i is affiliated with. Firm size reflects market dominance that measures the strength of a brand or firm in a geographic area relative to competitors (Athey and Schmutzler 2001).

I include several control variables in my model that may affect the outlet quality performance. To control for ownership effects, I include multiunit affiliation (MUA_{ij}) and measure it as a dichotomous variable that equals 1 if outlet i is affiliated with a multiunit brand j , otherwise 0

(Jin and Leslie 2009). To control the impact of multiple inspections, I include reinspection ($REINSP_i$) that equals 1 if outlet i is reinspected within the same year, otherwise 0. NYSDOH reinspects a food service establishment considering its previous compliance history and risk category. Food service establishments with complex cooking processes, such as full-service restaurants, are considered high-risk, fast-food restaurants are considered medium-risk, and coffee shops fall under the low-risk category. Therefore, $REINSP_i$ variable controls an outlet's risk category and compliance. In my dataset, 1730 outlets were inspected more than once within the same year. I also control for cluster size around the outlet i . I measure cluster size (CLS_i) as the total number of outlets (both same-brand and other-brand) within a 5-mile radius of outlet i .

Finally, I control market-specific effects by including the population (POP_k) and median family income (INC_k) at the zip code-level, the most granular level of available data. To control for the potential effect of outlets located in urban versus rural areas, I also include urban (URB_k) variable that equals 1 when a zip code k falls in an urban area, and 0 otherwise. Table 3 displays the sample's descriptive statistics and correlation matrix.

I undertook a multicollinearity diagnostic test to investigate a possible case of linear dependencies in my independent variables. The mean VIF (variance inflation factor)



Table 3 Descriptive statistics and correlation matrix (raw values)

		1	2	3	4	5	6	7	8	9	10
1	Outlet quality performance (quality violations)	–									
2	Intrabrand clustering	–0.04	–								
3	Interbrand clustering	–0.01	0.05	–							
4	Firm size	–0.04	0.05	0.06	–						
5	Multiunit affiliation	–0.07	0.17	0.00	0.36	–					
6	Reinspection	–0.10	–0.03	0.00	–0.01	–0.02	–				
7	Cluster size	0.00	0.02	0.60	0.07	0.05	0.04	–			
8	Population	–0.02	–0.08	0.00	0.05	0.04	0.09	0.18	–		
9	Income	0.08	–0.04	–0.01	0.00	0.00	0.14	0.01	0.04	–	
10	Urban	–0.07	–0.01	0.01	0.05	0.04	0.07	0.19	0.37	0.20	–
	Mean	2.38	0.02	0.46	20.45	0.38	0.09	69.20	19,200	85,307	0.86
	SD	3.28	0.08	0.49	69.70	0.49	0.28	125.36	15,519	35,611	0.35

$n = 20,226$

Correlations exceeding |0.01| are significant at $p < 0.05$, two-tailed

without interaction was 1.25, and with interactions was 2.00, well below the heuristic of 10 (Hair et al. 1995). Therefore, multicollinearity is likely not a concern in my model.

Model specification

I specify my model as follows:

$$\begin{aligned}
 QPER_i = & \alpha_0 + \alpha_1 INTRACL_i + \alpha_2 INTERCL_i + \alpha_3 FS_{ij} \\
 & + \alpha_4 INTRACL_i * INTERCL_i + \alpha_5 INTRACL_i * FS_{ij} \\
 & + \alpha_6 MUA_{ij} + \alpha_7 REINSP_i + \alpha_8 CLS_i \\
 & + \alpha_9 POP_k + \alpha_{10} INC_k + \alpha_{11} URB_k + u_i
 \end{aligned} \quad (1)$$

where QPER = Outlet quality performance (quality violations), INTRACL = Intrabrand clustering, INTERCL = Interbrand clustering, FS = Firm size (natural log-transformed), MUA = Multiunit affiliation, REINSP = Reinspection, CLS = Cluster size (natural log-transformed), POP = Population at the zip code-level (natural log-transformed), INC = Median family income at the zip code-level (natural log-transformed), URB = Zip code belonging to an urban area, and $u \sim N(\mu, \sigma^2)$.

The hypothesized predictors—intrabrand clustering (INTRACL_{*i*}), interbrand clustering (INTERCL_{*i*}), and firm size (FS_{*ij*})—are potentially endogenous. For example, a brand may strategically locate its outlet near the same-brand and other-brand outlets that creates a self-selection problem. Further, my specification could suffer from potential endogeneity caused by omitted variables that drive the regressors (intrabrand and interbrand clustering and firm size) and directly affect the outcome (outlet quality performance). To

test the potential endogeneity of my regressors, I conducted the Durbin–Wu–Hausman test. The results confirm the endogeneity problem.

I account for the endogeneity of intrabrand and interbrand clustering and firm size by relying on the Gaussian Copula method (Park and Gupta 2012). The Gaussian Copula is an instrument-free method for endogeneity correction. It involves constructing a multivariate distribution to capture the correlation between endogenous regressor and structural error. The resulting model likely does not suffer from the endogeneity problem and generates consistent estimates for model parameters (Park and Gupta 2012). Several marketing studies have used the Gaussian Copula approach (e.g., Butt et al. 2021; Datta et al. 2015; Papies et al. 2017; Vomberg et al. 2020).

The Gaussian Copula method's identification assumption is the non-normality of the endogenous regressor (Park and Gupta 2012; Vomberg et al. 2020). I thus use the Shapiro–Wilk test of normality for each of my three endogenous variables. The results reject the null hypothesis that the endogenous regressors are normal ($p < 0.01$), suggesting that the Gaussian Copula approach is suitable for the endogeneity correction. I specify the final model as:

$$\begin{aligned}
 QPER_i = & \beta_0 + \beta_1 INTRACL_i + \beta_2 INTERCL_i + \beta_3 FS_{ij} \\
 & + \beta_4 INTRACL_i * INTERCL_i + \beta_5 INTRACL_i * FS_{ij} \\
 & + \beta_6 MUA_{ij} + \beta_7 REINSP_i + \beta_8 CLS_i \\
 & + \beta_9 POP_k + \beta_{10} INC_k + \beta_{11} URB_k \\
 & + \delta_1 (INTRACL_i) * + \delta_2 (INTERCL_i) * + \delta_3 (FS_{ij}) * + e_i
 \end{aligned} \quad (2)$$

All terms are described previously, and $e \sim N(\mu, \sigma^2)$. The parameters δ_1 – δ_3 represent the Copula terms



Table 4 Zero-inflated negative binomial regression estimates

DV: outlet quality performance (quality violations)	Hypothesis	Model 1 without endogeneity correction		Model 2 without interactions		Model 3 full model	
		Coeff.	Robust S.E.	Coeff.	Robust S.E.	Coeff.	Robust S.E.
Intercept		-2.12**	0.13	-2.11**	0.14	-2.10**	0.14
Intrabrand clustering	H ₁	0.82	0.55	2.81**	0.58	5.91**	0.95
Interbrand clustering		-0.02	0.02	-0.23**	0.07	-0.10	0.06
Firm size ^a		-0.06**	0.01	-0.14**	0.01	-0.14**	0.01
Intrabrand clustering * interbrand clustering	H ₂	-7.39**	0.94	-	-	-2.62*	1.02
Intrabrand clustering * firm size ^a	H ₃	0.04	0.19	-	-	-0.83**	0.19
Multiuunit affiliation		0.19	0.11	0.06	0.12	0.07	0.12
Reinspection		-0.69**	0.04	-0.70**	0.04	-0.70**	0.04
Cluster size ^a		-0.06**	0.02	-0.09**	0.03	-0.09**	0.03
Population ^a		0.03**	0.01	0.04**	0.01	0.03**	0.01
Income ^a		0.36**	0.02	0.36**	0.02	0.36**	0.02
Urban		-0.34**	0.03	-0.35**	0.03	-0.34**	0.03
Copula term—intrabrand clustering		-	-	-0.97**	0.18	-1.24**	0.21
Copula term—interbrand clustering		-	-	0.04**	0.01	0.02	0.01
Copula term—firm size		-	-	0.20**	0.02	0.23**	0.03
Wald χ^2		758.71	790.48	855.48			

$n = 19,728$

** $p < 0.01$, * $p < 0.05$, two-tailed test

^aNatural log-transformed

(estimated from the Gaussian Copula method) for the endogenous variables.

The dependent variable in this study, the count of quality violations, has excess zeros when no violations were observed during inspections (35% of the sample). It also has a greater level of variance (10.79) than the mean (2.38). I account for these excess zeros and overdispersion issues using a zero-inflated negative binomial (zinb) regression in Stata. Zero-inflated negative binomial regression models count variables with excess zeros, usually for overdispersed count outcome variables (Long and Freese 2003). Several marketing studies relied on the zero-inflated negative binomial regression (e.g. Dhaoui and Webster 2021; Dotzel et al. 2013; Li and Xie 2020; Rubera and Kirca 2017; Sorescu and Spanjol 2008).

Results

Descriptive statistics

Table 3 provides summary statistics for my sample. The average number of quality violations committed by an

outlet is 2.38 (SD 3.28). The average count of same-brand outlets within a 5-mile radius of an outlet is 1.48 (intrabrand clustering 0.02, SD 0.08), which is considerably less than the average count of other-brand outlets, 68.64 (interbrand clustering 0.46, SD 0.49). These numbers show that interbrand clustering is more prevalent than intrabrand clustering in my data. The average firm size is 20.45 outlets (SD 69.70) (raw value).

On average, the probability of an outlet being associated with a multiunit brand is 0.38 (SD 0.49). The average possibility for an outlet to be reinspected is 0.09 (SD 0.28). On average, the cluster size within a 5-mile radius is approximately 69 outlets (raw value), the population per zip code is 19,200 (raw value), the median family income per zip code is USD 85,307, and the probability for a zip code to fall in an urban area is 0.86.

Regression estimates

Table 4 displays the results of the zero-inflated negative binomial regression. The full results are provided in Model 3 with the interaction terms and the endogeneity correction. The results support my baseline expectation for intrabrand



Table 5 Simple slopes analysis

	Estimated impact on outlet quality performance (quality violations) (simple slope)	<i>t</i> value
<i>Impact of intrabrand clustering on outlet quality performance (quality violations) at various levels of interbrand clustering</i>		
Interbrand clustering (Low)	5.91**	6.21
Interbrand clustering (Mean)	4.71**	4.14
Interbrand clustering (High)	3.29*	2.16
<i>Impact of intrabrand clustering on outlet quality performance (quality violations) at various levels of firm size</i>		
Firm size (Low)	5.91**	6.21
Firm size (Mean)	5.18**	6.29
Firm size (High)	0.91	1.34

** $p < 0.01$, * $p < 0.05$, two-tailed

clustering's negative impact on outlet quality performance. I find that a greater level of intrabrand clustering increases an outlet's quality violations (Coeff. = 5.91, $p < 0.01$), hence decreasing its quality performance. Therefore, I find strong support for hypothesis H_1 . The alternate hypothesis H_{1Alt} is not supported.

Hypothesis H_2 predicted a weakening effect of interbrand clustering on the association between intrabrand clustering and outlet quality performance. I find support for H_2 ; a higher intensity of interbrand clustering weakens the positive association between intrabrand clustering and quality violations (Coeff. = -2.62 , $p < 0.05$). It shows that the presence of other-brand outlets mitigates the negative impact of intrabrand clustering on outlet quality performance.

Hypothesis H_3 predicted a weakening effect of firm size on the association between intrabrand clustering and outlet quality performance. Similar to H_2 , my results provide robust support for H_3 . A larger firm size weakens the positive association between intrabrand clustering and quality violations (Coeff. = -0.83 , $p < 0.01$). It shows that an outlet's association with a larger-sized firm mitigates the negative consequences of intrabrand clustering. I will discuss these results in detail in the simple slopes analysis and discussion sections.

For control variables, I find that reinspection of an outlet (Coeff. = -0.70 , $p < 0.01$), cluster size (Coeff. = -0.09 , $p < 0.01$), and urban location (Coeff. = -0.34 , $p < 0.01$) decrease quality violations, therefore increasing outlet quality performance. Population (Coeff. = 0.03 , $p < 0.01$) and income (Coeff. = 0.36 , $p < 0.01$) increase quality violations, hence decreasing outlet quality performance. A mere affiliation with the multiunit brand does not significantly affect outlet quality performance (Coeff. = 0.07 , ns).

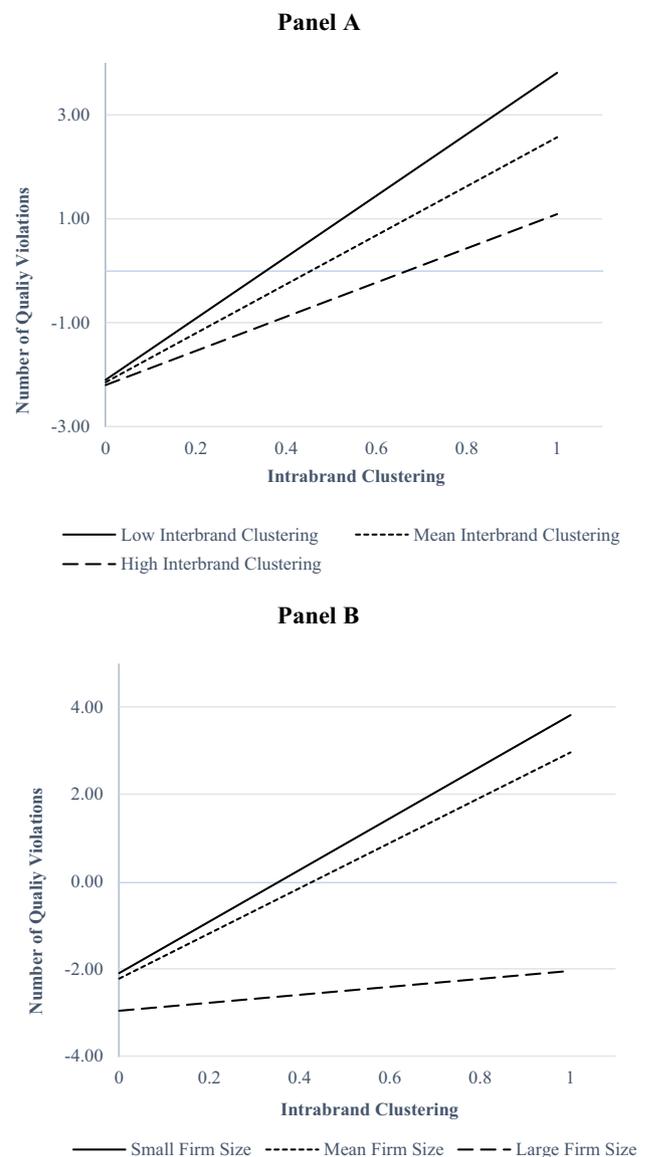
**Fig. 3** Simple slopes analysis

Table 6 Supplementary analysis: customer satisfaction as an alternate DV ordered probit regression estimates

DV: customer satisfaction (yelp rating)	Hypothesis	Full model	
		Coeff.	Robust S.E.
Intrabrand clustering	H ₁	−9.49**	0.93
Interbrand Clustering		−0.08	0.19
Firm size ^a		−0.15**	0.02
Intrabrand clustering * interbrand clustering	H ₂	0.34	1.25
Intrabrand clustering * firm size ^a	H ₃	1.07**	0.20
Multiunit affiliation		0.02	0.05
Reinspection		−0.31	0.19
Cluster size ^a		−0.05	0.02
Population ^a		−0.05**	0.01
Income ^a		−0.25	0.17
Urban		−0.06	0.03
Inverse mills ratio		−0.73	0.77
Copula term—intrabrand clustering		2.08**	0.20
Copula term—interbrand clustering		0.06**	0.01
Copula term—firm size		−0.18**	0.03
LR χ^2		1480.91	

The outcome variables quality violations and Yelp ratings are inversely related. Therefore, the results in Tables 4 and 6 can be compared and interpreted accordingly

$n = 11,908$

** $p < 0.01$, * $p < 0.05$, two-tailed test

^aNatural log-transformed

Post hoc analysis of significant interactions (simple slopes)

I analyzed simple slopes for significant interactions to better understand the moderating effects of interbrand clustering and firm size (Aiken and West 1991). Table 5 and Fig. 3 display the simple slope analysis of two-way interactions.

I find that a lower intensity of interbrand clustering strengthens the positive association between intrabrand clustering and quality violations (the simple slope of intrabrand clustering at low levels of interbrand clustering = 5.91, $p < 0.01$). However, the impact of intrabrand clustering on outlet quality performance weakens but stays positive and significant at higher levels of interbrand clustering (the simple slope of intrabrand clustering at high levels of interbrand clustering = 3.29, $p < 0.05$). This shows that interbrand clustering mitigates the negative outcome of intrabrand clustering and helps outlets perform better.

For firm size, I find that a higher intensity of intrabrand clustering increases quality violations at lower levels of firm size (the simple slope of intrabrand clustering at low levels of firm size = 5.91, $p < 0.01$). However, a higher level of firm size makes the relationship between intrabrand clustering and quality violations non-significant (the simple slope of intrabrand clustering at high levels of firm size = 0.91, ns). This result shows that the firm size has a more significant mitigating effect than interbrand clustering.

Supplementary analysis

I further test the impact of my main predictors on the alternate dependent variable—customer satisfaction (CS_{*i*}) measured as the customer ratings of food service establishments listed on the online review platform, Yelp. On Yelp, customers can demonstrate their satisfaction by rating food service establishments on a 1–5-star scale (5 refers to highly satisfied). Over time, Yelp has become a handy and efficient tool for customers to find good food service establishments. When a food service establishment secures a higher rating on Yelp, it will likely receive more customer traffic (Dai et al. 2018).

I used web scraping in Python to extract the rating of every food service establishment located in New York State and listed on the Yelp website in 2019. The web scraping of the Yelp website provided ratings of 12,132 food service establishments (out of 20,226 food establishments in my data set). Other restaurants either had no rating or were not listed on Yelp. To account for potential bias in regression estimates due to rating data not missing at random, I used Heckman's (1976) selection model in the first stage of the analysis that computed the selection bias parameter—Inverse Mills Ratio, which I included in the second stage of regression to control the selection bias. Similar to my main study, I corrected for the endogeneity



Table 7 Robustness check with 3-mile and 7-mile radii of clustering zero-inflated negative binomial regression estimates

DV: outlet quality performance (quality violations)	Hypothesis	3-Mile radius		7-Mile radius	
		Coeff.	Robust S.E.	Coeff.	Robust S.E.
Intercept		-1.44**	0.42	-2.11**	0.14
Intrabrand clustering	H ₁	5.62**	0.93	4.88**	0.86
Interbrand clustering		-0.20**	0.08	-0.10	0.06
Firm size ^a		-0.14**	0.01	-0.14**	0.01
Intrabrand clustering * interbrand clustering	H ₂	-3.23**	0.72	-4.17**	1.30
Intrabrand clustering * firm size ^a	H ₃	-1.05**	0.17	-0.45*	0.20
Multiuunit affiliation		0.04	0.13	0.07	0.12
Reinspection		-0.70**	0.04	-0.70**	0.04
Cluster size ^a		-0.12**	0.03	-0.12**	0.03
Population ^a		0.04**	0.01	0.03**	0.01
Income ^a		0.37**	0.02	0.36**	0.02
Urban		-0.34**	0.03	-0.34**	0.03
Copula term—intrabrand clustering		-1.25**	0.23	-0.93**	0.19
Copula term—interbrand clustering		0.04**	0.01	0.02	0.01
Copula term—firm size		0.22**	0.03	0.22**	0.03
Wald χ^2		874.21		847.99	

$n = 19,728$

** $p < 0.01$, * $p < 0.05$, two-tailed test

^aNatural log-transformed

of regressors using the Gaussian Copula approach (Park and Gupta 2012).

Due to the ordinal nature of the customer satisfaction measure, I relied on the ordered probit regression model for estimation. Table 6 displays the regression estimates. Despite a reduced sample size, my hypothesized results remain pretty robust. The results show that intrabrand clustering reduces customer satisfaction (Coeff. = -9.49, $p < 0.01$). Firm size mitigates the negative impact of intrabrand clustering on customer satisfaction (Coeff. = 1.07, $p < 0.01$). These results are in line with my empirical findings in the main study. Although I find the impact of interbrand clustering on the association between intrabrand clustering and customer satisfaction as non-significant (Coeff. = 0.34, ns), it still supports my assertion that firm size plays a more substantial role than interbrand clustering in mitigating the negative effect of intrabrand clustering.

Alternate specifications

I further assess the results' stability to alternate operationalization of clustering, the extent of clustering, alternate estimator, and alternate sample approaches.

Alternate operationalization of clustering variables

In this study, I use a 5-mile radius to measure intrabrand and interbrand clustering variables. To check the robustness of my findings, I recompute clustering variables using 3-mile and 7-mile radii instead. All my substantive results remain robust to this alternate operationalization of clustering variables. Table 7 displays the regression estimates with endogeneity correction.

Alternate model to exclude nonlinearity effects of clustering

To rule out a possible effect of the extent of clustering and to exclude the nonlinearity, I run an alternate model by including a quadratic term of intrabrand clustering. All my results stay robust to this alternate specification.

Alternate estimator

I use the standard Poisson regression as an alternate estimator to test my results' robustness. Poisson regression is used to model count dependent variables, such as the number of quality violations in this study. All my results stay robust to this alternate estimator.



Alternate sample

I check the robustness of my results to the presence of outliers. To reduce potential outliers' impact, I winsorize all my continuous predictor variables at 1% and 99% levels. All my results remain robust to this sampling variation.

Discussion

This research contributes to marketing theory and practice by extending the clustering and brand competition literature. Prior studies provided mixed results for the effect of clustering. While some studies demonstrated evidence of positive performance outcomes due to knowledge sharing (e.g., Butt et al. 2018) and monitoring efficiency (e.g., Lu and Wedig 2013), others showed its negative consequences owing to intense competition (e.g., Pancras et al. 2012). In brand management literature, research on brand competition provided empirical evidence mostly favoring its negative consequences (e.g., González-Benito et al. 2010).

This study shows that the relationship between clustering of same-brand outlets (intrabrand clustering) and outlet performance is not straightforward. It is contingent on what other-brand outlets are located nearby (interbrand clustering) and the firm size. My first hypothesis predicted both negative and positive effects of intrabrand clustering on the outlet's quality performance. I find support for the adverse impact owing to the intense brand competition brought about by clustering. My second hypothesis predicted the positive effect of a critical moderator—interbrand clustering. It is common to find outlets of competing brands located next to each other. The existence of competing brands close to same-brand outlets might have significant performance consequences for the same-brand outlets. My results show that the proximity of other-brand outlets is beneficial for same-brand outlets as it increases market size due to the agglomeration effect. Finally, my third hypothesis predicted the positive effect of firm size as a moderator. I find strong support for my third hypothesis. Firm size of clustered outlets plays a crucial role in mitigating the negative effect of intrabrand clustering due to experience and economies of scale advantages associated with larger firm size. My results show a more robust mitigating impact of firm size than interbrand clustering.

Overall, my work contributes to the growing work on clustering and its consequences. My research contributes to the brand management literature by considering brand competition in clustering situations. Extant research on brand competition mainly focused on grocery brands placed next to each other in grocery and convenient stores (Faulkner et al. 2014; González-Benito et al. 2010) and competition and cooperation in luxury markets (Depeyre et al. 2018).

That body of research used store-level scanner data and consumer surveys to provide critical insights into brand competition. However, the competition triggered by distance or geography is an under-researched topic in brand management literature. My research advances brand competition literature by focusing on geographical proximity or clustering of same- and other-brand outlets. Relying on the context of food service establishments located in New York State, this study provides novel insights to marketing and branding scholars and practitioners alike.

Managerial implications

The results of this study have some critical implications for marketing and brand managers who face such questions: *Is it recommended to cluster same-brand outlets? Is it recommended to locate close to other-brand outlets?* My study answers these crucial questions in the context of food service establishments located in New York State.

A crucial managerial implication of the results is that opening a food service establishment closer to the existing same-brand ones may have adverse performance outcomes. However, these negative consequences of intrabrand clustering can be mitigated by situating food service establishments near competing brands. Therefore, interbrand clustering helps same-brand food service establishments improve their quality performance.

The second important managerial insight relates to the firm size, which plays a more significant role in mitigating the negative effect of intrabrand clustering. The same-brand food service establishments associated with a larger-sized firm are less likely to be affected by intrabrand clustering. In fact, I find that a larger firm size is more instrumental in mitigating the adverse effects of intrabrand clustering. Therefore, marketing and brand managers of larger-sized firms may cluster their food service establishments without worrying about brand competition.

The results of some control variables have important managerial implications. I find that reinspecting a food service establishment decreases quality violations, which shows that more frequent inspections are better. However, there is a tradeoff. The regulators like NYSDOH are responsible for maintaining food and service quality and reducing the incidence of foodborne illness by inspecting food service establishments. They must perform their duties within budgetary limitations. As more frequent inspections mean more costs, NYSDOH may need to identify the food service establishments requiring more frequent inspections. For example, high-risk food service establishments are inspected more frequently; food service establishments with poor compliance history are expected to get more frequent inspections. Although costly, my results demonstrate the positive outcome of reinspections. Similarly, I find a positive effect



of locating food service establishments in urban areas than rural areas. Food service establishments in urban areas commit fewer quality violations than rural ones.

I have also conducted a supplementary analysis using an alternate dependent variable—customer satisfaction—operationalized as the customer ratings of food service establishments listed on Yelp. In line with my primary study, I find that intrabrand clustering has adverse effects—it decreases customer satisfaction, and firm size plays a substantial role in mitigating the negative impact of intrabrand clustering on customer satisfaction.

In sum, the results of this study provide vital insights to marketing and brand managers who want to locate and manage their outlets closer to their same-brand and other-brand outlets.

Conclusion, limitations, and future research directions

This study assesses the performance consequences of intrabrand clustering and its context-dependency on two critical factors—interbrand clustering and firm size. My examination of approximately 21,000 food service establishments in New York State in 2019 finds that intrabrand clustering decreases outlet quality performance. Interbrand clustering and firm size moderate this relationship and help to mitigate the negative effect of intrabrand clustering on outlet quality performance. Further, I find that firm size has a more substantial mitigating effect than interbrand clustering.

Like any research, this study is subject to some limitations. First, this research uses the New York State data available for 2019. I believe that my research findings would be generalizable. However, future research that uses data across various markets observed over multiple years would confirm my expectations. The second limitation pertains to the lack of data regarding the specific identity of the outlet concerning ownership, i.e., company-owned or franchised. The NYSDOH database does not provide this information. Future work that combines the outlet ownership data with the NYSDOH dataset and investigates the consequences of clustering considering some critical context dependencies would be welcome.

Moreover, this study provides rich insights into the actual behavior due to an archival dataset. However, the reliance on archival data cannot measure the underlying mechanisms of free-riding or shirking. Future work integrating archival and experimental data, although challenging to undertake, would significantly contribute to this topic.

A promising avenue to expand this research is to study the impact of digitalization in clustering and branding contexts. The trend of online shopping has grown immensely, along with the delivery and drive-throughs during the COVID-19

pandemic. Many retailers have reduced their physical presence through closures. Many now use their physical outlets more as fulfillment centers than retail shops, also called ‘dark stores’. How this digital, delivery, and drive-through trend will change clustering, brand competition, and their impact on outlet performance represents a potentially fruitful avenue for future research.

Another important area for future research is to investigate the financial impact of clustering. Specifically, a future study that assesses the effect of clustering on the financial value of brands—for example, on sales, profit, and stock price—and how some key factors moderate this relationship would generate valuable insights for brand managers and other stakeholders.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

- Aiken, L.S., and S.G. West. 1991. *Testing and interpreting interactions in multiple regression*. Berlin: Sage Publications.
- Argote, L., and E. Darr. 2000. 2 Repositories of knowledge in franchise organizations: Individual, structural, and technological. *The Nature and Dynamics of Organizational Capabilities* 82 (1): 51–65.
- Argote, L., and E. Miron-Spektor. 2011. Organizational learning: From experience to knowledge. *Organization Science* 22 (5): 1123–1137.
- Athey, S., and A. Schmutzler. 2001. Investment and market dominance. *RAND Journal of Economics* 32 (1): 1–26.
- Avery, J., T.J. Steenburgh, J. Deighton, and M. Caravella. 2012. Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time. *Journal of Marketing* 76 (3): 96–111.
- Bachmann, J.T., I. Ohlles, and T. Flatten. 2021. Effects of entrepreneurial marketing on new ventures’ exploitative and exploratory innovation: The moderating role of competitive intensity and firm size. *Industrial Marketing Management* 92: 87–100.
- Baum, J.A., and S.J. Mezas. 1992. Localized competition and organizational failure in the Manhattan hotel industry, 1898–1990. *Administrative Science Quarterly* 37: 580–604.
- Bergen, M., S. Dutta, and O.C. Walker Jr. 1992. Agency relationships in marketing: A review of the implications and applications of agency and related theories. *Journal of Marketing* 56 (3): 1–24.
- Bradach, J.L. 1997. Using the plural form in the management of restaurant chains. *Administrative Science Quarterly* 42: 276–303.
- Brickley, J.A., and F.H. Dark. 1987. The choice of organizational form the case of franchising. *Journal of Financial Economics* 18 (2): 401–420.
- Butt, M.N. 2017. *The impact of growth, governance, and geography on franchise performance*. Doctoral dissertation.
- Butt, M.N., K.D. Antia, B.R. Murtha, and V. Kashyap. 2018. Clustering, knowledge sharing, and intrabrand competition: A multiyear analysis of an evolving franchise system. *Journal of Marketing* 82 (1): 74–92.



- Butt, M.N., A.S. Baig, and F.J. Seyyed. 2021. Tobin's Q approximation as a metric of firm performance: An empirical evaluation. *Journal of Strategic Marketing*. <https://doi.org/10.1080/0965254X.2021.1947875>.
- Carpenter, G.S., and D.R. Lehmann. 1985. A model of marketing mix, brand switching, and competition. *Journal of Marketing Research* 22 (3): 318–329.
- Chang, S.E. 2009. Voice enabling mobile financial services with multimodal transformation. *International Journal of Mobile Communications* 7 (3): 346–362.
- Chung, W., and A. Kalnins. 2001. Agglomeration effects and performance: A test of the Texas lodging industry. *Strategic Management Journal* 22 (10): 969–988.
- Dai, W.D., G. Jin, J. Lee, and M. Luca. 2018. Aggregation of consumer ratings: An application to yelp. com. *Quantitative Marketing and Economics* 16 (3): 289–339.
- Datta, H., B. Foubert, and H.J. Van Heerde. 2015. The challenge of retaining customers acquired with free trials. *Journal of Marketing Research* 52 (2): 217–234.
- Davis, P. 2006. Spatial competition in retail markets: Movie theaters. *The RAND Journal of Economics* 37 (4): 964–982.
- Depeyre, C., E. Rigaud, and F. Seraidarian. 2018. Coopetition in the French luxury industry: Five cases of brand-building by suppliers of luxury brands. *Journal of Brand Management* 25 (5): 463–473.
- Dhaoui, C., and C.M. Webster. 2021. Brand and consumer engagement behaviors on Facebook brand pages: Let's have a (positive) conversation. *International Journal of Research in Marketing* 38 (1): 155–175.
- Dotzel, T., V. Shankar, and L.L. Berry. 2013. Service innovativeness and firm value. *Journal of Marketing Research* 50 (2): 259–276.
- Faulkner, M., O. Truong, and J. Romaniuk. 2014. Uncovering generalized patterns of brand competition in China. *Journal of Product & Brand Management* 23 (7): 554–571.
- Ganesan, S., A.J. Malter, and A. Rindfleisch. 2005. Does distance still matter? Geographic proximity and new product development. *Journal of Marketing* 69 (4): 44–60.
- González-Benito, Ó., Z.I. Loyola-Galván, and P.A. Muñoz-Gallego. 2010. Inter-size and inter-brand competition analysis within a product category: Scope of cannibalization effects. *Journal of Brand Management* 17 (4): 254–265.
- Guler, A.U. 2018. Inferring the economics of store density from closures: The Starbucks case. *Marketing Science* 37 (4): 611–630.
- Hair, J.F., Jr., R.E. Anderson, R.L. Tatham, and C. William. 1995. *Black (1995), Multivariate data analysis with readings*. Hoboken: Prentice Hall.
- Heckman, J.J. 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement* 5 (4): 475–492.
- Holmstrom, B., and P. Milgrom. 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *The Journal of Law, Economics, and Organization* 7: 24–52.
- Ibanez, M.R., and M.W. Toffel. 2020. How scheduling can bias quality assessment: Evidence from food-safety inspections. *Management Science* 66 (6): 2396–2416.
- Jin, G.Z., and P. Leslie. 2009. Reputational incentives for restaurant hygiene. *American Economic Journal: Microeconomics* 1 (1): 237–267.
- Kalnins, A. 2004. An empirical analysis of territorial encroachment within franchised and company-owned branded chains. *Marketing Science* 23 (4): 476–489.
- Kalnins, A., and K.J. Mayer. 2004. Relationships and hybrid contracts: An analysis of contract choice in information technology. *Journal of Law, Economics, and Organization* 20 (1): 207–229.
- Kalyanaram, G., W.T. Robinson, and G.L. Urban. 1995. Order of market entry: Established empirical generalizations, emerging empirical generalizations, and future research. *Marketing Science* 14 (3_supplement): G212–G221.
- Lafontaine, F., and M. Slade. 2007. Vertical integration and firm boundaries: The evidence. *Journal of Economic Literature* 45 (3): 629–685.
- Li, Y., and Y. Xie. 2020. Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of Marketing Research* 57 (1): 1–19.
- Liu, H. 1995. Market orientation and firm size: An empirical examination in UK firms. *European Journal of Marketing* 29 (1): 57–71.
- Liu, S., K. Wei, and B. Gao. 2022. Power of information transparency: How online reviews change the effect of agglomeration density on firm revenue. *Decision Support Systems* 153: 113681.
- Lomax, W., K. Hammond, R. East, and M. Clemente. 1997. The measurement of cannibalization. *Journal of Product and Brand Management* 6 (1): 27–39.
- Long, J.S., and J. Freese. 2003. *Regression models for categorical dependent variables*. College Station: Stata Press.
- Lu, S.F., and G.J. Wedig. 2013. Clustering, agency costs and operating efficiency: Evidence from nursing home chains. *Management Science* 59 (3): 677–694.
- Marshall, A. 1920. *Principles of economics*, 8th ed. London: McMillan.
- Nandan, S. 2005. An exploration of the brand identity–brand image linkage: A communications perspective. *Journal of Brand Management* 12 (4): 264–278.
- Pancras, J., S. Sriram, and V. Kumar. 2012. Empirical investigation of retail expansion and cannibalization in a dynamic environment. *Management Science* 58 (11): 2001–2018.
- Papies, D., P. Ebbes, and H.J. Van Heerde. 2017. Addressing endogeneity in marketing models. In *Advanced methods for modeling markets*, ed. P.S.H. Leeflang, J.E. Wieringa, T.H.A. Bijmolt, and K.H. Pauwels, 581–627. Cham: Springer.
- Park, S., and S. Gupta. 2012. Handling endogenous regressors by joint estimation using copulas. *Marketing Science* 31 (4): 567–586.
- Porter, M.E. 1998. *Clusters and competition: New agendas for companies, governments, and institutions*. Boston: Harvard Business School Press.
- Rubera, G., and A.H. Kirca. 2017. You gotta serve somebody: The effects of firm innovation on customer satisfaction and firm value. *Journal of the Academy of Marketing Science* 45 (5): 741–761.
- Rubin, P.H. 1990. *Managing business transactions: Controlling the cost of coordinating, communicating, and decision making*. New York: Free Press.
- Scherer, F.M., and D. Ross. 1990. Industrial market structure and economic performance. In *University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship*.
- Sorescu, A.B., and J. Spanjol. 2008. Innovation's effect on firm value and risk: Insights from consumer packaged goods. *Journal of Marketing* 72 (2): 114–132.
- Vomberg, A., C. Homburg, and O. Gwinner. 2020. Tolerating and managing failure: An organizational perspective on customer reacquisition management. *Journal of Marketing* 84 (5): 117–136.
- Wang, H.M.D. 2010. Corporate social performance and financial-based brand equity. *Journal of Product & Brand Management* 19 (5): 335–345.
- Zheng, X.V., L.J. Ji, and C. Su. 2020. Mitigating the negative effects of regional clustering in franchising: The roles of governance mechanisms. *Journal of Retailing* 96 (3): 434–444.



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Dr. Moeen Naseer Butt current research projects include assessing the impact of growth, governance, and geography on the performance of franchise businesses. Additionally, he works in the marketing-finance

interface. He relies on state-of-the-art econometrics and geographic information system (GIS)-informed spatial techniques to investigate the hypothesized relationships in the business-to-business (B2B) settings. He is also interested in the appropriate use of firm performance metrics by marketing scholars and practitioners alike. His research has been published in *Journal of Marketing*, *Marketing Science*, and *Journal of Strategic Marketing*. His ongoing research projects are under review in *Journal of Marketing Research* and *Journal of Marketing*.

