The Business Value of Virtual Showrooms

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Short Paper

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Abstract

A significant acceleration of research-online and purchase offline behavior makes online channels crucial for brick-and-mortar. Realizing this trend, many retail stores have been using a novel strategy called virtual appointments, whereby consumers can access rich information online before visiting the stores. This study investigates the multifaceted business value of virtual appointments by using a rich dataset related to the car dealers' business across the U.S. We empirically show that virtual appointments increase dealers' sales. However, the effect depends on the competition level. The presence of within-brand competitors decreases the benefits of virtual appointment services, while the existence of between-brand competitors increases the benefit of the service.

Keywords: Virtual Appointment, research-online purchase-offline, digitization, car dealership

Introduction

Given the accelerating growth of digital retailing, providing relevant and high-quality information to attract customers becomes crucial to creating a competitive advantage. High-quality information is vital not only for retailers that are purely online but also for retailers whose focus is more on physical stores. Paying attention to information quality becomes even more critical as recent industry reports indicate that 81% of customers are interested in doing research online but purchase offline (ROPO) (Lazor 2022). Thus, higher quality information can signal the high quality of products and services offered by retailers, attracting customers and enhancing the chance of store visits and sales. Realizing consumers' interests and needs, retailers have turned to providing services that facilitate ROPO. One novel strategy enabling ROPO is interactive virtual showroom services (Retail TouchPoints 2022). Retailers can use virtual showrooms to have one-on-one virtual interaction with customers, walk them through the physical showroom, and provide detailed information about products and services. These characteristics makes virtual showrooms different from other information channels, like chatbots and simple websites. The onset of the Covid-19 pandemic accelerated the burgeoning virtual showroom trend, and many practitioners argue that it will shape the future of retailing (Conferwith.io 2022). Virtual showrooms can facilitate decision-making by enabling customers to receive personalized service from retailers, enhancing their shopping experience (Kern 2022). However, given the recent emergence of virtual showroom services, no research studies or even industry reports examine this strategy's effectiveness and guide retail managers on how to benefit from this new service model. Thus, in this paper, we attempt to bridge this gap and, as the first study to do so, empirically quantify the value of virtual showrooms as a strategy that facilitates ROPO behavior.

We specifically focus on the automobile industry and investigate how adopting virtual showrooms impacts auto dealers, as retailers play a crucial role in this industry (Golara et al. 2021). In recent years, dealers have begun to invest in digitization in response to market pressures. One of their most significant digitization steps is adding virtual showrooms to their sales channel (Cars.com 2020). Traditionally, auto dealership visits have been a major cost factor and a pain point for consumers (Yavorsky and Honka 2021). So, the industry has been ripe for disruption, and various online platforms have emerged to provide automobile data for consumers. Yet, with automobiles being complex (Karnopp 2004) and expensive products with significant experiential aspects, online information about their complex attributes (such as feature set, fuel efficiency, etc.) can only go so far in satisfying customer search needs. Ultimately, much of the search process depends on physical dealer visits, limiting the number of cars and brands customers can research. Virtual showrooms facilitate this process by allowing customers to gather detailed and customized car information. This reduces the number of physical visits and will enable customers to search a broader geographical area. The above arguments would suggest that virtual showrooms can increase dealer sales.

However, physical visits are also a core part of dealers' marketing process, allowing them to pitch their products and services with full customer attention. Offering consultation and detailed pre-sale information online can also reduce face-to-face marketing opportunities and encourage free-riding behavior – where customers obtain information from a dealer but buy from another seller that offers a better deal (Mehra et al. 2018, Shin 2007). Recent research raises doubts about whether engaging customers online for products that ultimately need to be purchased offline is productive (Bar-Gill and Reichman 2021). The existing literature does not guide which of these opposing forces will be dominant for virtual showrooms and under what circumstances. This paper attempts to address this question by analyzing a large-scale dataset of dealers' daily sales and virtual showroom adoption across the U.S. from August 2020 to January 2022. Using panel data econometric models and various methods, we demonstrate that, on average, adding this service increases sales for a dealer. However, the effect largely depends on the competition level. We find that competition has a nuanced interaction effect such that virtual showrooms are more beneficial for dealers facing low within-brand competition (due to increased free-riding) but high between-brand competition (due to increased agglomeration effect and weaker free-riding). Our paper contributes to the literature on online retailing and channel integration. To the best of our knowledge, this is the first study that empirically investigates virtual showrooms' business value as an emerging and rapidly expanding omnichannel strategy. Our results also address the gap in the retail management literature on the implications of facilitating ROPO (Kleinlercher et al. 2020).

Literature Review

A fast-growing retailing and marketing trend is leveraging multiple channels to interact with customers. Integrating online and offline channels enables retailers to increase consumer touchpoints, enhancing consumer engagement and sales (Gallino and Moreno 2018). Thus, finding an effective strategy combining both channels becomes crucial for retailers, yet it remains challenging. Prior studies have examined the integration of online and offline channels and how that impacts retailers' business. Examining the impact of physical stores on customers' online shopping behavior, Forman et al. (2009) show that store entry reduces online sales of retailers in the store entry area in the book industry. Brynjolfsson et al. (2009) demonstrate that the relationship between online and offline channels can depend on the product type in the apparel industry. For mainstream products, an increase in the number of physical stores reduces online sales. However, for niche products, physical stores do not impact online stores. Bell et al. (2018) show that opening a showroom in the eyeglass industry can increase sales in both channels and decrease returns.

Avery et al. (2012) show that the presence of physical stores increases both offline and online sales in the apparel industry. Wang and Goldfarb (2017) show that opening a physical store on average increases online sales in the apparel industry. However, this relationship depends on the significance of brand presence in a location. An offline store decreases online sales in locations where a brand already has a presence. While in places where a brand does not have a significant presence, opening a store increases online sales. In addition, Kumar et al. (2019) show that opening a new physical store increases both online and offline sales in the apparel industry. The extant studies provide mixed results on the impact of channel integration on retailers' business. This can signal the interplay between online and offline channels requires more research in different contexts and is likely industry specific. Most current studies focus on products that involve less complex decision-making processes, such as books, apparel, and eyeglass, and are sold online and offline.

However, for complex products that are typically bought in-store (e.g., cars; Karnopp 2004), it is not evident how much business value is generated by the expansion of the online channel. Previous research shows that for complex purchases, especially for low-volume products, customers prefer physical locations over online channels for gathering information and shopping (Sousa et al. 2015). Since automobiles are highly complex and expensive products, these findings suggest that expanding the online channel should not significantly impact the car dealers' business. Further, a recent study (e.g., Bar-Gill and Reichman 2021) shows that engaging customers online might be counterproductive for this type of product and decrease offline sales. So, it is not evident how virtual showroom impacts dealers' business. In this study, we take a step forward to fill this gap by examining the impact of adding an online information channel on car dealers' business.

Research Setting

To build our sample, we gathered data pertaining to dealerships' sales and their virtual showroom status from a leading consumer-facing platform. Auto dealers use this platform to reach out to customers by posting cars in their inventory. We monitor the industry's dynamics by tracking this online activity. We captured information for more than seventeen thousand dealerships in all U.S. states over 16 months (333 days, from August 2020 to January 2022). For each dealer, we have detailed information on the inventory containing the brand, make, model, and price of each car as well as the dealer's name, address, virtual showroom service status, and other identifying information.

Following prior literature, we considered the total sales of a dealer as the dependent variable, Total Sales (Kumar et al. 2019). To calculate it, we added up all each dealer's monthly new and used automobiles. The primary independent variable is Virtual Showroom, which is a binary variable indicating whether the dealer is offering virtual showroom services in that month or not. We also control for other dealers' characteristics that can impact their sales, such as total inventory size, brand type (luxury or non-luxury), online reputation, and the level of local competition. To measure competition level, we follow previous works to measure the competition level for physical stores as the number of competitors within the same zip code (Kumar et al. 2018). The competitors' effects vary depending on whether they are in direct competition with the focal firm or not (Kumar et al. 2018). Thus, we define the direct competitor as the dealers who sell the same car brand as the focal dealer (within-brand competitors). And the indirect competitors are the ones within the same brand type as the focal dealer luxury vs. non-luxury, but they sell other brands (between-brand competitors). To control for the characteristics related to geographic locations, like population density and average income, we complemented our data with demographic data from the census. The definition of the variables is provided in Table 1.

Variable	Definition
Total Sales	Dealer's total monthly sales ($)
VirtAppt	1: if the dealer offers virtual showrooms; 0: otherwise
Inventory	Total number of cars in the inventory
OnlineRep	A common factor of rating score and the number of reviews
Brand Type	1: indicating a luxury car dealer; 0: otherwise
PopDens	Population density of the corresponding zip code
Income	Median household income of the corresponding zip code

CompWB	Number of within-brand rivals of a focal dealer in a zip code
CompBB	Number of between-brand rivals of a focal dealer in a zip code

Table1. Variable Definitions

Methodology

Staggered Difference-in-Difference Analysis

One of the most common quasi-experimental research designs for analyzing the effect of a treatment or policy is the difference-in-difference (DiD) framework (Goodman-Bacon 2021). This method compares the difference between treated and control groups over time, before and after the treatment, to recover the causal average treatment effect (ATE). The estimation is usually performed via a panel regression where the coefficient of the treatment indicator recovers the average treatment effects under a standard parallel trends assumption. Among the various approaches used in the literature, the two-way fixed effects (TWFE) model is commonly used where both group and time effects are controlled (De Chaisemartin and d'Haultfoeuille 2020, Wooldridge 2021). The canonical (or 2x2) DiD model includes two time periods (pre- and post-treatment) and two groups (treatment and control). However, our empirical setup deviates from the canonical DiD since it has multiple treatment periods and multiple treatment groups (cohorts), called staggered DiD.

The standard approach to estimate staggered DiD models has been to ignore variation in treatment timing and application of the standard TWFE model (Callaway and Sant'Anna 2021). However, recent econometric developments have revealed the standard TWFE model runs into certain issues for staggered intervention designs (Callaway and Sant'Anna 2021, Wooldridge 2021). Staggered interventions could be understood as a collection of several treatments that vary by cohort and timing, yielding several DiD setups. Recent literature has focused on introducing solutions to this shortcoming, realizing this issue. Wooldridge (2021) demonstrates that the issue can be addressed by extending the current TWFE to capture the treatment effect heterogeneity. This method, referred to as the Extended TWFE (ETWFE), adds flexibility by allowing the treatment effect to change across time, treatment cohort, and covariates.

In our setting, the treatment is the roll-out of the virtual showroom service. Let $t \epsilon \{1, \dots, q, \dots, T\}$ be the time period (in our case, the month number) and $\boldsymbol{d_t}$ be the vector of time dummies. Data collection starts from period t = 1 to T, but the treatments occur from period q to T. The ETWFE distinguishes treatment cohorts according to the time they were treated. Let $\boldsymbol{d_r}$ be the vector of dummy indicators for the cohort that is first treated in time $r \epsilon \{q, q+1 \dots, T\}$. Let w_{it} the binary, time-varying treatment indicator for dealer i, at time t, where $i \epsilon \{1, \dots, N\}$. Note, $w_{it} = Treat_i.Post_t$ where $Treat_i$ is binary variables indicating whether dealer i belongs to any of the treatment cohorts and $Post_t$ is the post-treatment time indicator. Subsequently, a fixed effects regression that allows w_{it} to vary by cohort and time can recover ATTs as Wooldridge (2021) demonstrates:

$$y_{it} = \alpha + \tau_{rs}(w_{it}\, \boldsymbol{d_r}\, \boldsymbol{d_t}) + \beta \boldsymbol{d_t} + u_i + e_{it} \qquad (1)$$

where α is the intercept, u_i is the unit-specific effect, x_{it} is the vector of covariates and e_{it} is the error term.

To gain additional flexibility, covariates can also be included, interacted with time dummies, and interacted with the treatment indicator to account for moderating effects. To aid in interpretation, the moderators could be centered with respect to cohort means. Let $\dot{\boldsymbol{x}}$ be the vector of cohort-mean-centered moderators such that $\dot{\boldsymbol{x}} = \boldsymbol{x} - E[x|\boldsymbol{d_r}]$. Including covariates makes the common trends assumption more plausible (Wooldridge 2021). Thus, the final Extended TWFE setup will be as follows:

$$y_{it} = \alpha + \tau_{rs}(w_{it}\, \boldsymbol{d_r}\, \boldsymbol{d_t}) + \tau'_{rs}(w_{it}\, \boldsymbol{d_r}\, \boldsymbol{d_t}\, \dot{\boldsymbol{x}}_{\boldsymbol{t}}) + \beta \boldsymbol{d_t} + \gamma\, \boldsymbol{x_t} + \delta\, \boldsymbol{x_{it}} \boldsymbol{d_t} + u_i + e_{it} \qquad (2)$$

For τ_{rs} to recover ATTs, two assumptions must be met: (a) the no-anticipation assumption, which requires the treatments to not be anticipated by the units before the treatment time, and (b) the parallel trends assumption, which stipulates that all treatment cohorts must have identical evolution trends over time (Wooldridge 2021). We notice that the intention to roll out the virtual showroom service is not visible to consumers on the online car search platforms. Instead, consumers observe a virtual showroom flag or label within their browsing listings. Thus, the no-anticipation assumption is plausibly satisfied.

The equation (2) specification is also attractive since it allows a simple test for parallel trends. To check whether the temporal trends of treatment cohorts are different, we can model trend heterogeneity across cohorts and test the significance of the estimate. To this end, we add the terms $\pi_r\, D_r\, t$, where the calendar time variable, t, is interacted with cohort dummies, D_r. The π_r parameters are the cohort-specific trend estimates, which, if jointly significant, indicate differences in trends and a failure of the parallel trends assumption (Wooldridge 2021). In our dataset, π_r estimates are jointly nonsignificant supporting for the parallel trend's assumption: F (16, 18992) = 1.06, p = 0.3934.

Results

Main Effect

Table 2 below shows the average estimates obtained from the extended two-way fixed effects specification. Focusing on the main model, the average effect of virtual showrooms on the treated group is positive and significant ($\tau = 648275;\ p = 0.0000$). This indicates that implementing the virtual showroom service has increased monthly dealer sales by $648275. This result is in agreement with the transaction theory, based on which consumers are interested in having a lower transaction cost to have an efficient transaction (Williamson 1975). Including virtual showroom services provide an opportunity for consumers to gain a detailed level of information about cars, salesperson, and a dealer's environment before physically entering the dealership. Consequently, the provided service reduces search costs and fits uncertainty for consumers, improving their purchasing experience.

	Main Model	Interaction Model
VirtAppt	648275*** (0.000)	652685*** (0.000)
VirtAppt x CompWB		-169110** (0.029)
VirtAppt x CompBB		38758** (0.033)
CompWB	-56366*** (0.005)	-66430** (0.048)
CompBB	44241*** (0.000)	37798* (0.062)
Control Variables	Y	Y
Time F.E.	Y	Y
Observations	249512	249512

Table2. Extended Two-Way Fixed Effects Estimation Results

Moderating Effect of Competition

The interaction model suggests that virtual showrooms are less beneficial when within-brand competition is higher ($\tau' = -169110, p = 0.029$)[1]. In other words, the presence of an additional competitor from the same brand reduces the benefits of the virtual showroom service by $169110. Conversely, the virtual showroom roll-out leads to higher monthly sales under higher between-brand competition ($\tau' = 38758, p = 0.033$). In other words, the presence of an additional dealer from rival brands increases the returns of the virtual showroom strategy by $38758. These two opposite effects are obscured when an overall competition metric is used.

These findings could be explained by the presence of two opposite mechanisms to the competition: (a) attraction effect and (b) free-riding behavior. On the one hand, locations with higher levels of competition usually attract more consumers. This dynamic is well documented in the agglomeration literature (e.g., Baum and Haveman 1997). Virtual showrooms can be a marketing tool for brand awareness, particularly under fierce competition. So, more consumers would be attracted to the dealers that offer this service, enhancing dealers' sales. On the other hand, providing pre-sales information through virtual showrooms can create a consumer free-riding behavior (Shin 2007). Consumers may acquire information about a car from one dealer but find a deal or service from another dealer more attractive. In that case, they will make their final purchase from the competitor. This behavior is more prominent when the products and services are highly comparable (Kumar et al. 2018). Cars of the same brand are more comparable than that of different brands as they share more features. As a result, information gained via virtual showrooms from one dealer is more applicable to transactions with another dealer within the same brand. However, free-riding is less significant under higher between-brand competition because comparing cars across the dealers of other brands is not very straightforward.

Robustness Checks

One concern about our analysis is the potential endogeneity of rolling out virtual showrooms. Dealers may be starting to use this strategy according to the characteristics of the corresponding market and the expected market share. The ETWFE model primarily addresses this issue by using untreated, not-yet-treated, and already-treated units as counterfactuals. To enhance the robustness of the results and further mitigate endogeneity concerns, we use coarsened exact matching (CEM). Matching is one of the most common causal inference methods. Matching methods attempt to control for the confounding effects by achieving balance in the covariates of observational data. In standard matching techniques, the imbalance level is discovered after the fact, and the analyst needs to repeat the process with different choices if a satisfactory balance is not achieved (Iacus et al., 2012). Notably, standard methods such as propensity score matching (PSM) or Mahalanobis Distance Matching (MDM) may produce a matching solution that addresses imbalance on most variables but leaves some variables imbalanced. The CEM methodology takes a different approach and bounds the imbalance of all variables ex-ante, thus allowing the analyst to limit the level of model dependence and estimation error beforehand (Iacus et al. 2009). It is robust to measurement error, efficient, and guarantees that the maximum imbalance is limited (Blackwell et al. 2009). CEM first temporarily coarsens each control variable, and then an exact matching algorithm is used, and data is stratified such that each stratum has the same values of control variables and removes any observation that does not have a match. Iacus et al. (2009, 2011) and King et al. (2011) demonstrate the CEM consistently outperforms other common methods such as PSM and MDM in reducing the imbalance, model dependence, estimation bias, and error.

This paper follows the CEM implementations default Sturges rule for cutting a variable into several bins. The Sturges method divides the range of a variable into Log2(n) +1 bins, where n is the sample size (Blackwell et al. 2009). As we can see in table 3, the results from the matched sample are in line with those

[1]p-values in parentheses; * p<0.10, ** p<0.05, *** p<0.01

from the unmatched sample. The main effect of virtual showrooms is positive and significant ($\tau = 727715;\ p = 0.081$)[2]. Moreover, the moderating effect of the within-brand competition is significantly negative ($\tau' = -121907, \mathrm{p} = 0.015$)., while the moderating effect of the between-brand is significantly positive ($\tau' = 45592, \mathrm{p} = 0.019$). We also note that matching diminishes the sample size; therefore, some reduction in significance levels is expected.

	Main Model	Interaction Model
VirtAppt	727,715* (0.081)	731,453* (0.072)
VirtAppt x CompWB		-121,907** (0.015)
VirtAppt x CompBB		45,592** (0.019)
CompWB	-22,002*** (0.000)	-18,890*** (0.009)
CompBB	94,731*** (0.000)	71,830*** (0.000)
Control Variables	Y	Y
Time Effects	Y	Y
Observations	44,924	44,924

Table3. CEM K2K Sturges Results

Conclusion and Discussion

Realizing customers' interest in the research-online-purchase-offline model, many retail stores have rolled out a new strategy called virtual showrooms. However, due to the recent emergence of this strategy, no studies have investigated its business value and how it impacts retailers' business. On the one hand, retailers can benefit from this strategy because it enables them to interact with customers and offer detailed and personalized information. On the other hand, providing detailed pre-sales information can increase competition, incentivize customer free-riding, and negatively impact retailers' sales. This study tries t reconcile these opposing mechanisms by exploring the impact of virtual showrooms on car dealers' business. Using a panel dataset related to car dealers across the U.S. and conducting multiple empirical analyses, we show that car dealers can benefit from virtual showrooms. However, not all dealers benefit the same from this new service. The presence of within-brand competitors diminishes the value of virtual showrooms as it facilitates free-riding. The information gained from a virtual showroom at one dealer could easily be used to purchase from another dealer of the same brand. In contrast, virtual showrooms can be more beneficial when more between-brand competitors are nearby. Offering virtual showrooms under higher between-brand competition allows the dealer to strengthen its reach to customers while limiting free-riding and cross-application of information shared during showrooms.

Our paper contributes to the literature of online retailing and channel integration. Our study is the first one that examines the business value of virtual showrooms. Moreover, this study is among the few studies that reveal the importance of considering the geographical competition on the effectiveness of channel integration strategies. Our study also has multiple managerial implications. It demonstrates how retail stores can enhance their business by improving their online information channel. Furthermore, our results show that retail stores need to consider the level and types of local competition to benefit more from online

[2] p-values in parentheses; * p<0.10, ** p<0.05, *** p<0.01

channels. In the future, we plan to extend this study by examining the moderating effect of other essential features, like product type and dealers' online presence. Moreover, we will conduct further robustness checks and explore the underlying mechanisms at a deeper level.

References

Avery, J., Steenburgh, T. J., Deighton, J., and Caravella, M. 2012. "Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities over Time," *Journal of Marketing* (76:3), pp. 96–111.

Bar-Gill, S., and Reichman, S. 2021. "Stuck Online: When Online Engagement Gets in the Way of Offline Sales," *MIS Quarterly* (45:2), pp. 755–788.

Baum, J. A., and Haveman, H. A. 1997. "Love Thy Neighbor? Differentiation and Agglomeration in the Manhattan Hotel Industry, 1898-1990," *Administrative Science Quarterly*, pp. 304–338.

Bell, D. R., Gallino, S., and Moreno, A. 2018. "Offline Showrooms in Omnichannel Retail: Demand and Operational Benefits," *Management Science* (64:4), pp. 1629–1651.

Blackwell, M., Iacus, S., King, G., and Porro, G. 2009. "Cem: Coarsened Exact Matching in Stata," *The Stata Journal* (9:4), pp. 524–546.

Brynjolfsson, E., Hu, Y. (Jeffrey), and Rahman, M. S. 2009. "Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition," *Management Science* (55:11), pp. 1755–1765.

Callaway, B., and Sant'Anna, P. H. 2021. "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics* (225:2), pp. 200–230.

Cars.com. 2020. "Making It Even Easier to Safely Find and Buy a Car from Home | News," Cars.Com. (https://www.cars.com/articles/making-it-even-easier-to-safely-find-and-buy-a-car-from-home-420300/, accessed March 5, 2022).

Conferwith.io. 2021. "Virtual Appointments: The Future of Retail?," Confer With, , March 31. (https://conferwith.io/knowledge-base/virtual-appointments/virtual-appointments-retail-future/, accessed February 26, 2022).

De Chaisemartin, C., and d'Haultfoeuille, X. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review* (110:9), pp. 2964–96.

Forman, C., Ghose, A., and Goldfarb, A. 2009. "Competition between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live," *Management Science* (55:1), pp. 47–57.

Gallino, S., and Moreno, A. 2018. "The Value of Fit Information in Online Retail: Evidence from a Randomized Field Experiment," *Manufacturing & Service Operations Management* (20:4), pp. 767–787.

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), pp. 3560–3578.

Goodman-Bacon, A. 2021. "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics* (225:2), pp. 254–277.

Iacus, S., King, G. and Porro, G., 2009. "CEM: Software for coarsened exact matching," Journal of Statistical Software (30), pp.1-27.

Iacus, S.M., King, G. and Porro, G., 2011. "Multivariate matching methods that are monotonic imbalance bounding," *Journal of the American Statistical Association*, (106:493), pp.345-361.

Karnopp, D. 2004. "Automobiles," in Vehicle Stability, CRC Press, pp. 114–162.

Kern, T. 2022. "Retail Keeps the Digital-Physical Line Blurred with Virtual Appointments and Live Streaming on Retail," MarketScale, , March 29. (https://marketscale.com/industries/retail/retail-keeps-the-digital-physical-line-blurred-with-virtual-appointments-and-live-streaming-on-retail/, accessed April 15, 2022).

King, G., Nielsen, R., Coberley, C., Pope, J.E. and Wells, A., 2011. "Comparative effectiveness of matching methods for causal inference," Unpublished manuscript, *Institute for Quantitative Social Science*, Harvard University, Cambridge, MA.

Kleinlercher, K., Linzmajer, M., Verhoef, P. C., and Rudolph, T. 2020. "Antecedents of Webrooming in Omnichannel Retailing," *Frontiers in Psychology* (11), pp. 3342–3355.

Kumar, A., Mehra, A., and Kumar, S. 2019. "Why Do Stores Drive Online Sales? Evidence of Underlying Mechanisms from a Multichannel Retailer," *Information Systems Research* (30:1), pp. 319–338.

Kumar, N., Qiu, L., and Kumar, S. 2018. "Exit, Voice, and Response on Digital Platforms: An Empirical Investigation of Online Management Response Strategies," *Information Systems Research* (29:4), pp. 849–870.

Lazor, M.-J. 2022. "Webrooming Facts That Power More Sales | ReadyCloud." (https://www.readycloud.com/info/webrooming-facts-that-power-more-sales, accessed April 5, 2022).

Mehra, A., Kumar, S., and Raju, J. S. 2018. "Competitive Strategies for Brick-and-Mortar Stores to Counter' Showrooming,'" *Management Science* (64:7), pp. 3076–3090.

Retail TouchPoints. 2022. "Retail TouchPoints," Retail TouchPoints, , February 27. (https://www.retailtouchpoints.com/resources/more-than-30-of-consumers-are-influenced-by-sponsored-content, accessed February 27, 2022).

Shin, J. 2007. "How Does Free Riding on Customer Service Affect Competition?," *Marketing Science*, pp. 488–503.

Sousa, R., Amorim, M., Rabinovich, E., and Sodero, A. C. 2015. "Customer Use of Virtual Channels in Multichannel Services: Does Type of Activity Matter?," *Decision Sciences* (46:3), pp. 623–657.

Wang, K., and Goldfarb, A. 2017. "Can Offline Stores Drive Online Sales?," *Journal of Marketing Research* (54:5), pp. 706–719.

Williamson, O. E. 1975. "Markets and Hierarchies: Analysis and Antitrust Implications: A Study in the Economics of Internal Organization," University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.

Wooldridge, J. M. 2021. "Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators," *SSRN*.

Yavorsky, D., and Honka, E. 2021. "Consumer Search in the U.S. Auto Industry: The Value of Dealership Visits," *Quantitative Marketing and Economics* (19:1), pp. 1–52.