Cross-channel competition and complementarities in US retail*

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Abstract

We estimate how the spatial assortment of offline stores near consumers affects their online spending. Our data on US business locations and internet usage permit a comparison of this relationship across retailers and product categories, revealing the relative sizes of competitive effects, showrooming effects, and cross-channel complementarities (CCCs). We find that spending at a multichannel retailer's online store falls (0.5–1.9%) when a rival adds a nearby storefront but rises (4.5–17.9%) when the retailer opens its own storefront, consistent with large CCCs. Offline stores often boost Amazon's sales, especially for the books category in which showrooming is especially relevant.

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1 Introduction

Contemporary retail markets feature competition between retailers that operate exclusively offline, exclusively online, or through both offline and online channels. Understanding the relationships between the spatial assortment of offline stores and consumers' online shopping behaviour is important for marketing and policy purposes, as these relationships partly determine the merits of retailers' channel choices, the extent to which online and offline retail constitute a common market, and the role of offline stores in the digital age. The relationships between offline stores and online sales can be multi-dimensional: offline stores can present online stores with benefits and harms that are heterogeneous in terms of channel ownership and product types.

Our study aims to characterize the heterogeneous relationships between offline stores and online spending. The relationships depend on channel ownership and product categories. First, consider the relationship between a retailer's online sales and the offline stores of rival retailers. Rival offline stores may affect a retailer's online sales negatively due to standard *competitive effects*. However, they may also boost the retailer's online sales by *showrooming effects*, i.e., benefits that a retailer derives from informative or promotional services offered by rival retailers. For example, a bookstore may invest in informative services by installing product displays and allowing visitors to read unpurchased books in the store. Some consumers who learn about the products via such in-store services may then choose to purchase them from a rival online retailer. Such showrooming is differentially relevant across retailers and product categories. For example, online-only retailers such as Amazon may enjoy larger showrooming benefits compared to multichannel retailers, if the former can undercut rivals on prices more flexibly. Also, showrooming is likely to be especially relevant for experience goods and in categories wherein multiple competing retailers sell a common set of products. Books are examples of such products.

Next, consider the relationship between a particular retailer's offline stores and the same retailer's own online sales. The retailer's offline stores will exert the competitive effect and showrooming effect described above.[1] However, there may be another, positive effect of the retailer's offline stores on its own online sales, an effect that we term *cross-channel complementarities* (CCCs). For example, an offline store may boost consumer awareness of and tastes for the retailer. Also, an offline store may complement the retailer's online store by offering in-store pick-ups and returns of products purchased online.

To assess the heterogeneous relationships between offline stores and online spending, we combine data on online transactions by US consumers in 2007–2008 with data on store locations of various retailers in the same period. Our sample contains information on each consumer's online expenditures at various websites and the locations of retailers' offline stores, allowing us to examine the heterogeneous relationships of interest. We focus particularly on retailing categories that are well represented in our data: large cross-category retailers (Walmart, Costco, Target, and Amazon) and specialized retailers in the categories of books, electronics, and office supplies (e.g., Barnes & Noble for books). The data also contain consumer characteristics including ZIP code of residence, web browsing history, and various demographic variables.

Our sample period, 2007–2008, is well suited to measuring cross-channel competition. Each category that we study then contained several multichannel chains: e.g., Barnes & Noble, Books-A-Million, and Borders in books. This provides the cross-retailer variation needed to separate the effects of own and rival stores. Subsequent consolidation eliminated many of these chains, collapsing several categories toward fewer (even a single) offline survivor(s) and Amazon. Moreover, after this period, much of consumer online shopping tended to move from the personal computers monitored by Comscore to mobile devices, thus reducing the data's coverage.

To interpret the relationships between offline stores and online spending as causal effects of the former on the latter, we need to address an endogeneity problem that arises when unobserved consumer tastes correlate with offline store counts. Bookstores, for example, may choose to open near avid readers who like buying books both online and offline.

[1] The negative effect of competition within the same retailer can also be called a *cannibalization effect*.

Our approach to overcoming the endogeneity problem involves controlling for a rich set of consumer and neighbourhood characteristics that proxy for unobserved tastes. The first group of such controls comprises descriptors of consumers' web browsing behaviour. Although they are likely imperfect proxies for unobserved tastes, our analysis suggests that they reduce bias in an expected manner. Specifically, we find that the coefficient on the number of stores in a regression of online sales can be positive without the web browsing controls but negative with them. The former finding suggests bias from the endogeneity problem described above whereas the latter suggests that the web browsing controls proxy for unobserved consumer tastes and thereby reduce this bias. The second group of controls is local demographic characteristics, similar to the instrumental variables used by Waldfogel [2003] and Cao et al. [2024]. Local demographics likely affect both offline store presence (e.g., by affecting retailers' location) and online spending (e.g., by sorting consumers with specific tastes into specific neighbourhoods, or by generating peer effects), so controlling for them further reduces bias. In addition to the variables described above, we control for various consumer demographics including income, age, and race; household characteristics such as household size and the presence of a child; census region fixed effects; and year fixed effects.

To establish robustness, we additionally estimate the effect of offline stores on online spending using the disc instrumental variables (IVs) of Cao et al. [2024]. A disc IV is the fraction of a particular subpopulation (defined, e.g., by income, age, or any other demographic variable) that lives at least as close to the central business district (CBD) of the consumer's metro area as the consumer. These IVs are relevant, i.e., predictive of nearby store counts, because (i) resident characteristics such as income and household size vary systematically with the distance from the CBD (Duranton and Puga 2015) and (ii) entry and store density of chains are differentially influenced by the mix of the resident characteristics (Waldfogel 2003). The exogeneity and exclusion restriction rely on the spatial structure of the design. We control for consumers' own demographics, so the disc IVs do not reflect individual demand heterogeneity. Moreover, the IVs are constructed using demographics in other, possibly distant, places located at similar or closer distances from the CBD, rather than from consumers' immediate neighbourhoods alone. This design mitigates concerns that the local demographics directly correlate to spending via local demand unobservables, and suggests that our IVs plausibly affect spending primarily through store proximity.

Our first main finding is that a consumer's spending at a retailer's online store tends to fall as the number of rival offline stores within 20km of the consumer increases. We summarize the relationships between rival offline stores and a retailer's online sales using measures defined as the average percentage change in spending at the retailer's online store when a rival store opens within 20km of the consumer. For multichannel retailers, these measures range from -0.5% (electronics) to -1.9% (cross-category). For Amazon, in contrast, the measures are weaker or positive—e.g., 0.8% for books—so that the averages over all retailers, including Amazon, range from 0.5% (books) to -1.1% (cross-category). In general, rival offline stores affect Amazon's sales less negatively than they affect multichannel retailers' online sales. This is consistent with showrooming effects: Amazon may freeride on rival offline stores' informative services and, aided by its cost-savings on such services, undercut rivals on prices. Our results suggest that offline bookstores are especially positively correlated with Amazon's book sales, which aligns with our expectation that the books category is prone to showrooming.

Our second main finding is that a consumer's spending at a multichannel retailer's online store tends to be higher as the number of the retailer's own offline stores within 20km of the consumer increases. An additional offline store of a retailer raises the sales at the same retailer's online store among nearby consumers by 4.5% (electronics) to 17.9% (books). This is consistent with the presence of strong CCCs.

These findings hold on the extensive margin as well. Measuring outcomes by the probability that a consumer makes any purchase at an online store, we find that rival offline stores reduce this probability for multichannel retailers in every category—by 0.7% (electronics) to 2.4% (cross-category)—and that a retailer's own offline stores raise it by 5.6% (cross-category) to 16.0% (books). Because purchase incidence is unaffected by the large idiosyncratic variation in spending amounts, these extensive-margin estimates are considerably more precise than the spending estimates: the rival and own effects on the probability of purchase are statistically significant in all four categories. Additionally, the qualitative results remain largely similar across different functional forms, definitions of local markets, and region fixed effects.

The results based on the disc IV approach support several key findings from our preferred approach. First, the rival effects on multichannel retailers are negative: e.g., -5.3% (vs. -1.9% in our main results) for cross-category retailers and -5.1% (vs. -1.1%) for bookstores. Second, the rival effects on Amazon are weaker: -2.6% (vs. -0.5%) for cross-category retailers and -1.9% (vs. 0.8%) for bookstores. Consequently, the averages over all retailers are -3.8% (vs. -1.1%) and -2.4% (vs. 0.5%), respectively. Finally, the own effect is 18.3% (vs. 14.1%) for cross-category retailers and 30.7% (vs. 17.9%) for bookstores. Although some estimates are quantitatively different from the main estimates, these results suggest that negative rival effects that are relatively weak against Amazon and positive own effects are fairly robust phenomena for cross-category retailers and bookstores.

Our results provide a unified explanation for previous research findings, and also useful implications for retail strategies and policies. The earlier literature on the relationship between offline store presence and online sales typically finds that online and offline retail are substitutes, whereas more recent studies of a single retailer often find that they are complements (see Section 1.1 for a literature review). On one hand, our results suggest that the two channels are competing, and the competitive effects generally outweigh showrooming effects, explaining substitutability found in the first strand of the literature. On the other hand, our results also suggest the presence of strong CCCs that outweigh the negative competitive effects net of the showrooming effects, explaining the complementarity documented in the later literature. The weaker negative effects of rival stores on Amazon, especially for books, also suggest the presence of showrooming effects for Amazon. These effects can be key determinants of retailers' product lines and entry. They will also affect policy decisions, such as resale price maintenance. Although we do not attempt to quantify each effect or conduct policy analysis, our results can be a stepping stone for investigating these issues in more detail.

The remainder of this article is organized as follows. We review the relevant literatures in the rest of this section. Section 2 provides a conceptual framework for studying multichannel retailing. Section 3 describes our data. In Section 4, we present our regression model and identification approach. Empirical results are presented in Section 5. Section 6 discusses implications of our results. Section 7 concludes.

1.1 Related literature

We contribute to the literature on the relationship between offline and online retail. Earlier studies on cross-channel competition (e.g., Goolsbee 2001, Sinai and Waldfogel 2004, Forman et al. 2009, Brynjolfsson et al. 2009) document evidence for channel substitution, without distinguishing multichannel retailers from single-channel ones.[2] Another, more recent literature studies substitutability and complementarity between a particular retailer's online and offline retail channels for apparel and home furnishings (Avery et al. 2012, Wang and Goldfarb 2017, Kumar et al. 2019, Shriver and Bollinger 2022), eyewear (Bell et al. 2018), and groceries (Chintagunta et al. 2012, Pozzi 2013). A few recent studies (e.g., Dolfen et al. 2023, Relihan 2024) use consumer-level data on credit and debit card transactions at multiple retailers. Our study complements those literatures by investigating competition between multichannel retailers,[3] using data on consumer-level expenditures at various online retailers linked to rich characteristics of consumers and their local environment.

Our study also relates to the literature on showrooming and associated free-riding problems (e.g., Wu et al. 2004, Shin 2007, Jing 2018, Kuksov and Liao 2018, Mehra et al. 2018). Götz et al. [2025] find that bookstore closures in Germany in the 2010s decreased

[2] Prince [2007] measures the elasticity of demand for computers at online retailers with respect to offline prices and argues that the cross-price elasticity increased following the rise in multichannel operations.

[3] For offline revenues and prices, a few studies (e.g., Davis 2006, Davis et al. forthcoming) investigate how the effects of entry depend on whether the new entrant has the same owner as the incumbent or it has a different owner.

overall book sales, and suggest that service provision in offline stores could be a mechanism behind the result. Some studies (e.g., Kumar et al. 2019) more closely investigate the underlying mechanisms behind the effects of offline stores on online sales. Others examine business and policy implications of showrooming, such as pricing strategies and resale price maintenance (RPM).[4] Although our study does not investigate the mechanisms or the business and policy implications as closely, it complements the previous studies by documenting the heterogeneous relationship between online and offline channels, which can serve as a stepping stone for further understanding of showrooming.

Last, our study relates to a broad literature on the evolution of the retail sector, especially the rise of e-commerce and the rise of certain types of offline retail, such as big-box retailers and dollar store chains. Hortaçsu and Syverson [2015] review the evolution of US retail, emphasizing e-commerce and warehouse clubs/supercenters as two leading forces of the recent retail landscape. A large literature studies the impacts of the entry by Wal-Mart on retail prices (Basker 2005a, Basker and Noel 2009, Arcidiacono et al. 2020), product quality (Matsa 2011), rivals' exit (Jia 2008, Ellickson and Grieco 2013), consumer welfare (Hausman and Leibtag 2007), and labor market outcomes (Basker 2005b, Neumark et al. 2008). An emerging literature on dollar stores (Cao 2022, Caoui et al. 2024, Chenarides et al. 2024, Caoui et al. 2025, Schneier 2025) similarly examines how they shape the local competitive environment. For e-commerce, the literature documents how online retail affects market structure and product sorting (Goldmanis et al. 2010, Jin and Kato 2007), how local sales taxes affect online purchases (Goolsbee 2000, Einav et al. 2014), welfare gains from e-commerce and their sources (Dolfen et al. 2023, Edgel et al. 2023, Quan and Williams 2018), and the labor market impacts of e-commerce (Chava et al. 2024). Although this extant literature characterizes the role of various store formats and selling channels in contemporary retail, it generally does not characterize heterogeneity based on ownership structure and product category. Our article aims to fill this gap.

[4]For example, Carlton and Chevalier [2001] find that manufacturers internalize freeriding by online retailers in their distribution and pricing strategies, and MacKay and Smith 2014 discuss minimum RPM, which is often rationalized by showrooming, and provide empirical evidence on the effects of RPM.

2 Conceptual Framework

To guide our empirical analysis, we provide a simple conceptual framework that decomposes the effects of offline stores on online retail sales in the presence of multichannel retailing into four forces: competitive effects, showrooming effects, cannibalization, and cross-channel complementarities.

The first two forces concern how a rival offline store affects a focal retailer's online sales. First, the entry of a new offline rival reduces the focal retailer's online sales through a standard *competitive effect*: holding fixed consumers' interest in and information about their purchasing options, the rival offline store provides a new substitute for the focal retailer's online store and is likely to steal at least some of its business. The second force, the *showrooming effect*, reflects that consumers' interest and information generally respond to offline entry — in particular, offline stores may boost rivals' online sales by providing informative or promotional services that bolster demand for particular products or product categories, irrespective of which retailer sells them. For example, an offline bookstore may offer product displays that allow visitors to read unpurchased books in the store, and some of those visitors may then purchase the books at a rival retailer's online store. Thus, the showrooming effect implies a positive effect of offline stores on rival retailers' online sales.

The importance of showrooming depends on retailers and product categories. The benefits of showrooming to online retailers derive from the ability of these retailers to undercut the prices of the offline store generating the showrooming effect. This implies that online-only retailers such as Amazon may benefit more from showrooming than multichannel retailers, as online-only retailers do not face the costs of providing offline informative services and are thus positioned to maintain profitability at prices lower than their multichannel rivals. Also, the benefits of showrooming will be large for experience goods (Nelson 1970), because pre-sale services allow consumers to try products and reduce the uncertainty of the product quality.[5] Showrooming is likely to be especially important in

[5]Previous studies document that demand for experience goods is influenced by information about quality from various sources, such as advertising (Ackerberg 2003), labelling (Jin and Leslie 2003), expert

categories in which multiple retailers sell a common set of products. The books category fits these descriptions, so bookstores are likely to exhibit relatively large showrooming effects.

The final two forces govern how a retailer's own offline stores affect its online sales. First, a retailer's own offline stores are likely to reduce its online sales by the same substitution logic as the competitive effect and increase it by the same showrooming logic described above; we refer to the former, within-retailer business-stealing, as *cannibalization*. However, a retailer's own offline stores may further increase its online sales through what we call *cross-channel complementarities* (CCCs). These complementarities may arise because offline stores increase consumers' awareness of and preference for the retailer. They may also arise from convenient in-store services that complement online purchases, such as in-store pickup and returns.

3 Description of data

Our primary data sources are the Comscore Web Behavior Database and the Data Axle business locations database, both for 2007–2008.[6] Comscore provides online browsing and transactions records for a panel of US web users, henceforth *consumers*. Because there is limited overlap in the dataset's consumers across years, we define an observation by a consumer-year pair. The data feature 147,852 observations. We focus on 2007–2008 for three reasons. First, the period provides the variation our design requires: each category contained several competing multichannel chains, whereas later consolidation left many categories with a single offline survivor. Second, online shopping in this period occurred primarily on personal computers rather than on mobile devices, and our panel tracked the former.[7] Third, offline store networks in this period reflect location decisions made before e-commerce reshaped the sector; store closures in later years were concentrated

opinions (Reinstein and Snyder 2005, Berger et al. 2010, Hilger et al. 2011, Reimers and Waldfogel 2021), and crowd ratings (Reimers and Waldfogel 2021).

[6]We also possess data for 2017–2018, but focus on 2007–2018 for the reasons provided below. See Online Appendix O.1 for details.

[7]Consistent with this, the panel's coverage of transactions is higher in 2007–2008 than in later years, as documented in Online Appendix O.1.

among chains losing ground to online rivals, so later-period store counts would be more strongly selected on the outcomes we study. Variables include consumer characteristics, descriptors of website visits, and descriptors of online transactions.[8]

We limit attention to a few product categories and a few retailers within each category that are well represented in the Comscore sample. We study both a set of "cross-category" retailers, which sell a broad range of products, and a few specialized product categories, namely books, electronics, and office supplies. Within each category, we focus on a few large offline retailers: Costco, Target, and Walmart for cross-category retailers; Barnes & Noble, Books-A-Million, Borders, and Waldenbooks for books; Apple, Best Buy, Circuit City, and Radio Shack for electronics; and Office Depot, Office Max, and Staples for office supplies.[9] We aggregate the other offline stores into a single group of "other" stores within each category.[10] The online stores included in our analysis are Amazon and the online stores associated with each large offline retailer listed above.[11]

We use per-consumer spending at various online retailers in various categories as main outcomes. Table 1 describes our spending data. The average amount spent at each retailer is driven by a relatively small number of consumers with positive spending.

Comscore also provides three types of variables that are used as controls in our analysis. First, we use consumer characteristics, including household size and indicators for: household income ($\geq$\$75,000 or not); presence of children in the household; broadband internet access; head-of-household's race (white, black, or other); Hispanic identity; educational attainment (having graduated from college or not);[12] and age ($<$40 years old, between 40 and 54 years old, or $\geq$55 years old). Second, we construct variables describing each consumer's web browsing. Specifically, we compute the number of times that the consumer visits a website in each of several categories, including: adult, advert, career, dating, di-

[8] See Online Appendix O.1 for a discussion of the Comscore dataset's representativeness.

[9] We chose these retailers based on national store counts. See Online Appendix O.1 for details.

[10] As explained in Section 4, when analyzing specialized categories, we additionally control for the store counts of Costco, Target, and Walmart separately.

[11] In our analysis, we only include sales within the product category in question. In the analysis of cross-category retailers, we include all sales, including books, electronics, and office supplies.

[12] To keep observations with missing education, we also include an indicator for missing education.

Table 1: Summary of spending data

Category	Store	Avg. spend (all)	Positive spending (%)	Avg. spend (pos.)
Cross-category	Amazon	18.51	14.32	129
	Costco	3.27	0.54	607
	Target	3.84	3.47	111
	Walmart	7.16	6.07	118
Bookstores	Amazon	6.90	8.28	83
	Barnes & Noble	1.08	1.83	59
	Books-a-Million	0.07	0.13	55
Electronics	Amazon	4.12	1.83	226
	apple.com	2.82	0.68	416
	Best Buy	2.75	0.88	311
	Circuit City	2.47	0.76	323
	Radioshack	0.10	0.11	95
Office supplies	Amazon	0.08	0.10	83
	Office Depot	4.36	0.57	768
	Office Max	0.39	0.11	350
	Staples	5.47	0.84	653

Note: "Avg. spend (all)" reports the mean amount spent per consumer (in dollars). "Positive spending (%)" reports the share of observations with positive spending. "Avg. spend (pos.)" reports the mean amount spent among observations with positive spending. In the books category, we do not analyze online stores for Borders and Waldenbooks, because our data include no online sales for these retailers.

rectory, downloads, finance, gaming, government, information, internet/wireless services, malware, media, news, portal, retail, social media, sports, travel, video, weather, and web service.[13] Finally, we construct measures of the demographic profiles of the local areas surrounding consumers. These measures are averages of the consumer characteristics among consumers within 20km of the ZIP code of the consumer in question.[14]

Our main independent variables, the numbers of local offline stores, are constructed by combining the Comscore sample with the other data source, Data Axle. Its database reports the locations (latitude and longitude) of all US businesses annually. We use these data to compute, for each consumer and retailer, the number of retailer locations within 20km of the consumer. Table 2 describes these variables.

In robustness checks with "disc" instruments, we need information on the aforementioned

[13]Online Appendix O.1 describes our procedure for categorizing websites.

[14]We assign consumers to the centroid of the five-digit ZIP code in which they live.

Table 2: Summary of offline store counts

Category	Store	# stores (20km)		Min. distance	
		Mean	Median	Mean	Median
Cross-category	Costco	2.34	0	75.13	25.77
Cross-category	Target	7.48	4	33.41	7.44
Cross-category	Walmart	8.33	6	8.66	5.34
Books	Barnes	5.66	2	26.37	11.10
Books	Books-a-Million	0.51	0	474.97	134.02
Books	Borders	4.35	2	45.23	14.29
Books	Waldenbooks	1.73	1	53.92	23.64
Electronics	Apple	1.46	0	86.19	36.70
Electronics	Best Buy	4.95	2	23.75	9.59
Electronics	Circuit City	4.16	2	33.75	10.79
Electronics	Radio Shack	24.41	12	7.01	3.27
Office Supplies	Office Depot	7.11	4	26.09	9.31
Office Supplies	Office Max	4.73	2	29.18	12.19
Office Supplies	Staples	10.63	2	41.76	9.05

Note: "# stores (20km)" reports the mean and median store counts within 20km of the consumer. "Min. distance' reports the mean and median distances from the consumer to the closest store of each retailer.

demographics for various zip codes, including those absent in our sample. We use the American Community Survey for 2007–2011 for this purpose.

4 Estimation and Identification

Our estimating equation is

$$\mathbb{E}[y_{it} \mid x_{it}] = f\left(h(n_{it})'\alpha + z_{it}'\beta + w_{it}'\delta + \rho_{R_{it}}^{\mathrm{FE}} + \rho_t^{\mathrm{FE}}\right) \tag{1}$$

Here, the outcomes y_{it} are consumer i's online spending in year t (in dollars) at various retailers and in various categories.[15] The vector x_{it} includes the right-hand side variables n_{it}, z_{it}, w_{it}, R_{it}, and t. The function f governs the shape of the relationship between the explanatory variables and the outcome; in practice, we specify $f(x) = e^x$ to impose a non-negativity constraint on spending y_{it} and estimate the equation via Poisson regression. The main right-hand side variable of interest is n_{it}, a vector of store counts of offline retailers within 20km of consumer i. The function h transforms the store counts by $x \mapsto \log(x + 1)$. The remaining variables on the right-hand side of (1) are z_{it}, which is a vector including the consumer characteristics enumerated in Section 3 and the log of

[15]We omit indicators for retailers and categories for notational simplicity.

the population within 20km of the consumer; w_{it}, which we describe below; $\rho^{\text{FE}}_{R_{it}}$, which is a fixed effect for the consumer's census region R_{it}; and ρ^{FE}_t, which is a year fixed effect. The offline retailers included are those listed in Section 3, as well as the other retailers aggregated into a single group ("other"). For specialized product categories, we also control for the counts of Costco, Target, and Walmart stores within 20km. The parameter of interest is the coefficient vector α, which shows the relationship between the local store presence of various offline retailers and online spending at various online retailers.

For the α parameters to represent causal effects of the offline stores on online spending, it is necessary to address the endogeneity problem that arises when unobserved tastes that contribute to consumers' online shopping behaviour correlate with offline stores' location. For example, bookstores may locate their new store in the neighbourhood of avid readers who like to purchase books both online and offline.

Our approach to overcoming the endogeneity problem involves controlling for a rich set of consumer and neighbourhood characteristics w_{it} that proxy for the unobserved tastes of consumers. The first set of variables in w_{it} are the internet usage controls, which proxy for unobserved taste characteristics such as interests, personality, and aesthetic preferences. The categories of websites that a consumer visits are likely to reflect these characteristics. For example, a consumer who visits news and information websites may have an interest in learning and language, and thus may be more interested in buying books. The second set of variables in w_{it} includes local demographic characteristics in region r_{it} that influence the spending outcomes of consumer i.[16] For example, conditional on consumer i's own income, her shopping tastes will vary depending on whether she lives in a high-income neighbourhood or in a low-income neighbourhood. This may be due to consumer sorting (e.g., those who prefer a luxury or intellectual life live in a high-income neighbourhood) or peer effects (e.g., those who live in a high-income neighbourhood prefer a luxury or intellectual life). Local demographics may also influence retailers'

[16] We allow r_{it} to be different from R_{it} in Eq. (1). For example, the place effects of region R_{it} may capture the effects of the climate in the region, whereas the effects of neighbourhood r_{it} may capture the average income of the neighbours within driving distance (see below for the details of the latter effects).

location choices. Therefore, omitting them may generate an endogeneity problem. Thus, we control for them in our regression equation (1).

In contrast to the IV approach often used in this literature, we use local demographics as controls in our preferred specification. We elaborate on our rationale for doing so in Section 4.2, where we also develop an alternative approach that uses the local demographics as instruments.

We estimate equation (1) by Poisson regression after trimming observations in which the spending outcome exceeds its 98th percentile conditional on positive spending.

4.1 Evidence that the controls attenuate endogeneity bias

To assess whether the controls w_{it} plausibly reduce endogeneity bias, we provide several pieces of empirical evidence. We begin with the internet usage controls. To assess their scope for mitigating bias, we regress an indicator for whether a consumer bought a book online on the number of offline bookstores within 20km and the internet usage controls. Table 3 provides the results. The internet usage variables predict book purchases in reasonable ways: visits to websites in the information, finance, and news categories positively predict an online book purchase. Book purchasing also positively relates to the number of retail website visits, a control that captures a consumer general proclivity toward online shopping, an unobservable that is especially prone to induce endogeneity bias. Most notably, omitting the internet usage controls leads to a large *positive* shift in the estimated coefficient on the number of nearby stores. This pattern is consistent with the idea that bookstore locations are positively correlated with otherwise unobserved demand for books, and that the internet usage controls absorb part of this correlation. Thus, including these controls appears to reduce the upward bias in the estimated store-count coefficient.

Next, we discuss the effectiveness of neighbourhood demographics controls. Conditional on their own demographics, the demographics of a consumer's neighbours may be correlated with the consumer's online shopping behaviour. For example, conditional on the consumer's own income, a consumer in a high-income neighbourhood may shop differently than a consumer in a low-income area due to a desire to fit in with neighbours. This pattern contributes to the endogeneity problem because local demographics may also influence retailers' location choices.

The data support this concern. Table 4 shows that, conditional on their own incomes, consumers in higher-income areas spend significantly more at Costco's online store, moderately more at Target's, and less at Walmart's. This is consistent with Costco (Walmart) appealing relatively more to consumers of higher (lower) socio-economic status, who are more (less) likely to live in high-income areas. Table 5 additionally shows that counts of nearby offline stores of each cross-category retailer are correlated with the local high-income share. Thus, controlling for average local demographics stands to further attenuate endogeneity bias.

Fixed effects approaches? Another possible solution to the endogeneity problem is to specify fixed effects for small geographical regions. However, this approach limits our ability to use cross-region variation and therefore reduces estimation precision, especially because we observe at most two data points per consumer. Also, if measurement error accounts for a large portion of the time-series variation in store counts, then relying on this variation will bias estimates of offline stores' effects. This concern is relevant here because local store counts typically do not change much year-to-year, while aggregation to the year level introduces measurement error.[17] The possibility of bias from measurement error underlies a common argument against the fixed effects approach to production function estimation (see, e.g., Ackerberg et al. 2007).

Sources of conditional variation in store counts? Conditional on our controls, variation in offline store counts may reflect, for example, frictions in real estate markets, including the variety of properties contemporaneously listed for sale to prospective residents and store owners, as well as buyers' and sellers' bargaining strategies. We assume that these

[17] Basker [2005a] estimates the effects of Walmart entry on local prices of various consumer goods, addressing measurement error in imputed quarterly Walmart entry by constructing an instrument based on planned entry. Such an approach is difficult to implement in our multiple-retailer setting.

Table 3: Regression of online book shopping on nearby stores and internet usage

		Controls included		Controls excluded	
Variable type	Note	Estimate	t-statistic	Estimate	t-statistic
N. stores (log-transformed)		-0.18	-3.30	0.10	1.73
N. visits	Adult	-1.10	-10.98		
N. visits	Advert	-1.17	-7.72		
N. visits	Career	-1.19	-3.01		
N. visits	Finance	2.30	19.64		
N. visits	Gaming	-0.44	-7.45		
N. visits	Government	1.03	4.10		
N. visits	Info	4.86	28.33		
N. visits	Malware	-0.33	-7.82		
N. visits	Media	0.39	4.22		
N. visits	Other	0.02	4.50		
N. visits	Portal	0.21	16.97		
N. visits	Retail	3.02	48.43		
N. visits	Social Media	-0.11	-3.61		
N. visits	Video	-0.70	-6.59		
N. visits	Weather	0.14	1.92		
N. visits	Webservice	-0.50	-8.88		
N. visits	Dating	-0.20	-0.95		
N. visits	Internet Wireless	0.50	6.57		
N. visits	News	1.16	13.91		
N. visits	Sports	-0.22	-1.86		
N. visits	Travel	5.53	18.05		
N. visits	Downloads	-0.55	-4.75		
N. visits	Directory	10.14	2.46		
	R^2	0.080		0.011	

Note: The dependent variable is an indicator for whether the panelist purchased a book online. "N. stores (log-transformed)" is the number of stores within 20km transformed by $x \mapsto \log(x+1)$. "N. visits" is the number of visits to a website in the category (in hundreds). The regressions include region fixed effects, year fixed effects, and the consumer characteristics listed in Section 3 (omitted from the table).

factors are independent of consumer tastes for online shopping, so that they do not generate an endogeneity problem. Plausibly exogenous tastes for neighbourhoods may also induce variation in proximity to stores conditional on our controls. Consider, for example, two consumers with the same tastes for online shopping who prefer to live in different neighbourhoods because of differences in family location. Such factors can generate variation in store proximity even after conditioning on the rich set of controls in (1).

Table 4: Regressions of online spending on high-income share

	Spending		
	costco.com	target.com	walmart.com
	(1)	(2)	(3)
N. stores (log-transformed)	2.551	0.040	−1.319
	(0.159)	(0.059)	(0.113)
High income	0.659	0.620	−0.237
	(0.352)	(0.165)	(0.248)
High income (average)	2.667	0.632	−0.769
	(0.638)	(0.300)	(0.447)
Mean dep. var.	2.51	3.19	5.70
Observations	147,836	147,749	147,673

Note: The dependent variables are the online spending (in dollars) of consumers at each retailer. "N. stores (log-transformed)" is the log of one plus the number of the retailer's offline stores within 20km. "High income (average)" is the share of people within 20km that have household incomes exceeding $75,000. The regressions include region fixed effects, year fixed effects, and the consumer characteristics listed in Section 3 (omitted from the table). To limit the influence of outliers, we trim observations for which the spending variable exceeds its 98th percentile conditional on positive spending.

Table 5: Dependence of offline retail environment on local demographics

	Costco	Target	Walmart
	(1)	(2)	(3)
High income (average)	0.793	1.015	0.536
	(0.008)	(0.011)	(0.009)
Observations	147,852	147,852	147,852
R^2	0.223	0.225	0.137

Notes: the table reports results from a consumer-level regression of the number of a retailer's stores within 20km of a consumer on variables characterizing the demographic profile of the region within 20km of the consumer's ZIP code of residence. The measures of the demographic profile included are: share of population with household income exceeding $75,000 ("High income (average)"); the share of the population in white and black racial groups; the share of the population under the age of 40 and between the ages of 40 and 54; the average household size; the share with a child in the household; the share that is Hispanic; the share with broadband internet; and the share having graduated from college. All estimates except that for "High income (average)" are omitted from the table.

4.2 The disc instrument approach

The insight that local demographics influence firms' entry and pricing decisions has motivated researchers to use the former as instrumental variables (IVs) for the latter (Waldfogel 2003, Berry and Haile 2016, Cao et al. 2024). In our primary specification, we instead use local demographics as controls in our regressions because—as suggested by the results in Table 4—they may not be excluded from the spending equation, e.g., due to consumer sorting or peer effects. The validity of our approach thus depends on how well our controls capture the determinants of local store counts that also affect online spending. If, for example, retailers' location choices are based mostly on observable information about local consumers' demographics and access to their websites, in addition to other unobserved idiosyncratic factors, then residualizing store counts with respect to the observed controls will substantially reduce endogeneity bias, whereas using the same variables as IVs could introduce substantial bias. The presence of unobservables driving both store location and consumer choice that are not captured by our control variables, however, would threaten our approach. If this is indeed the case and there are certain transformations of local demographics that are uncorrelated to consumer preferences conditional on our controls, then using these transformations as IVs would be preferable to our main approach.

Disc IVs (Cao et al. 2024) provide an example of a transformation that may be uncorrelated to consumer online shopping preferences yet shift consumers' offline retail environments. To assess robustness of the results from our preferred specification, we additionally estimate the impact of offline stores on online spending using the disc IVs approach. For each of various demographic groups within a metropolitan area, the disc IV is the fraction of the group's population that live at least as close to the metro area's central business district (CBD) as the consumer. The relevance of these IVs comes from the observations that (i) resident characteristics such as income and household size vary systematically with the distance from the CBD (Duranton and Puga 2015) and (ii) entry and store density of chains are differentially affected by the mix of the resident characteristics (Waldfogel 2003). Intuitively, the disc IVs predict the store counts near consumers by capturing how the mix of the potential customer base, hence attractiveness of retail entry, varies with the consumers' distance from the metro area's centre.

The exogeneity and exclusion restriction of the IVs rely on the spatial structure of the design. Note first that we control for consumers' own demographics, so the IVs do not reflect individual demand heterogeneity. Moreover, the disc IVs are *not* based solely on the demographics of the focal consumer's immediate neighbourhoods. They are also based on the demographic profiles in other parts of the metro area that are within the same radius of the CBD but are possibly distant from the consumer's location. Compared to the former, the latter are much less likely to be correlated to local demand unobservables. Indeed, by the construction of the disc IV, locations along the same ring around a CBD share the same predicted distance to each chain, regardless of the differences in local neighbourhood characteristics. Thus, conditional on controls, the IVs plausibly affect spending primarily through store proximity rather than local demand shocks.

For each of various demographic characteristics, the disc IVs are computed as follows. First, within each core-based statistical area (CBSA), we divide the population into groups based on the characteristic. We then compute the fraction of each group that lives at least as close to the CBD as the consumer in question. A disc IV is defined for each group as the interaction of this fraction with an indicator for the consumer belonging to the group.

Consider income as an example. We divide the population into high-income or low-income groups, and compute the fraction of high-income population that live at least as close to the CBD as the consumer,

$$sh_i^{\mathrm{HInc}} = \frac{\#(\text{ high-income population in } \mathrm{CBSA}_i \text{ living within } d(i) \text{ of } \mathrm{CBD}_i)}{\#(\text{ high-income population in } \mathrm{CBSA}_i)}, \quad (2)$$

where CBSA_i and CBD_i are the CBSA and CBD, respectively, to which consumer i belongs, and $d(i)$ is the distance of consumer i from CBD_i. Analogously, we compute sh_i^{LInc}, the fraction of low-income population that live at least as close to the CBD as i. Note that these shares depend only on the CBSA and d.[18] We then use sh_i^{HInc}, sh_i^{LInc}, $\mathrm{HInc}_i \cdot sh_i^{\mathrm{HInc}}$ and $\mathrm{HInc}_i \cdot sh_i^{\mathrm{LInc}}$ as disc IVs, where HInc_i is the indicator of i belonging to the high-income group. By interacting the shares with the own high-income indicator, we may predict that consumers at the same distance from the same CBD have different

[18]We identify a unique CBD for each CBSA, by the following procedure. First, for each CBSA, we find the city with the largest number of locations of leading retail categories in 2007. We then find the geographical median of these locations within the city.

counts of nearby stores, depending on whether they are high- or low-income.

We compute similar IVs for the following demographic variables: race (white, black, or other groups); Hispanic (yes/no); having a child (yes/no); household size (at least three individuals or not); and income (income above \$75,000 or not). The first two variables are measured at the individual level, whereas the rest are measured at the household level. Further, following Cao et al. [2024], we create additional IVs by multiplying the baseline disc IVs by the fraction of the total population in the CBSA that live at least as close to the CBD as i. These IVs will add the predictive power for store counts, because they exploit variation related to the population density across different rings around CBDs. Also, we run first-stage regressions separately for each store-count variable, allowing for the disc IVs to have differential effects on the store presence of different chains.

Just as in our main analysis, we use expenditures at each online store as the dependent variables and estimate the Poisson regression. To incorporate the disc IVs in the Poisson regression, we use a control function approach. For each store-count variable, we first regress the store count on the disc IVs as well as the non-store-count controls included in the spending regressions, and then include the residual as a control in all spending regressions that include the corresponding store-count variable. We compute the standard errors of the coefficient estimates that are robust to heteroskedasticity and to over- or under-dispersion (quasi-MLE), and adjust them for the first-stage estimation error using the standard formula for two-step estimators (Newey and McFadden 1994).

4.3 Measures of rival effects and own effects

To facilitate interpretation of our results, we compute scale-free measures of offline stores' effects. The basic measure, θ_{js}, is the percentage change in the expected spending of a consumer at online store s when the number of retailer j's offline stores in their vicinity rises from its mean $\bar{n}_j$ to $\bar{n}_j + 1$, conditional on the mean values of the other variables. We then define a store-specific rival effect θ_s^{rival} as the average of θ_{js} across rival multichannel retailers j, weighting each j by that retailer's total number of storefronts. Taking a further average of θ_s^{rival} across online retailers s within each category (weighting retailers by their total online sales) yields the category-specific average rival effect $\bar{\theta}^{\text{rival}}$. We compute two measures of the rival effects: one with Amazon's store-specific rival effects included in the average, and one without. Last, we define an average own effect as the average of θ_{ss} across multichannel retailers s, weighting each retailer by its total online sales. Online Appendix O.2 provides further details of these measures.

To the best of our knowledge, we are the first to study the differences between the own and rival effects (with or without Amazon) and across categories. Thus, the measures may be of interest in themselves. Moreover, based on the conceptual framework in Section 2, the comparison between the own and the rival effects will be informative of the CCCs, whereas the comparison of the rival effects with and without Amazon and how the comparison depends on product categories will be informative of the showrooming effects.[19]

5 Results

We first present tables to summarize our results, and then discuss the results by retail category. Table 6 shows results for regressions Eq.(1), with each consumer's overall online spending within a given category as outcomes and category-level store counts within 20km of the consumer as main independent variables. These regressions show overall relationships between store counts and online sales. Table 7 reports measures of average rival and own effects as described in Section 4.3, obtained from regressions with store-level online spending and store counts, highlighting heterogeneous effects. Although we mainly focus on expenditures as outcomes, we also present the effects on the probability of positive spending for our preferred specification. Panel (a) of Table 7 presents effects on expenditure levels, and panel (b) presents effects on the probability of positive spending. The extensive-margin estimates in panel (b) are considerably more precise as the positive-spending indicator is unaffected by the large idiosyncratic variation in spending amounts.

[19] Comparing rival effects across product categories will not necessarily be informative of the magnitude of the showrooming effects, because the comparison is affected by the competitive effects that may differ across categories. Thus, we instead infer showrooming by examining how Amazon's relative benefits from the presence of rival offline stores depend on product categories.

Store-level effects on the probability of positive spending appear in Online Appendix Table A5; they mirror the store-level expenditure results reported below, with positive own effects for every multichannel retailer and negative rival effects for ten of the twelve multichannel retailers.

Table 6: Overall spending regressions

	Cross-category retailers (1)	Bookstores (2)	Electronics (3)	Office supplies (4)
N. Stores: Total				
Spending	−0.044	0.109	0.067	0.140
	(0.017)	(0.024)	(0.026)	(0.068)
Positive spending	−0.001	0.103	0.014	0.015
	(0.007)	(0.014)	(0.014)	(0.030)
Mean spending ($)	187.35	9.14	47.37	12.91
Positive-spending share (%)	51.99	12.49	15.97	3.66
Observations	145,345	146,506	146,404	146,765

Notes: this table presents estimated coefficients from Poisson regressions of a consumer's overall spending within a given category ("Spending") and of an indicator for positive spending within the category ("Positive spending") on the category-level store counts within 20km of the consumer. "Mean spending" presents the average of the spending outcome in dollars; "Positive-spending share" presents the percentage of observations with positive spending. Observations refer to the spending regressions; the positive-spending regressions include 146,873 observations in each category, because the trimming of extreme spending values does not apply to the binary outcome. Standard errors appear in parentheses.

Cross-category retailers. Column (1) of Table 6 provides the result for the regression of overall spending by a consumer on the total number of stores near the consumer operated by all retailers. Offline stores are negatively associated with online spending, suggesting substitutability between the online and offline channels. The corresponding positive-spending coefficient is essentially zero, indicating that substitution operates on spending amounts rather than on whether consumers shop online at all.

This aggregate estimate, however, conceals heterogeneity across retailers. Table 8a displays estimates for regressions of retailer-specific spending on retailer-specific store counts. The estimated relationships between rival offline stores and a focal retailer's online sales are primarily negative, and the handful of positive estimates are statistically insignificant, except for the coefficient on Costco in the regression for Amazon. We interpret the negative rival effects as evidence that competitive effects generally outstrip showrooming effects for cross-category retailers. Conversely, the estimated relationship between

Table 7: Category-level rival and own effects

(a) Expenditures

	Cross-category retailers (1)	Bookstores (2)	Electronics (3)	Office supplies (4)
Rival (multichannel)	-0.019	-0.011	-0.005	-0.010
	(0.005)	(0.006)	(0.004)	(0.007)
Rival (Amazon)	-0.005	0.008	0.006	0.030
	(0.003)	(0.003)	(0.004)	(0.023)
Rival (all retailers)	-0.011	0.005	-0.002	-0.010
	(0.003)	(0.002)	(0.003)	(0.007)
Own	0.141	0.179	0.045	0.158
	(0.022)	(0.030)	(0.032)	(0.022)

(b) Positive spending

	Cross-category retailers (1)	Bookstores (2)	Electronics (3)	Office supplies (4)
Rival (multichannel)	-0.024	-0.019	-0.007	-0.023
	(0.003)	(0.004)	(0.002)	(0.004)
Rival (Amazon)	-0.001	0.006	0.003	0.018
	(0.002)	(0.002)	(0.002)	(0.016)
Rival (all retailers)	-0.011	0.001	-0.002	-0.021
	(0.002)	(0.002)	(0.002)	(0.003)
Own	0.056	0.160	0.087	0.124
	(0.005)	(0.019)	(0.019)	(0.011)

Note: Each column presents the category-level average rival effects and own effects, computed using the estimates of store-specific Poisson regressions. Panel (a) reports effects on expenditure levels (percentage changes in spending); panel (b) reports effects on the probability of positive spending (percentage changes in the probability), with averaging weights proportional to each online store's share of consumers with positive spending. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.

multichannel retailers' offline store counts and their own online sales are positive and statistically significant.

Next, Table 8b presents estimates of scale-free measures of rival and own effects for cross-category retailers. The "Average" column aggregates these effects across the multichannel retailers' online stores, weighting each store by its mean spending; this sales-weighted average is estimated more precisely than the store-specific effects. For all retailers, the rival measure is negative and the own measure is positive. Additionally, the rival and own measures are heterogeneous across retailers. One notable finding is that the (negative) effect of rival offline stores on Amazon's sales is weaker than the effects of such stores on multichannel retailers' online sales. Specifically, Amazon's sales fall by 0.5% in response to an additional offline rival store, whereas the online sales of Costco, Target, and Walmart fall by 1.9%, 1.8%, and 2.0%, respectively.

These store-level results yield the main estimates in Column (1) of Table 7: the rival effect on multichannel retailers' online sales is negative (−1.9%) whereas the rival effect on Amazon is weaker (−0.5%). This implies that the average over all retailers is smaller in magnitude (−1.1%). The own effect is large and positive (14.1%).

Books. Column (2) of Table 6 presents the result from the regression of overall books spending on the total number of nearby bookstores. The estimated coefficient is positive. The corresponding positive-spending coefficient (0.103) is similar in magnitude and precisely estimated: nearby bookstores raise the probability that a consumer buys books online, not only the amounts spent. One possible interpretation is that the positive showrooming effect and CCC combined outweigh the negative competitive effect. Next, Table 9 reports the results of store-level regressions and associated rival and own effects. The results are similar to those for cross-category retailers in suggesting that a multichannel retailer's own offline stores raise its online sales. It is less clear, though, that a retailer's online sales suffer from rival offline stores' presence given that we estimate positive rival effects for Amazon. This suggests that offline bookstore experiences lead consumers to purchase books online due to showrooming effects. Consequently, as shown in Column (2) of Table 7, the rival measure is negative for multichannel bookstores (−1.1%) but positive and statistically significant for Amazon (0.8%); the average over all retailers is positive (0.5%). The own-sales measure is positive and large (17.9%).

Electronics. The overall spending result for electronics appears in Column (3) in Table 6, and the rival and own measures for electronics appear in Column (3) of Table 7

Table 8: Store-specific cross-category spending

(a) Coefficients

	Spending			
	amazon	costco.com	target.com	walmart.com
	(1)	(2)	(3)	(4)
N. Stores: Costco	0.051	1.135	0.068	0.029
	(0.030)	(0.167)	(0.056)	(0.050)
N. Stores: Target	−0.018	−0.005	0.153	−0.182
	(0.031)	(0.189)	(0.060)	(0.045)
N. Stores: Walmart	−0.092	−0.190	−0.195	0.162
	(0.026)	(0.119)	(0.049)	(0.044)
Mean dep. var.	14.10	2.51	3.20	5.71
Observations	146,451	146,857	146,770	146,694

(b) Rival effects and own effects

	amazon	costco.com	target.com	walmart.com	Average
	(1)	(2)	(3)	(4)	(5)
Rival	-0.005	-0.019	-0.018	-0.020	-0.019
	(0.003)	(0.015)	(0.009)	(0.006)	(0.005)
Own		0.538	0.030	0.029	0.141
		(0.097)	(0.012)	(0.008)	(0.022)

Note: The "Average" column reports the weighted average of the effects across the category's multichannel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

(see Table 10 for store-level results). Overall spending again positively relates to the total number of offline stores. The rival effect on multichannel electronics retailers is negative on average and the own effect is positive. The rival effect on Amazon, however, is positive, raising the average over all retailers towards zero. These estimates, however, are imprecise. The extensive margin is estimated more sharply: in panel (b) of Table 7, rival stores reduce the probability that a consumer buys from a multichannel electronics retailer online by 0.7%, and a retailer's own stores raise this probability by 8.7%, with both estimates statistically significant. Offline electronics stores thus measurably shift

Table 9: Store-specific books spending

(a) Coefficients

	Spending		
	amazon	barnesandnoble.com	booksamillion.com
	(1)	(2)	(3)
N. Stores: Barnes	−0.003	0.563	0.390
	(0.041)	(0.081)	(0.383)
N. Stores: Books-a-Million	0.078	−0.079	0.941
	(0.044)	(0.105)	(0.329)
N. Stores: Borders	0.094	−0.295	−0.388
	(0.038)	(0.088)	(0.316)
N. Stores: Waldenbooks	0.005	0.141	−0.216
	(0.034)	(0.067)	(0.284)
Mean dep. var.	5.53	0.86	0.06
Observations	146,629	146,819	146,869

(b) Rival effects and own effects

	amazon	barnesandnoble.com	booksamillion.com	Average
	(1)	(2)	(3)	(4)
Rival	0.008	-0.011	-0.011	-0.011
	(0.003)	(0.006)	(0.022)	(0.006)
Own		0.140	0.736	0.179
		(0.021)	(0.334)	(0.030)

Note: The "Average" column reports the weighted average of the effects across the category's multi-channel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

whether consumers shop at a given online store, even though their effects on spending levels are somewhat imprecise.

Table 10: Store-specific electronics spending

(a) Coefficients

	Spending				
	amazon	apple.com	bestbuy.com	circuitcity.com	radioshack.com
	(1)	(2)	(3)	(4)	(5)
N. Stores: Apple	0.063	−0.095	−0.181	−0.096	0.790
	(0.086)	(0.161)	(0.115)	(0.126)	(0.376)
N. Stores: Best Buy	0.030	0.003	0.340	−0.330	0.085
	(0.110)	(0.209)	(0.136)	(0.180)	(0.373)
N. Stores: Circuit City	−0.022	0.126	−0.306	0.335	−0.028
	(0.111)	(0.195)	(0.137)	(0.180)	(0.539)
N. Stores: Radio Shack	0.215	0.284	0.115	−0.072	−0.710
	(0.122)	(0.214)	(0.157)	(0.174)	(0.385)
Mean dep. var.	3.22	2.39	2.31	2.13	0.08
Observations	146,819	146,853	146,847	146,850	146,869

(b) Rival effects and own effects

	amazon	apple.com	bestbuy.com	circuitcity.com	radioshack.com	Average
	(1)	(2)	(3)	(4)	(5)	(6)
Rival	0.006	0.010	-0.014	-0.015	0.034	-0.005
	(0.004)	(0.007)	(0.005)	(0.006)	(0.025)	(0.004)
Own		-0.043	0.090	0.099	-0.051	0.045
		(0.070)	(0.038)	(0.056)	(0.027)	(0.032)

Note: The "Average" column reports the weighted average of the effects across the category's multichannel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

Office supplies. Column (4) in Table 6 presents the result for the regression of overall office supplies spending on the overall counts of nearby office supplies stores. The estimated overall coefficient is positive and statistically significant. We also find positive own-store measures and mostly negative rival measures at the store level, and the exceptional positive rival measures are imprecisely estimated (see Table 11). These estimates translate to generally negative associations between rival stores and own online sales together with positive associations between a multichannel retailer's own stores and its online sales; see Table 7. As with electronics, the rival measure for office supplies is imprecise on the expenditure margin but negative and precisely estimated on the extensive margin (-2.3% in panel (b) of Table 7).

Results with disc instruments. Tables 12 and 13 summarize the results of the regressions of overall online spending within each category and the measures of category-level rival and own effects, respectively, using the disc instruments described in Section 4.2.[20] The results in Table 12 are mostly consistent with the regression results of overall online spending, reported in Table 6. Specifically, offline stores are negatively associated with online spending for cross-category retailers, whereas they are positively associated with online spending for bookstores and electronics. The association is negative for office supplies, although the estimate is imprecise.

Table 13, derived from regression estimates reported in Online Appendix O.4, also exhibits patterns similar to our main results displayed in Table 7. First, the rival effects for multichanel cross-category retailers and bookstores are negative and (marginally) significant, whereas the effects are imprecisely estimated for electronics and office supplies. Second, when Amazon is included, the category-level rival effects become less negative (and remain statistically significant) for cross-category retailers and bookstores. Finally, for these two categories, the own effects are positive and marginally statistically significant.

Other robustness checks. In Online Appendix O.5, we present robustness checks for the main results. Specifically, we show that the qualitative results reported in Tables 6 and

[20] We report the first-stage diagnoses in Table A6 in the Online Appendix.

7 remain largely unchanged if we change functional forms (from Poisson to linear), the definition of local markets (from 20km distance bands to 10km or 50km distance bands), and region fixed effects (from census regions to states).

Table 11: Store-specific office supplies spending

(a) Coefficients

	Spending			
	amazon	officedepot.com	officemax.com	staples.com
	(1)	(2)	(3)	(4)
N. Stores: Office Depot	0.474	0.866	−0.581	−0.060
	(0.349)	(0.186)	(0.279)	(0.119)
N. Stores: Office Max	0.221	0.225	0.984	−0.278
	(0.254)	(0.132)	(0.378)	(0.095)
N. Stores: Staples	0.215	−0.011	−0.375	0.802
	(0.284)	(0.118)	(0.236)	(0.109)
Mean dep. var.	0.07	3.59	0.33	4.54
Observations	146,870	146,856	146,869	146,848

(b) Rival effects and own effects

	amazon	officedepot.com	officemax.com	staples.com	Average
	(1)	(2)	(3)	(4)	(5)
Rival	0.030	0.010	-0.045	-0.024	-0.010
	(0.023)	(0.012)	(0.018)	(0.008)	(0.007)
Own		0.187	0.293	0.126	0.158
		(0.044)	(0.127)	(0.018)	(0.022)

Note: The "Average" column reports the weighted average of the effects across the category's multichannel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

6 Discussion

Cross-channel complementarities. A robust finding is that a multichannel retailer's offline stores tend to boost its own online sales, in contrast to typically negative sales effects of rival offline stores. This is consistent with the presence of strong CCCs that outweigh

Table 12: Overall spending regressions with disc instruments (expenditures)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
N. Stores: Total	−0.245	0.262	0.335	−0.218
	(0.062)	(0.054)	(0.124)	(0.197)
Mean dep. var.	187.32	9.22	47.31	12.70
Observations	135,965	137,049	136,955	137,295

Note: This table presents estimated coefficients from Poisson regressions of the overall spending of a consumer within a given category on the category-level store counts within 20km of the consumer. The "Mean dep. var" row presents the averages of the dependent variable (expenditures in dollars). Heteroskedasticity-robust standard errors that account for first-stage estimation error are in parentheses.

Table 13: Category-level rival and own effects with disc instruments (expenditures)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
Rival (multichannel)	-0.053	-0.051	0.004	-0.014
	(0.021)	(0.029)	(0.028)	(0.029)
Rival (Amazon)	-0.026	-0.019	0.011	0.008
	(0.013)	(0.013)	(0.022)	(0.128)
Rival (all retailers)	-0.038	-0.024	0.006	-0.014
	(0.012)	(0.012)	(0.020)	(0.029)
Own	0.183	0.307	0.123	0.217
	(0.104)	(0.168)	(0.225)	(0.146)

Note: Each column presents the category-level average rival effects and own effects as described in Section 4.3. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.

the negative competitive effects of offline stores (net of positive showrooming effects). Although we do not attempt to formally identify the sources of the CCCs, leaving such exercises to the literature (e.g., Kumar et al. 2019) and future work, we briefly discuss several possibilities. First, the option of in-store returns for online purchases can make online ordering more appealing to consumers near offline stores. All archived websites that we checked[21] indicate the offering of such services. Second, the "buy online, pickup in-store" (BOPIS) service can encourage online shopping by allowing consumers to purchase

[21] They include the websites for Walmart, Target, Costco, Barnes & Noble, Staples, Office Max, Best Buy, and Circuit City.

items online for pickup at an offline store without charging shipping fees.[22] Third, loyalty programs applying to both online and offline purchases[23] can also generate CCCs by encouraging consumers to join the programs at an offline store and then shop more from the associated retailers online. Fourth, some retailers put geographic restrictions on their online services.[24] The final possibility is offline stores' function as advertisements for their associated retailers and in providing consumers with information about the fit-and-feel characteristics of retailers' exclusive products.

Showrooming effects. Our findings of generally negative rival effects suggest that negative competitive effects outweigh positive showrooming effects. Still, our results suggest the possibility of the presence of showrooming effects, especially for Amazon. As discussed in Section 2, showrooming effects are likely large for Amazon (with its ability to cut prices flexibly while freeriding on rivals' offline services), especially for the books category (experience goods such that multiple retailers sell a common set of products). Our results summarized in Table 7 are consistent with this prediction. Specifically, in three of the four categories (cross-category, books, and electronics), including Amazon to compute category-specific rival effects leads to much less negative (or even positive) effects of a rival store, and this pattern is especially intense for books; for office supplies, the estimate is essentially unchanged. To explore whether the relatively weak rival effect for Amazon is due to its ability to charge lower prices than multichannel retailers, we document price differences between Amazon and rival retailers, for books and electronics. The price differences characterized by Table 14 suggest that Amazon indeed charges lower prices than its rivals, especially for books.

Implications for retail strategy. Our results have implications for retail strategies. First, they will affect single-channel retailers' decisions to add another channel. For example, strong CCCs may induce online-only retailers to open an offline channel, despite the

[22]For instance, in March 2007, Walmart launched its "Site to Store" program—which allows consumers to ship items listed online to offline stores for pickup without paying fees.

[23]E.g., Target's "Red Card" program or the "Staples Rewards" program.

[24]Staples, for example, restricted furniture deliveries placed online to consumers living within 20 miles of an offline Staples location in 2007.

Table 14: Price differences across retailers

(a) Books

Retailer	Price ratio with Amazon
barnesandnoble.com	1.23
booksamillion.com	1.08

(b) Electronics

Retailer	Price ratio with Amazon
bestbuy.com	1.08
circuitcity.com	1.06
apple.com	1.08

Notes: This table reports average ratios of products' prices at various multichannel retailers to their prices at Amazon. We compute these averages for the books and electronics categories, and we take the averages over distinct product/year pairs, weighting each by the observed number of corresponding transactions. The books considered are those for which we observe sales and that were either (i) a *New York Times* best-seller in either fiction or non-fiction for at least one week in 2007 or 2008 or (ii) one of Amazon's top selling books of 2007. This yields 26 titles across which we observe 1696 transactions. The included electronics are the iPod Shuffle (1GB), the iPod Nano (4GB), and the 40GB, 60GB, and 80GB versions of the PlayStation 3. We observe 355 iPod purchases and 89 PS3 purchases. We obtain a price for each product at each retailer by taking a median over transaction prices for the product.

costs associated with opening and operating physical stores. Amazon, the predominant online retailer with mostly online-only operation in its history, has recently expanded into brick-and-mortar retail.[25] Similarly, Warby Parker, an eyewear retailer, expanded from a primarily online model to a multichannel model (Bell et al. 2018). The multichannel strategy is in stark contrast to the retailer's original business plan to "cut out the middlemen and sell directly to customers" by, e.g., "avoiding landlords and their demands for long, expensive leases" (see King 2023). A possible explanation of this trend is that the online retailers have come to realize the large benefits of CCCs from operating physical stores.[26] Second, the possibility of showrooming influences multichannel retailers' decisions about product offerings. For example, they may be able to counter online-only rivals' freeriding by developing exclusive product lines.

Implications for policy. Our results have implications for policy. A notable example is resale price maintenance (RPM). While RPM can dampen competition both at the manufacture and retailer levels (Rey and Vergé 2010), it can benefit consumers by encouraging the retailers to provide valuable pre-sale services (Telser 1960). Without price regulations, such services can be under-provided, because online retailers can attract some of

[25]For example, Amazon achieves this through its acquisition of Whole Foods and its introduction of offline stores under brands Amazon Go, Fresh, and Style.

[26]This view raises the question of how Amazon gained its dominance without enjoying the benefits of CCCs until recently. A possible reason is cost-side economies of scale and scope (e.g., Houde et al. 2022).

the consumers who are made willing to purchase a product by such services, without offering the services by themselves. RPM can mitigate the freeriding problem and facilitate the provision of such services. Our results can also inform other policies, e.g., in defining relevant product markets for antitrust cases. Although there are some arguments that online and offline retail constitute distinct markets,[27] our results suggest how online and offline markets can be competing in a multi-dimensional manner.

7 Conclusion

In this article, we estimated relationships between offline stores and online shopping that vary across retailers and retailing categories. The estimated relationships are conditional on a rich set of consumer and local characteristics, controlling for which alters the relationship between offline stores and online sales in expected ways. Our findings suggest that offline store presence of a retailer is negatively associated with a rival retailer's online sales whereas it is positively associated with the retailer's own online sales. On one hand, the positive own-store effects are consistent with the presence of cross-channel complementarities (CCCs). On the other hand, the patterns of rival-store effects, namely that Amazon (the sole online-only retailer in our sample) faces relatively weak rival effects, especially for books (experience goods such that multiple retailers sell a common set of products), are suggestive of the presence of showrooming effects.

The current study leaves several interesting issues for future work. First, the relationship between offline and online retail is bi-directional, yet this paper only focuses on the effects of the former on the latter. Effects in the other direction can also encompass rich heterogeneity, e.g., competitive effects, "webrooming" effects (e.g., Jing 2018), and possibly analogues of CCCs. Second, this paper does not quantify each effect separately. Such an exercise could be facilitated by estimating a model of competition between multi-

[27] In the recent lawsuit against Amazon, the US Federal Trade Comission (FTC) argued that "[t]he online superstore market is a relevant product market" and that "brick-and-mortar stores and online stores with a more limited selection are not reasonably interchangeable with online superstores for the same purposes and are thus properly excluded from the online superstore market" (Federal Trade Commission and States of New York et al. 2023, paragraph 122).

channel retailers (and Amazon). Finally, simulating the effects of counterfactual policies, e.g., in price regulations or market definitions, will again require an explicit model of competition, and is left for future research.

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Online Appendix

O.1 Data processing

We chose the specialized offline retailers to analyze (Table 2) based on national store counts reported by Tables A1 through A3. In particular, we chose retailers that appear within the top three retailers in their respective categories for at least one year, excluding retailers that specialize in a narrow subcategory of their respective retailing categories (e.g., we do not include a large religious book retailer, Family Christian Book Store, in our analysis).

We identify offline stores in the book and office supplies categories by querying the Data Axle data for business locations with the following six-digit Standard Industrial Classification (SIC) codes: 594201 ("Book Stores") for books and 594301 ("Office Supplies") for office supplies. For electronics, we query for stores with the following four-digit SIC codes: 5731 ("Radio, Television, and Consumer Electronics Stores"), 5734 ("Computer and Computer Software Stores"), and 5946 ("Camera and Photographic Supply Stores").

Table A1: Top book retailers by store count

	2007		2008	
Rank	Retailer	Count	Retailer	Count
1	Barnes and Noble	929	Barnes and Noble	929
2	Borders Books and Music	566	Borders Books and Music	566
3	Waldenbooks	383	Waldenbooks	383
4	Family Christian Book Store	269	Family Christian Book Store	269
5	Books-a-Million	177	Books-a-Million	177

Table A2: Top electronics retailers by store count

	2007		2008	
Rank	Retailer	Count	Retailer	Count
1	Radio Shack	5699	Radio Shack	5699
2	Best Buy	993	Best Buy	993
3	Circuit City	753	Circuit City	753
4	Ritz Camera Ctr	413	Ritz Camera Ctr	413
5	Compusa	235	Magnolia Home Theatre	235

Table A3: Top office supplies retailers by store count

	2007		2008	
Rank	Retailer	Count	Retailer	Count
1	Staples	1609	Staples	1609
2	Office Depot	1307	Office Depot	1307
3	Office Max	1068	Office Max	1068
4	Cartridge World	77	Corporate Express	77
5	Corporate Express	55	Indoff Inc	55

Our procedure for categorizing websites begins by identifying the most popular sites in the Comscore browsing data by visits and unique users. In particular, for each of the time periods

(i) January to February 2007, (ii) November to December 2008, (iii) January to February 2017, and (iv) November to December 2018, we construct a list of the top 500 sites by the number of visits in the Comscore browsing data as well as a list of the top 500 sites by the number of unique visitors in these data. We then concatenate these lists and drop duplicated sites from the combined list. For each site, we manually determine in which of the aforementioned categories the site belongs. Some sites are not well described by any of these categories, and we do not place these sites in any category. Additionally, we do not place sites that are not in our list in any category.

De Los Santos et al. [2012] find that the Comscore data was largely representative of online buyers in the United States via a comparison of Comscore's 2002 and 2004 datasets with data from the census and from a market research company. We arrive at a similar conclusion. Table A4 characterizes the representativeness of Comscore panelists for 2007 by comparing these panelists to demographic distributions reported in publications for the 2007 Current Population Survey (CPS) of the US census. The table suggests that the Comscore panelists are broadly representative of US internet users, with a few exceptions. We replicate the finding of De Los Santos et al. [2012] that Comscore over-samples Hispanic people relative to the share of Hispanic internet users reported by the CPS Computer and Internet Supplement. We additionally find that Comscore over-samples white people and under-samples Asian people. Note that we use the CPS for all households to obtain information on variables that are not available in the CPS Computer and Internet Use Supplement (e.g., household income and census region of residence).

One reason for which we focus on the 2007–2008 time period because the Comscore panel's coverage of transactions is lower in 2017–2018, the other time period for which we have data. In 2017 and 2018, for example, there were respectively 92 and 101 million US members of Amazon Prime, Amazon's premium subscription service.[28] Additionally, in an October 2017 survey, 92% of Prime members reported ordering from Amazon at least once a month, as did 61% of survey respondents who did not subscribe to Prime.[29] Yet only 18.3% of Comscore panelists made a transaction at Amazon in the 2017–2018 time period. Together, the facts that (i) most US consumers used Amazon in 2017–2018, (ii) Amazon reported only 81 million

[28]Source: https://www.digitalcommerce360.com/2019/07/11/82-of-us-households-have-a-amazon-prime-membership/

[29]Source: https://www.forbes.com/sites/louiscolumbus/2018/03/04/10-charts-that-will-change-your-perspective-of-amazon-primes-growth/?sh=42b198b43fee

active accounts (Prime or non-Prime) in 2008,[30] and (iii) the share of Comscore panelists using Amazon increased only from 14.3% in 2007–2008 to 18.3% in 2017–2018 suggest that the Comscore panel's coverage of e-commerce transactions markedly decreased between our time periods.

Table A4: Representativeness of the Comscore Web Behavior Database for 2007

Variable	Comscore	CPS (All households)	CPS (Internet users)
Age: Under 24	0.02	0.06	0.06
Age: 25-34	0.15	0.16	0.18
Age: 35-44	0.27	0.19	0.23
Age: 45-54	0.28	0.21	0.24
Age: 55+	0.27	0.38	0.30
Hispanic	0.23	-	0.08
Race: White	0.94	-	0.84
Race: Black	0.05	-	0.09
Race: Asian	0.01	-	0.07
Race: Other	0.00	-	0.00
Household size: 1	0.06	0.28	-
Household size: 2	0.34	0.33	-
Household size: 3	0.24	0.16	-
Household size: 4	0.19	0.14	-
Household size: 5+	0.17	0.10	-
Census region: Northeast	0.19	0.18	-
Census region: North Central	0.22	0.22	-
Census region: South	0.39	0.37	-
Census region: West	0.20	0.22	-
Household income: Under 15k	0.13	0.13	-
Household income: 15-24k	0.08	0.12	-
Household income: 25-34k	0.10	0.11	-
Household income: 35-49k	0.15	0.14	-
Household income: 50-74k	0.22	0.18	-
Household income: 75-99k	0.14	0.11	-
Household income: 100k+	0.18	0.20	-
Broadband	0.87	-	0.82

Notes: This table compares the distribution of demographic variables among 2007 Comscore Web Behavior Database panelists with the distributions of these variables from the household-level 2007 Current Population Survey—which is labelled "CPS (All households)" in the table—and the 2007 Computer and Internet Use Supplement of the Current Population Survey, which is labelled "CPS (Internet users)" in the table. The table's figures from the Computer and Internet Use Supplement describe the distribution of demographic variables within the population of householders that uses the internet.

[30]Source: https://www.nytimes.com/2008/10/12/business/12giants.html

O.2 Measures of rival effects and cross-channel complementarities

This section develops scale-free measures of offline stores' effects on online spending that facilitate comparisons across regressions. Let $\mathcal{J}^{\text{off}}$ ($\mathcal{J}^{\text{on}}$) denote the set of offline (online) retailers. We omit the retail category from our notation for simplicity, although we run our analysis separately for each category.

We first define a measure of the effect of an offline store j on the spending at an online store s. Consumer i's expected spending at store s conditional on the regressors is

$$\mathbb{E}[y_{it}^s \mid x_{it}] = f\left(h(n_{it})'\alpha_s + z_{it}'\beta_s + w_{it}'\delta_s + \rho_{R_{it},s}^{\text{FE}} + \rho_{t,s}^{\text{FE}}\right) \tag{A1}$$

We measure the effect of n_{ijt} on spending by the percentage change in expected spending when the number n_{ijt} of stores of offline retailer j is exogenously increased from $\bar{n}_j$ to $\bar{n}_j + 1$, where $\bar{x}$ denote the mean of a random variable x_{it}, while holding all other explanatory variables fixed at their mean values. That is, we define the relative effect of j on s as

$$\begin{aligned}\theta_{js} &= \frac{\mathbb{E}\left[y_i^s \mid \bar{n}_j + 1, \bar{n}_{-j}, \bar{z}, \bar{w}, \bar{\rho}_{R,s}^{\text{FE}}, \bar{\rho}_{t,s}^{\text{FE}}\right] - \mathbb{E}\left[y_i^s \mid \bar{n}_j, \bar{n}_{-j}, \bar{z}, \bar{w}, \bar{\rho}_{R,s}^{\text{FE}}, \bar{\rho}_{t,s}^{\text{FE}}\right]}{\mathbb{E}\left[y_i^s \mid \bar{n}_j, \bar{n}_{-j}, \bar{z}, \bar{w}, \bar{\rho}_{R,s}^{\text{FE}}, \bar{\rho}_{t,s}^{\text{FE}}\right]} \\ &= \frac{f\left(h(\bar{n}_j + 1, \bar{n}_{-j})'\alpha_s + \bar{z}'\beta_s + \bar{w}'\delta_s + \bar{\rho}_{R,s}^{\text{FE}} + \bar{\rho}_{t,s}^{\text{FE}}\right)}{f\left(h(\bar{n}_j, \bar{n}_{-j})'\alpha_s + \bar{z}'\beta_s + \bar{w}'\delta_s + \bar{\rho}_{R,s}^{\text{FE}} + \bar{\rho}_{t,s}^{\text{FE}}\right)} - 1\end{aligned} \tag{A2}$$

We estimate θ_{js} by substituting our estimates of unknown parameters into (A2).

Using the store-pair-specific effects defined by (A2), we define the measures of rival and own effects. First, define the *store-specific average rival effect* as

$$\theta_s^{\text{rival}} = \sum_{j \in \mathcal{J}^{\text{off}} \setminus \{s\}} w_{js}^{\text{off}} \theta_{js} \tag{A3}$$

where $\{w_{js}^{\text{off}}\}_j$ are weights for offline retailers j satisfying $\sum_{j \in \mathcal{J}^{\text{off}}} w_{js}^{\text{off}} = 1$ and $w_{ss}^{\text{off}} = 0$. We set w_{js}^{off} proportional to retailer j's number of stores in the analysis period.

The rival effect defined in (A3) includes all effects of rival offline stores on online spending. Therefore, a positive value for this measure would indicate that a showrooming effect outweighs the competitive effect as long as the former effect is positive and the latter is negative. The converse of this statement is true for a negative rival effect.

We take θ_{ss} as a measure of *store-specific own effect*. This measure will be positive (negative) if cross-channel complementarities are larger (smaller) than cannibalization net of showrooming effects, assuming that the former are positive and the latter are negative.

We also interpret averages of our store-specific average rival and own effects for each retailing category in each time period. These averages are defined as

$$\bar{\theta}^{\text{rival}} = \sum_{s \in \mathcal{J}^{\text{on}} \cap \mathcal{J}^{\text{off}}} w_s^{\text{on}} \theta_s^{\text{rival}} \tag{A4}$$

$$\bar{\theta}^{\text{own}} = \sum_{s \in \mathcal{J}^{\text{on}} \cap \mathcal{J}^{\text{off}}} w_s^{\text{on}} \theta_{ss} \tag{A5}$$

for weights $\{w_s^{\text{on}}\}_s$ on stores s that sum to one across s. In practice, we set w_s^{on} proportional to the mean of y_i^s. Note that each of the average measures defined above is taken over multichannel retailers $s \in \mathcal{J}^{\text{on}} \cap \mathcal{J}^{\text{off}}$. We also compute an average of rival effects over all online retailers, including Amazon:

$$\bar{\theta}^{\text{rival}}_{\text{incl}} = \sum_{s \in \mathcal{J}^{\text{on}}} w_s^{\text{on}} \theta_s^{\text{rival}}.$$

Alongside these two averages, we report Amazon's rival measure, θ_s^{rival} for $s = \text{Amazon}$, separately.

O.3 Store-level effects on the probability of positive spending

Table A5 reports the store-level rival and own effects on the probability of positive online spending. They exhibit patterns similar to the store-level rival and own effects on online expenditures, reported in Tables 8 thgough 11. Specifically, the own effects are positive, the rival effects are mostly negative, and the rival effects on Amazon tend to be less negative (or even positive).

O.4 Regression results and store-level effects with disc instruments

Table A6 summarizes the first-stage results of the regressions using the disc instrumental variables (IVs) described in Section 4.2, and Tables A7 through A10 present the estimates of the store-level regression coefficients and rival/own effects for each category. The first-stage F statis-

Table A5: Store-level rival and own effects on the probability of positive spending

(a) Cross-category retailers

	amazon (1)	costco.com (2)	target.com (3)	walmart.com (4)	Average (5)
Rival	-0.001	-0.017	-0.016	-0.030	-0.024
	(0.002)	(0.009)	(0.006)	(0.004)	(0.003)
Own		0.402	0.023	0.044	0.056
		(0.061)	(0.008)	(0.005)	(0.005)

(b) Bookstores

	amazon (1)	barnesandnoble.com (2)	booksamillion.com (3)	Average (4)
Rival	0.006	-0.018	-0.031	-0.019
	(0.002)	(0.004)	(0.013)	(0.004)
Own		0.118	0.743	0.160
		(0.015)	(0.195)	(0.019)

(c) Electronics

	amazon (1)	apple.com (2)	bestbuy.com (3)	circuitcity.com (4)	radioshack.com (5)	Average (6)
Rival	0.003	0.007	-0.011	-0.015	0.005	-0.007
	(0.002)	(0.004)	(0.004)	(0.004)	(0.015)	(0.002)
Own		0.028	0.084	0.155	0.002	0.087
		(0.044)	(0.028)	(0.036)	(0.020)	(0.019)

(d) Office supplies

	amazon (1)	officedepot.com (2)	officemax.com (3)	staples.com (4)	Average (5)
Rival	0.018	-0.013	-0.021	-0.030	-0.023
	(0.016)	(0.006)	(0.012)	(0.005)	(0.004)
Own		0.161	0.159	0.094	0.124
		(0.021)	(0.057)	(0.011)	(0.011)

Note: Each panel reports rival and own effects on the probability of positive spending (percentage changes in the probability), computed from Poisson regressions of positive-spending indicators on store counts with the same controls as the main specification. The "Average" column reports the weighted average of the effects across the category's multichannel online stores (i.e., excluding Amazon), with weights proportional to each store's share of consumers with positive spending. Standard errors appear in parentheses.

tics, obtained by partialling out other controls, indicate that the disc IVs are strong.

Table A7 presents the estimates of the regression coefficients and effects for cross-category retailers. The rival effects are mostly negative, although estimates are less statistically significant than our main estimates. Also, among own-store coefficients, only Costco's is positive and statistically significant. When aggregated to the level of online stores, the rival effect is negative for all stores, and statistically significant for Amazon and Target. The own effect is positive and marginally significant for Costco, and imprecisely estimated for the other multichannel stores.

Table A8 presents the results for bookstores. Although the regression estimates are again less precise than our main estimates, the rival-store coefficients tend to be negative, and the own-store coefficient for Barnes & Noble is positive and statistically significant. For Barnes & Noble, the rival effect is negative and the own effect is positive, both in a statistically significant manner.

Tables A9 and A10 show the results for electronics and office supplies, respectively. For these categories, the regression estimates are much noisier, as are the store-level effects.

O.5 Robustness to alternative specifications

In this section, we evaluate robustness of our main results shown in Section 5 to alternative specifications. Specifically, we show that the qualitative results reported in Tables 6 and 7 remain largely unchanged if we change functional forms (from Poisson to linear), the definition of local markets (from 20km distance bands to 10km or 50km distance bands), and region fixed effects (from census regions to states).

Tables A11 through A14 present the results of overall regressions with the aforementioned specification changes. All the estimates show the same sign as the main results in Table 6: the coefficients on the number of stores are negative for cross-category retailers whereas they are positive for specialized retailers. Although the estimates are occasionally imprecise, they are robustly precise for books.

Tables A15 through A18 display category-level rival and own effects under alternative regression specifications. The results are again similar to the main results. Specifically, in all specifications,

Table A6: First-stage results for the disc instruments approach

Store count	R^2	F
Booksellers		
Barnes	0.18	588.30
Books-a-Million	0.08	236.48
Borders	0.13	426.33
Waldenbooks	0.06	165.34
Electronics retailers		
Apple	0.21	722.12
Best Buy	0.09	270.54
Circuit City	0.08	244.37
Radio Shack	0.12	387.28
Office-supply retailers		
Office Depot	0.08	226.70
Office Max	0.09	278.26
Staples	0.10	298.89
Cross-category retailers		
Costco	0.10	321.23
Target	0.06	169.25
Walmart	0.13	401.98
Total store count, by category		
Cross-category	0.08	223.91
Books	0.22	766.42
Electronics	0.06	178.65
Office	0.13	397.19

Notes: each entry summarizes the first stage for one endogenous store-count regressor in the disc-instrument version of the spending model (Section 4.2), with one row per store. The endogenous variable is the number of the indicated chain's offline stores within 20 km of the consumer; the rows in the final panel instead use the total number of a category's stores within 20 km, the regressor in that category's overall-spending specification. Following the control-function procedure of Section 4.2, each store count is regressed on the disc instruments of Cao et al. [2024] together with all consumer characteristics, web-browsing controls, and fixed effects described in the main text. The excluded instruments are the baseline disc IVs, constructed for race, Hispanic origin, presence of children, household size, and income and each interacted with the consumer's own group, together with their population-weighted counterparts. We report diagnostics for these instruments after the controls are partialled out of both the store count and the instruments: R^2 is the partial R^2 attributable to the disc instruments alone, and F is the joint F-statistic for the excluded instruments in the partialled-out regression. Larger values indicate stronger instruments; all values here lie well above conventional weak-instrument thresholds. A separate first stage is estimated for each store-count variable. Because each store's first stage does not depend on the spending category, a chain that enters more than one category's spending regressions has identical R^2 and F throughout and is reported once, with stores grouped by retailer type. The estimation sample is all 2007–2008 consumers with non-missing disc instruments.

Table A7: Store-specific cross-category spending (disc instruments)

(a) Coefficients

	Spending			
	amazon	costco.com	target.com	walmart.com
	(1)	(2)	(3)	(4)
N. Stores: Costco	−0.052	1.587	−0.138	0.097
	(0.125)	(0.633)	(0.231)	(0.199)
N. Stores: Target	0.142	−0.374	−0.180	−0.322
	(0.146)	(0.680)	(0.266)	(0.231)
N. Stores: Walmart	−0.426	−0.295	−0.614	0.009
	(0.093)	(0.363)	(0.174)	(0.150)
Mean dep. var.	14.23	2.64	3.21	5.51
Observations	136,997	137,378	137,298	137,232

(b) Rival effects and own effects

	amazon	costco.com	target.com	walmart.com	Average
	(1)	(2)	(3)	(4)	(5)
Rival	-0.026	-0.059	-0.089	-0.029	-0.053
	(0.013)	(0.052)	(0.039)	(0.029)	(0.021)
Own		0.826	-0.034	0.002	0.183
		(0.438)	(0.049)	(0.027)	(0.104)

Note: The "Average" column reports the weighted average of the effects across the category's multichannel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

the own effects are positive and the rival effects are negative among multichannel retailers, and the rival effects become less negative (and positive for bookstores in particular) when Amazon is included.

Table A8: Store-specific book spending (disc instruments)

(a) Coefficients

	Spending		
	amazon	barnesandnoble.com	booksamillion.com
	(1)	(2)	(3)
N. Stores: Barnes	0.111	1.231	−1.025
	(0.254)	(0.531)	(1.970)
N. Stores: Books-a-Million	0.179	−0.030	−0.069
	(0.210)	(0.450)	(1.868)
N. Stores: Borders	−0.573	−0.358	1.846
	(0.223)	(0.451)	(1.882)
N. Stores: Waldenbooks	−0.205	−0.987	0.689
	(0.228)	(0.497)	(1.648)
Mean dep. var.	5.57	0.88	0.06
Observations	137,164	137,343	137,390

(b) Rival effects and own effects

	amazon	barnesandnoble.com	booksamillion.com	Average
	(1)	(2)	(3)	(4)
Rival	-0.019	-0.062	0.100	-0.051
	(0.013)	(0.029)	(0.179)	(0.029)
Own		0.331	-0.039	0.307
		(0.164)	(1.051)	(0.168)

Note: The "Average" column reports the weighted average of the effects across the category's multi-channel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

Table A9: Store-specific electronics spending (disc instruments)

(a) Coefficients

	Spending				
	amazon	apple.com	bestbuy.com	circuitcity.com	radioshack.com
	(1)	(2)	(3)	(4)	(5)
N. Stores: Apple	0.391	0.122	−0.230	0.638	0.062
	(0.393)	(0.675)	(0.510)	(0.607)	(1.144)
N. Stores: Best Buy	−0.890	−0.881	−0.513	−1.241	−3.663
	(0.862)	(1.304)	(1.051)	(1.261)	(2.177)
N. Stores: Circuit City	0.569	0.993	−1.779	1.347	8.318
	(0.855)	(1.689)	(1.125)	(1.394)	(3.438)
N. Stores: Radio Shack	0.375	0.687	1.205	−1.017	−0.638
	(0.872)	(1.536)	(1.089)	(1.159)	(3.021)
Mean dep. var.	3.26	2.44	2.34	2.21	0.08
Observations	137,343	137,375	137,369	137,372	137,391

(b) Rival effects and own effects

	amazon	apple.com	bestbuy.com	circuitcity.com	radioshack.com	Average
	(1)	(2)	(3)	(4)	(5)	(6)
Rival	0.011	0.032	-0.023	-0.044	1.376	0.004
	(0.022)	(0.054)	(0.021)	(0.030)	(1.605)	(0.028)
Own		0.058	-0.122	0.461	-0.045	0.123
		(0.327)	(0.235)	(0.573)	(0.210)	(0.225)

Note: The "Average" column reports the weighted average of the effects across the category's multi-channel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

Table A10: Store-specific office supplies spending (disc instruments)

(a) Coefficients

	Spending			
	amazon	officedepot.com	officemax.com	staples.com
	(1)	(2)	(3)	(4)
N. Stores: Office Depot	2.057	1.941	2.682	−0.548
	(2.180)	(1.141)	(2.368)	(1.029)
N. Stores: Office Max	−1.217	0.509	−1.064	0.409
	(0.930)	(0.437)	(1.180)	(0.503)
N. Stores: Staples	−0.182	−0.344	1.211	0.328
	(1.013)	(0.574)	(1.103)	(0.419)
Mean dep. var.	0.07	3.62	0.34	4.57
Observations	137,391	137,378	137,390	137,370

(b) Rival effects and own effects

	amazon	officedepot.com	officemax.com	staples.com	Average
	(1)	(2)	(3)	(4)	(5)
Rival	0.008	-0.014	0.191	-0.029	-0.014
	(0.128)	(0.048)	(0.212)	(0.035)	(0.029)
Own		0.470	-0.242	0.050	0.217
		(0.333)	(0.233)	(0.065)	(0.146)

Note: The "Average" column reports the weighted average of the effects across the category's multi-channel online stores (i.e., excluding Amazon), with weights proportional to mean consumer spending at each online store. Standard errors appear in parentheses.

Table A11: Overall spending regressions (linear)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
N. Stores: Total	−10.493	0.914	2.792	1.603
	(2.863)	(0.209)	(1.203)	(0.891)
Mean dep. var.	187.35	9.14	47.37	12.91
Observations	145,345	146,506	146,404	146,765

Table A12: Overall spending regressions (10km)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
N. Stores: Total	−0.030	0.117	0.038	0.158
	(0.014)	(0.020)	(0.021)	(0.055)
Mean dep. var.	187.35	9.14	47.37	12.91
Observations	145,345	146,506	146,404	146,765

Table A13: Overall spending regressions (50km)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
N. Stores: Total	−0.100	0.190	0.116	0.041
	(0.024)	(0.036)	(0.044)	(0.107)
Mean dep. var.	187.35	9.14	47.37	12.91
Observations	145,345	146,506	146,404	146,765

Table A14: Overall spending regressions (state fixed effects)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
N. Stores: Total	−0.018	0.097	0.060	0.178
	(0.017)	(0.025)	(0.027)	(0.072)
Mean dep. var.	187.35	9.14	47.37	12.91
Observations	145,345	146,506	146,404	146,765

Note: Tables A11 through A14 present estimated coefficients from regressions of the overall spending on offline store counts, using a linear specification (A11), 10km distance bands (A12), 50km distance bands (A13), or state fixed effects (A14) instead of the main specification in Table 6. The "Mean dep. var" row presents the averages of the dependent variable (expenditures in dollars). Heteroskedasticity-robust standard errors in parentheses.

Table A15: Category-level rival and own effects on expenditures (linear)

	Cross-category retailers (1)	Bookstores (2)	Electronics (3)	Office supplies (4)
Rival (multichannel)	-0.016	-0.011	-0.006	-0.005
	(0.008)	(0.023)	(0.057)	(0.017)
Rival (Amazon)	-0.006	0.008	0.006	0.033
	(0.003)	(0.009)	(0.030)	(0.121)
Rival (all retailers)	-0.010	0.005	-0.003	-0.005
	(0.004)	(0.008)	(0.040)	(0.017)
Own	0.112	0.176	0.045	0.116
	(0.044)	(0.419)	(0.343)	(0.105)

Note: Each column presents the category-level average rival effects and own effects as described in Section 4.3. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.

Table A16: Category-level rival and own effects on expenditures (10km)

	Cross-category retailers (1)	Bookstores (2)	Electronics (3)	Office supplies (4)
Rival (multichannel)	-0.034	-0.024	-0.006	-0.006
	(0.010)	(0.007)	(0.006)	(0.012)
Rival (Amazon)	-0.014	0.012	0.012	-0.014
	(0.005)	(0.004)	(0.005)	(0.062)
Rival (all retailers)	-0.023	0.007	-0.001	-0.006
	(0.005)	(0.003)	(0.004)	(0.012)
Own	0.135	0.244	0.075	0.280
	(0.033)	(0.047)	(0.051)	(0.043)

Note: Each column presents the category-level average rival effects and own effects, computed using store-specific regressions with 10km distance bands to define local markets. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.

Table A17: Category-level rival and own effects on expenditures (50km)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
Rival (multichannel)	-0.005	-0.002	-0.003	-0.004
	(0.002)	(0.003)	(0.002)	(0.002)
Rival (Amazon)	0.002	0.004	0.006	0.011
	(0.001)	(0.001)	(0.002)	(0.009)
Rival (all retailers)	-0.001	0.003	-0.000	-0.004
	(0.001)	(0.001)	(0.001)	(0.002)
Own	0.046	0.068	0.020	0.061
	(0.008)	(0.013)	(0.017)	(0.008)

Note: Each column presents the category-level average rival effects and own effects, computed using store-specific regressions with 50km distance bands to define local markets. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.

Table A18: Category-level rival and own effects on expenditures (state fixed effects)

	Cross-category retailers	Bookstores	Electronics	Office supplies
	(1)	(2)	(3)	(4)
Rival (multichannel)	-0.014	-0.014	-0.007	-0.001
	(0.006)	(0.006)	(0.004)	(0.007)
Rival (Amazon)	-0.005	0.007	0.006	0.022
	(0.003)	(0.003)	(0.004)	(0.027)
Rival (all retailers)	-0.009	0.004	-0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.007)
Own	0.117	0.175	0.052	0.127
	(0.023)	(0.031)	(0.034)	(0.022)

Note: Each column presents the category-level average rival effect and own effects, computed using store-specific regressions with state fixed effects. "Rival (multichannel)" and "Rival (all retailers)" average the rival effects across the multichannel retailers' online stores and across all online stores (including Amazon), respectively, weighting each store in proportion to mean consumer spending; "Rival (Amazon)" is the rival effect on Amazon's online sales. "Own" averages the own effects across the multichannel retailers' online stores.