Value Of Local Showrooms To Online Competitors

Paper Replication with R

Author: Jayarajan Samuel, Zhiqiang (Eric) Zheng, Ying Xie

Group Members: Luoying Chen, Beyza Celik, Duc Vu, Yihong Liu

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Outline I

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Outline II

- Propensity Score Matching
- Causal Forest

Background I

- Online Shopping vs Offline
  - Online Info Hub
    1. Usually lower price
    2. Various types
    3. Less time
  - Offline Showroom
    1. Physically experienced
    2. Real-time assistance
    3. Instant gratification
- Customer interacts between online and offline

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Background II

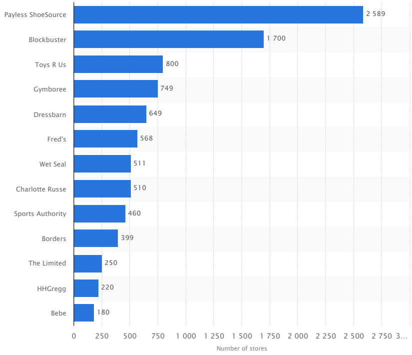

Figure 1: Num Of Store Closures by Selected Retailers in US From 2010 to 2020 [1]

- Values of offline store closures for online retailers?

[1] source link: statista.com

Research Questions

1. How would a retailer closing a physical store impact
    - its customers' shopping searching behaviors,
    - their resultant purchasing behaviors

   with an online competitor?

Data Description

- Natural Experiment: Circuit City closed 155 local stores (physical showroom providers) due to severe competitions (exogenous event) on Nov, 2008
- Data Scheme: individual customer click-stream dataset (search and purchase) during each month of 2008 and 2009
  - time stamp
  - visited domain
  - referring domain
  - # of pages
  - Duration
  - Purchase Flag
  - Paid Amount
  - Zip Code
  - Demographics
- Focused Online Retailer: Amazon (pure) and Bestbuy (multi)
- Treatment: Residents in 155 Zip codes / 5-miles radius of 155
- Control: Residents who never had CC stores within 5 miles

Data Process

- Referring Domain Filter: blank or search engine
- Target Domain Filter: amazon, staples, dell, walmart, bestbuy
- Product Categories Filter: only types sold at CC
- Variables Construction:
  - `CCStorePresent`
  - AfterStoreClosing
  - BBStorePresent
  - NoReferringDomain
  - ReferringDomainIsSearchEngine
  - Dependent Variables
- Panel Data Aggregation
  - Group by Zip Code, Month-Year, Target Domain
  - Calculate Dependent Variables
  - Unbalanced Data Imputation

Effects on Online Sales I

To examine whether a competing online retailer benefits from the presence of a local showroom, we run the following regressions for Amazon and BestBuy

$$\begin{aligned}
&\log\left(\texttt{TotalMonthlySales}+1\right)_{i,t} \\
&= \mu_i + \tau_t \\
&+ \beta_1\ \texttt{CCStorePresent}_i \times \texttt{AfterStoreClosing}_t \\
&+ \beta_2\ \texttt{CCStorePresent}_i \times \texttt{AfterStoreClosing}_t \times \texttt{BBStorePresent}_i \\
&+ \epsilon_{i,t}
\end{aligned} \tag{1}$$

Effects on Online Sales II

Table 1: Results of the Sales Effect (All Product Categories)

	log(TotalMonthlySales + 1)			
	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles
	(1)	(2)	(3)	(4)
β_1	0.014	−0.005	−0.002	−0.002
	(0.015)	(0.008)	(0.033)	(0.008)
β_2	−0.033	0.003	0.009	0.002
	(0.022)	(0.010)	(0.036)	(0.010)
Observations	68,472	75,096	14,664	16,848
R^2	0.00003	0.00001	0.00002	0.00000
Adjusted R^2	-0.044	-0.044	-0.045	-0.045
F Statistic	1.091 (df = 2; 65594)	0.278 (df = 2; 71942)	0.154 (df = 2; 14028)	0.035 (df = 2; 16121)

Note: *p<0.1; **p<0.05; ***p<0.01

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Effects on Online Search Behavior I

To measure the impact of the exit of local showrooms on consumer online search intensity and the moderating effect of Best Buy Stores as an alternative local showroom, we run the following regressions

$$
\begin{aligned}
&\log\left(\texttt{PagesPerDollar}+1,\ \texttt{MinsPerDollar}+1\right)_{i,t}\\
&=\mu_i+\tau_t\\
&+\beta_1\ \texttt{CCStorePresent}_i\times\texttt{AfterStoreClosing}_t\\
&+\beta_2\ \texttt{CCStorePresent}_i\times\texttt{AfterStoreClosing}_t\times\texttt{BBStorePresent}_i\\
&+\epsilon_{i,t}
\end{aligned}
\tag{2}
$$

Effects on Online Search Behavior II

Table 2: Results of the Search Effect (All Product Categories)

	log(PagesPerDollar + 1)				log(MinsPerDollar + 1)			
	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1	0.003	-0.019^{***}	0.001	0.002	0.004	-0.021^{***}	0.001	0.003
	(0.012)	(0.007)	(0.016)	(0.004)	(0.012)	(0.007)	(0.013)	(0.003)
β_2	-0.068^{***}	0.018^{**}	0.003	−0.001	-0.057^{***}	0.022^{***}	0.0004	−0.002
	(0.018)	(0.009)	(0.018)	(0.005)	(0.017)	(0.008)	(0.014)	(0.004)
Observations	68,472	75,096	14,664	16,848	68,472	75,096	14,664	16,848
R^2	0.0004	0.0001	0.00003	0.00004	0.0003	0.0001	0.00001	0.0001
Adjusted R^2	-0.043	-0.044	-0.045	-0.045	-0.044	-0.044	-0.045	-0.045
F Statistic	12.530^{***} (df = 2; 65594)	3.985^{**} (df = 2; 71942)	0.202 (df = 2; 14028)	0.337 (df = 2; 16121)	8.867^{***} (df = 2; 65594)	5.187^{***} (df = 2; 71942)	0.046 (df = 2; 14028)	0.451 (df = 2; 16121)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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Effects on Online Sales vs Prod Types I

We then test whether the show-rooming effect upon online sales is stronger for experience goods.

Table 3: Results of the Sales Effect: Experience and Search Products

	log(TotalMonthlySales + 1)							
	Amazon-0 Mile-Exp	Amazon-5 Miles-Exp	Amazon-0 Mile-Search	Amazon-5 Miles-Search	BestBuy-0 Mile-Exp	BestBuy-5 Miles-Exp	BestBuy-0 Mile-Exp	BestBuy-5 Miles-Search
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1	0.005	−0.007	0.005	−0.008	−0.011	−0.009	−0.001	−0.010
	(0.017)	(0.010)	(0.013)	(0.006)	(0.009)	(0.007)	(0.023)	(0.008)
β_2	−0.043*	0.009	−0.002	0.009		0.013	0.000	0.009
	(0.024)	(0.012)	(0.018)	(0.008)		(0.008)	(0.028)	(0.010)
Observations	32,112	35,568	52,392	57,648	10,224	11,712	5,664	6,600
R^2	0.0002	0.00002	0.00000	0.00003	0.0001	0.0002	0.00000	0.0002
Adjusted R^2	-0.044	-0.044	-0.044	-0.044	-0.046	-0.045	-0.048	-0.047
F Statistic	2.775* (df = 2; 30749)	0.318 (df = 2; 34061)	0.101 (df = 2; 50184)	0.774 (df = 2; 55221)	1.377 (df = 1; 9774)	1.297 (df = 2; 11199)	0.004 (df = 2; 5403)	0.746 (df = 2; 6300)

Note: *p<0.1; **p<0.05; ***p<0.01

Effects on Online Search Behavior vs Prod Types I

We want to test whether the show-rooming effect is stronger for experience goods

Table 4: Results of the Online Search Effect: Experience Products

	log(PagesPerDollar + 1)				log(MinsPerDollar + 1)			
	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1	0.007	-0.037^{***}	0.006^{**}	0.001	0.006	-0.039^{***}	0.003	0.001
	(0.015)	(0.008)	(0.002)	(0.002)	(0.015)	(0.008)	(0.002)	(0.001)
β_2	-0.077^{***}	0.030^{***}		-0.0001	-0.067^{***}	0.034^{***}		-0.001
	(0.020)	(0.010)		(0.002)	(0.020)	(0.010)		(0.002)
Observations	32,112	35,568	10,224	11,712	32,112	35,568	10,224	11,712
R^2	0.001	0.001	0.001	0.00003	0.001	0.001	0.0003	0.0001
Adjusted R^2	-0.043	-0.044	-0.045	-0.046	-0.044	-0.044	-0.046	-0.046
F Statistic	12.857^{***} (df = 2; 30749)	10.009^{***} (df = 2; 34061)	5.763^{**} (df = 1; 9774)	0.143 (df = 2; 11199)	10.349^{***} (df = 2; 30749)	11.626^{***} (df = 2; 34061)	2.508 (df = 1; 9774)	0.438 (df = 2; 11199)

Note: *p<0.1; **p<0.05; ***p<0.01

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Effects on Online Search Behavior vs Prod Types II

Table 5: Results of the Online Search Effect: Search Products

	log(PagesPerDollar + 1)				log(MinsPerDollar + 1)			
	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles	Amazon-0 Mile	Amazon-5 Miles	BestBuy-0 Mile	BestBuy-5 Miles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_1	0.001	0.006	0.001	0.009*	0.003	0.004	0.0001	0.009*
	(0.012)	(0.006)	(0.014)	(0.005)	(0.012)	(0.006)	(0.012)	(0.005)
β_2	−0.019	−0.002	−0.000	−0.007	−0.019	0.001	−0.000	−0.008
	(0.017)	(0.008)	(0.017)	(0.006)	(0.017)	(0.008)	(0.015)	(0.006)
Observations	52,392	57,648	5,664	6,600	52,392	57,648	5,664	6,600
R^2	0.00005	0.00002	0.00000	0.001	0.00004	0.00003	0.00000	0.001
Adjusted R^2	-0.044	-0.044	-0.048	-0.047	-0.044	-0.044	-0.048	-0.047
F Statistic	1.138 (df = 2; 50184)	0.553 (df = 2; 55221)	0.011 (df = 2; 5403)	1.590 (df = 2; 6300)	0.935 (df = 2; 50184)	0.696 (df = 2; 55221)	0.0001 (df = 2; 5403)	1.927 (df = 2; 6300)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Effects on Referring Domain I

To capture the expected change in the odds ratio of the impact of Circuit City store closures and the moderating effect of Best Buy stores as an alternative local showroom, we run the following regressions:

$$
\begin{aligned}
&\mathrm{Logit}\left(\texttt{ReferringDomainIsSearchEngine}, \texttt{NoReferringDomain}\right)_{i,t} \\
&= \mu_i + \tau_t \\
&+ \beta_1 \ \texttt{CCStorePresent}_i \times \texttt{AfterStoreClosing}_t \\
&+ \beta_2 \ \texttt{CCStorePresent}_i \times \texttt{AfterStoreClosing}_t \times \texttt{BBStorePresent}_i \\
&+ \epsilon_{i,t}
\end{aligned}
\tag{3}
$$

Table 6 presents the effect of store closure on referring domain.

Effects on Referring Domain II

Table 6: Results of Logistic Regression for Referring Domain

	ReferringDomainIsSearchEngine		NoReferringDomain	
	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile
	(1)	(2)	(3)	(4)
β_1	-0.817^{*}	-15.12^{***}	0.325	-0.223
	(0.337)	(0.611)	(0.346)	(1.259)
β_2	0.697	14.43^{***}	-0.415	0.916
	(0.564)	(0.944)	(0.544)	(1.615)
Observations	10,791	1,225	10,791	1,225

Note: *p$<$0.05; **p$<$0.01; ***p$<$0.001

Alternative Measure of Search Intensity I

By applying more traditional online search measures, we perform the same DID analysis for Amazon and bestbuy.com, to further investigate if the increase in search intensity manifests itself independent of sales amount.

Table 7: Results of the Online Sales and Search Effect (All Product Categories)

	log(SalesPerTransaction + 1)		log(PagesPerTransaction + 1)		log(MinsPerTransaction + 1)	
	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.012	−0.001	0.004	0.0002	0.006	0.0002
	(0.013)	(0.032)	(0.009)	(0.017)	(0.011)	(0.020)
β_2	−0.018	0.010	−0.021*	0.005	−0.021	−0.003
	(0.019)	(0.034)	(0.013)	(0.018)	(0.016)	(0.021)
Observations	68,472	14,664	68,472	14,664	68,472	14,664
R^2	0.00002	0.00003	0.0001	0.00004	0.00003	0.00001
Adjusted R^2	-0.044	-0.045	-0.044	-0.045	-0.044	-0.045
F Statistic	0.539 (df = 2; 65594)	0.213 (df = 2; 14028)	1.867 (df = 2; 65594)	0.304 (df = 2; 14028)	0.939 (df = 2; 65594)	0.066 (df = 2; 14028)

Note: *p<0.1; **p<0.05; ***p<0.01

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Self-selection of Store Location I

- To further investigate if the increase in search intensity has a causal link to the Circuit City store closures, not due to other endogenous reason
- We adopt CEM to match each zip code from the treatment group with an equivalent zip code from the control group, using zip code level demographics.
- The matching results left us with 56 zip codes in each group. Using the data from the combined 112 zip codes, we ran the models for sales and search.

Self-selection of Store Location II

Table 8: Results of the Online Sales and Search Effect After Matching Zip Codes: TotalMonthlySales, PagesPerDollar, and MinsPerDollar (All Product Categories)

	log(TotalMonthlySales + 1)		log(PagesPerDollar + 1)		log(MinsPerDollar + 1)	
	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.019	−0.0002	0.006	−0.001	0.003	−0.0002
	(0.019)	(0.002)	(0.012)	(0.003)	(0.011)	(0.002)
β_2	−0.026		−0.023		−0.024*	
	(0.024)		(0.016)		(0.013)	
Observations	1,776	384	1,776	384	1,776	384
R^2	0.001	0.00002	0.001	0.0001	0.002	0.00003
Adjusted R^2	-0.058	-0.113	-0.057	-0.113	-0.056	-0.113
F Statistic	0.740 (df = 2; 1677)	0.008 (df = 1; 344)	1.183 (df = 2; 1677)	0.030 (df = 1; 344)	1.931 (df = 2; 1677)	0.012 (df = 1; 344)

Note: *p<0.1; **p<0.05; ***p<0.01

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Heterogeneity within a Zip Code I

To examine the possible heterogeneity within the geographic zip code area which may be unaccounted for, we add location specific demographics in the regression equations as interaction terms with DID term.

Table 9: Results of the Online Sales and Search Effect with Zip Code Demographics as Interactions and Time Fixed Effects (All Product Categories)

	log(TotalMonthlySales + 1)		log(PagesPerDollar + 1)		log(MinsPerDollar + 1)	
	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	−0.00001	−0.00001	0.0001	0.00001	0.0001	0.00000
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
β_2	−0.00001	−0.0001	−0.0002*	0.00002	−0.0002	0.00001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	68,472	14,664	68,472	14,664	68,472	14,664
R^2	0.00000	0.00004	0.00005	0.00002	0.00003	0.00001
Adjusted R^2	-0.044	-0.045	-0.044	-0.045	-0.044	-0.045
F Statistic	0.019 (df = 2; 65594)	0.255 (df = 2; 14028)	1.478 (df = 2; 65594)	0.114 (df = 2; 14028)	1.131 (df = 2; 65594)	0.053 (df = 2; 14028)

Note: *p<0.1; **p<0.05; ***p<0.01

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Serial Correlation I

In order to address the serial correlation issue, the first solution is to ignore the time series and the results is in Table 10.

Table 10: Results of the Online Sales and Search Effect After Matching Zip Codes: TotalMonthlySales, PagesPerDollar, and MinsPerDollar (All Product Categories)

	log(TotalMonthlySales + 1)		log(PagesPerDollar + 1)		log(MinsPerDollar + 1)	
	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.023	−0.001	0.007	−0.003	0.009	−0.001
	(0.015)	(0.003)	(0.010)	(0.006)	(0.008)	(0.004)
β_2	−0.026		−0.023		−0.024*	
	(0.024)		(0.015)		(0.013)	
Observations	1,776	208	1,776	208	1,776	208
R^2	0.001	0.0003	0.001	0.001	0.002	0.0004
Adjusted R^2	-0.043	-0.083	-0.043	-0.083	-0.042	-0.083
F Statistic	1.169 (df = 2; 1700)	0.052 (df = 1; 191)	1.182 (df = 2; 1700)	0.197 (df = 1; 191)	1.663 (df = 2; 1700)	0.078 (df = 1; 191)

Note: *p<0.1; **p<0.05; ***p<0.01

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Serial Correlation II

Another solution is to to use a White-like estimator to calculate the variance-covariance matrix of the error term.The results is in Table 11.

Table 11: Results of the Online Sales and Search Effect with Arbitrary Variance-Covariance Matrix Corrections (All Product Categories)

	log(TotalMonthlySales + 1)		log(PagesPerDollar + 1)		log(MinsPerDollar + 1)	
	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile	Amazon-0 Mile	BestBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.019	-0.001	0.006	-0.003	0.003	-0.001
	(0.019)	(0.003)	(0.006)	(0.006)	(0.011)	(0.004)
β_2	-0.026		-0.023^{***}		-0.024^{***}	
	(0.028)		(0.001)		(0.006)	
Observations	1,776	208	1,776	208	1,776	208
R^2	0.001	0.0002	0.001	0.001	0.002	0.0003
Adjusted R^2	-0.058	-0.156	-0.057	-0.156	-0.056	-0.156
F Statistic	0.740 (df = 2; 1677)	0.036 (df = 1; 179)	1.183 (df = 2; 1677)	0.136 (df = 1; 179)	1.931 (df = 2; 1677)	0.054 (df = 1; 179)
Note:						*p<0.1; **p<0.05; ***p<0.01

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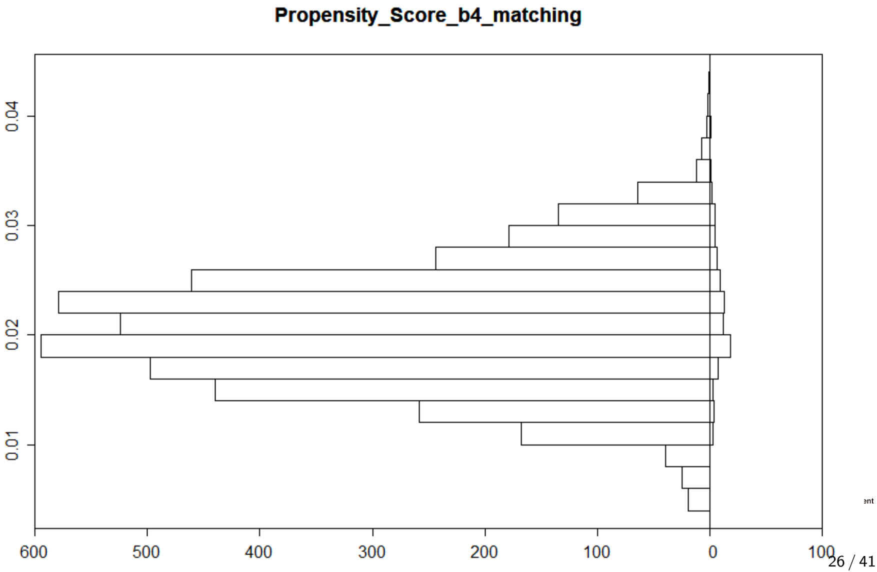
Takeaways

1. Showrooms do add value to online retailers
    - Not necessarily in increasing sales
    - But perhaps in customers' level of purchase readiness
2. Large online only retailers such as Amazon should differentiate between customers from H/L showroom concentration
3. Online retailers should evaluate their product reviews and descriptions for showroom experience customers
4. My Questions
    - Newly Opening Physical Showroom

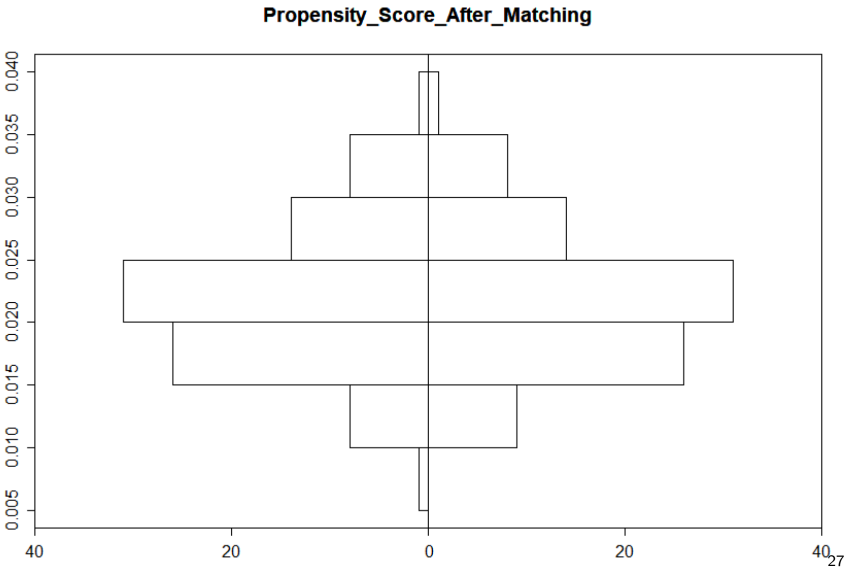
Propensity Score Matching

- Nearest propensity score matching is used to match each zipcode from treatment group with an equivalent control group, using zip code level demographics.
    - Household size
    - Household oldest age
    - Household income
    - Number of children
    - Internet speed
- After matching, we have left with 89 matched zip codes. Below are the propensity score before and after matching.

Propensity Score Matching



Propensity Score Matching



Propensity Score Matching

Table 12: Results of the Online Sales and Search Effect After Nearest Propensity Score Matching: TotalMonthlySales, PagesPerDollar, and MinsPerDollar (All Product Categories)

	log(TotalMonthlySales + 1)		log(PagesPerDollar + 1)		log(MinsPerDollar + 1)	
	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile	Amazon-0 Mile	BesyBuy-0 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.029	0.0002	0.00004	0.0001	0.002	0.00000
	(0.024)	(0.031)	(0.020)	(0.009)	(0.019)	(0.005)
β_2	−0.033	0.009	−0.068***	0.003	−0.057***	0.0004
	(0.028)	(0.031)	(0.023)	(0.009)	(0.022)	(0.005)
Observations	3,000	768	3,000	768	3,000	768
R^2	0.001	0.001	0.004	0.001	0.003	0.00004
Adjusted R^2	-0.052	-0.078	-0.048	-0.078	-0.049	-0.079
F Statistic	0.935 (df = 2; 2850)	0.192 (df = 2; 711)	6.219*** (df = 2; 2850)	0.185 (df = 2; 711)	4.693*** (df = 2; 2850)	0.014 (df = 2; 711)

Note: *p<0.1; **p<0.05; ***p<0.01

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Look-Ahead Propensity Score Matching

- LA-PSM requires some treated observations occur over different periods t and $t+k$.
- Basic idea in LA-PSM is to match treated observations in period t with observations which were in control group in period t but in treatment group in period $t+k$.
- In this paper, Circuit City closed all their stores at the same time: November 2008.
- Therefore, LA-PSM method is not applicable.

Data Preparation for the Application

- Our analysis is based on data individual transactions.
- For each transaction $i = 1, \ldots, n$,
  - $W_i = \texttt{CCStorePresent}_i \times \texttt{AfterStoreClosing}_i$
  - $Y_i = \log\left(\texttt{prod\_totprice}, \texttt{PagesPerDollar}, \texttt{MinsPerDollar}\right)$ [2]
  - **10 categorical**: hoh_most_education, census_region, household_size, hoh_oldest_age, children, racial_background, connection_speed, country_of_origin, prod_category_type and BBStorePresent
  - **4 real-valued covariates**: pages_viewed[3], duration[4], prod_qty, household_income
  - We expanded out categorical random variables via one-hot encoding, thus resulting in covariates $X_i \in \mathbb{R}^p$ with $p = 38$ or $p = 37$.

[2] right-skewed

[3] not PagesPerDollar is dependent variable

[4] not MinsPerDollar is dependent variable

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The potential outcomes framework I

For a set of i.i.d. subjects $i = 1, ..., n$, we observe a tuple (X_i, Y_i, W_i), comprised of

- A **feature vector** $X_i \in \mathbb{R}^p$,
- A **response** $Y_i \in \mathbb{R}$, and
- A **treatment assignment** $W_i \in \{0, 1\}$

Following the **potential outcomes** framework (Imbens and Rubin, 2015) , we posit the existence of quantities $Y_i(0)$ and $Y_i(1)$

- These correspond to the response we would have measured given that the i-th subject received treatment $(W_i = 1)$ or no treatment $(W_i = 0)$.

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The potential outcomes framework II

Goal is to estimate the **conditional average treatment effect**

$$\tau(x) = \mathbb{E}\left[Y(1) - Y(0) \mid X = x\right]$$

However in experiments we only get to see $Y_i = Y_i(W_i)$

The potential outcomes framework III

If we make no further assumptions, estimating $\tau(x)$ is not possible.

- Literature often assumes **unconfoundedness** (Rosenbaum and Rubin, 1983)

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i \mid X_i.$$

- When this assumption holds, methods based on matching or propensity score estimation are usually consistent.

Causal Forests for Observational Studies

All analyses are carried out using the R package **grf**, version 1.2.0 (Tibshirani et al., 2018).

- $e(x) = \mathbb{P}[W_i \mid X_i = x]$ for the propensity score
- $m(x) = \mathbb{E}[Y_i \mid X_i = x]$ for the expected outcome marginalizing over treatment
- An application of causal forests using **grf** (Athey and Wager, 2019):
  1. fitting two separate regression forests to estimate $m(\cdot)$ and $e(\cdot)$ (`Y.forest` and `W.forest`)
  2. It then makes out-of-bag predictions using these two first-stage forests, and uses them to grow a causal forest
  3. training a pilot random forest on all the features, and then train a second forest on only those features that saw a reasonable number of splits in the first step.

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Average Treatment Effect of Circuit City Stores Closure on amazon.com Sales

The package **grf** has a built-in function for average treatment effect estimation called `average_treatment_effect`. Using this function we obtain:

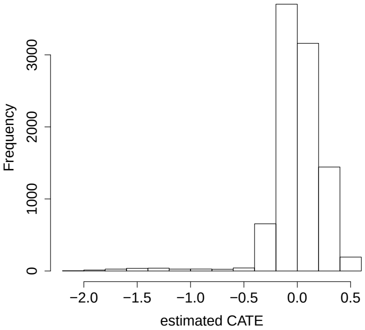

Figure 2: Histogram of out-of-bag CATE

Table 13: 90% CI for the ATT

5%	$\hat{\tau}_t$	95%
-0.42	-0.22	-0.03

Average Treatment Effect of Circuit City Stores Closure on bestbuy.com Sales

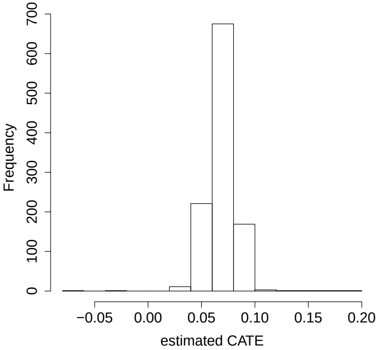

Figure 3: Histogram of out-of-bag CATE estimates from a causal forest

Table 14: 90% CI for the ATT

5%	$\hat{\tau}_t$	95%
-0.39	0.08	0.55

Average Treatment Effect of Circuit City Stores Closure on amazon.com Pages Per Dollar of Sales

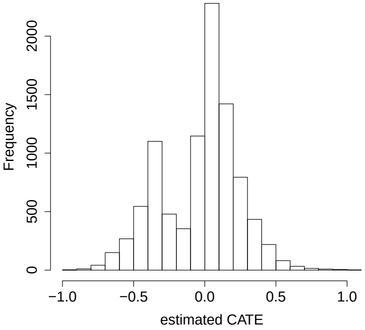

Figure 4: Histogram of out-of-bag CATE estimates from a causal forest

Table 15: 95% CI for the ATT

2.5%	$\hat{\tau}_t$	97.5%
0.02	0.27	0.52

Average Treatment Effect of Circuit City Stores Closure on bestbuy.com Pages Per Dollar of Sales

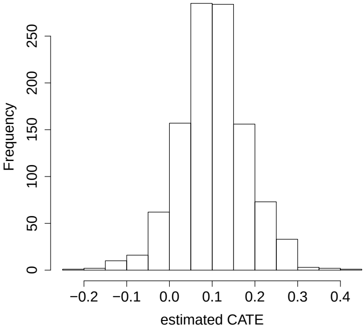

Figure 5: Histogram of out-of-bag CATE estimates from a causal forest

Table 16: 90% CI for the ATT

5%	$\hat{\tau}_t$	95%
-0.47	0.09	0.65

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Average Treatment Effect of Circuit City Stores Closure on amazon.com Minutes Per Dollar of Sales

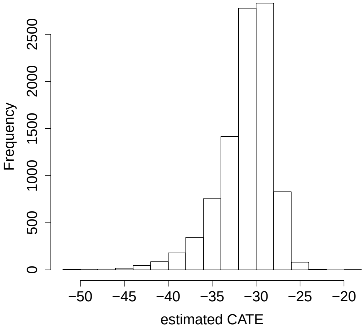

Figure 6: Histogram of out-of-bag CATE estimates from a causal forest

Table 17: 90% CI for the ATT

5%	$\hat{\tau}_t$	95%
-110.76	-24.32	62.13

Average Treatment Effect of Circuit City Stores Closure on bestbuy.com Minutes Per Dollar of Sales

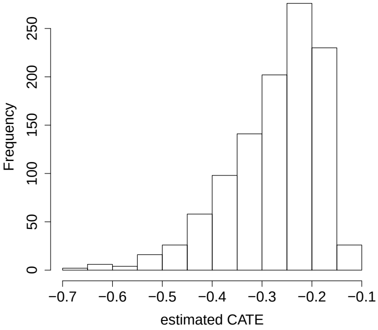

Figure 7: Histogram of out-of-bag CATE estimates from a causal forest

Table 18: 90% CI for the ATT

5%	$\hat{\tau}_t$	95%
-0.63	-0.29	0.05

Reference I

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