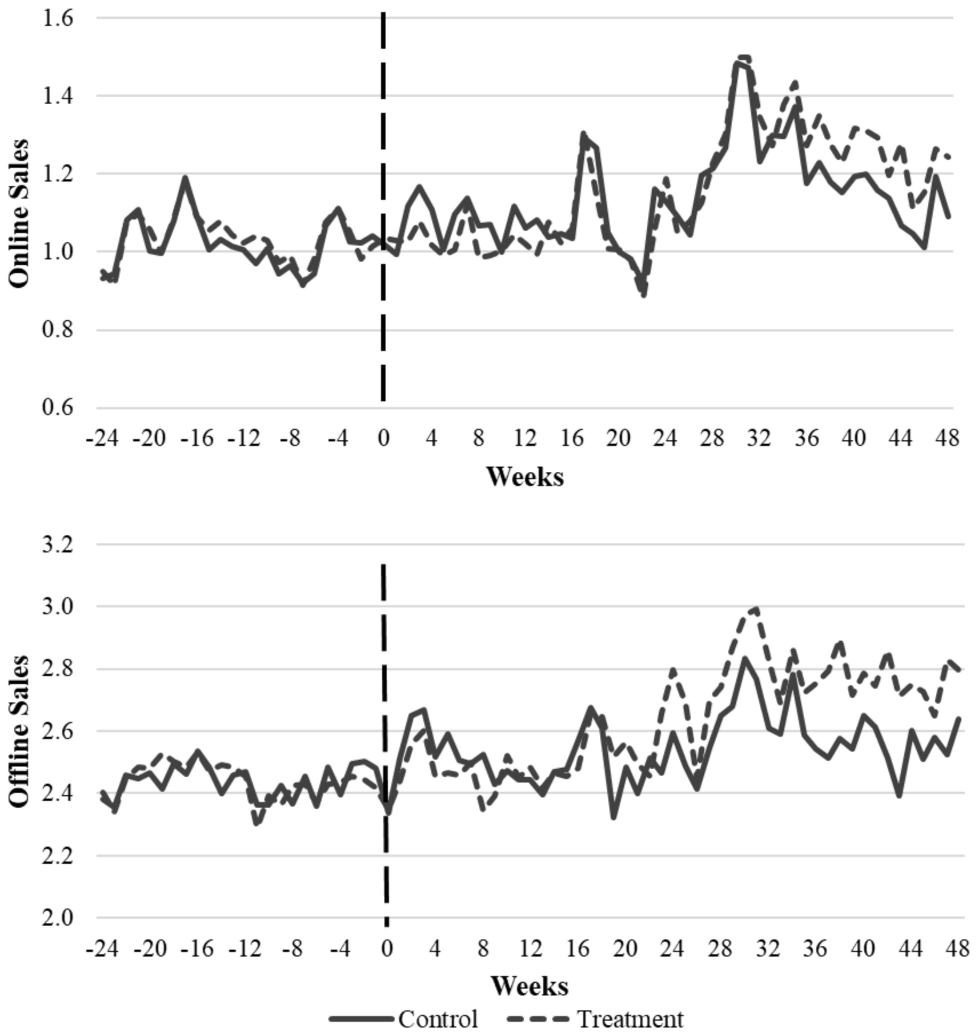
Web Appendix A: Supplementary Figures and Tables

Figure WA1. Example of Consumer Complaints

Figure WA2. Pretreatment Parallel Trends and Posttreatment Effect on Sales



Notes. Product sales are aggregated at the week level. Week 0 indicates the week of the policy change.

Table WA1. Comparison between Uniform Pricing and Price Matching Policies

Feature	Uniform Pricing Policy	Price Matching Policy
Motivation to search within retailer	**Low**. Prices and value proposition are the consistent.	**High.** Within-retailer search is rewarding if price discrepancies are detected.
Consumer effort and cost	**Low.** Reduced concern about being price discriminated by the retailer.	**High.** The consumer must act as an auditor to spot price discrepancies.
Consumer focus	Product, and/or between-retailer comparison.	Within-retailer price discrepancies and between-retailer comparison.
Retailer's goal	**Omnichannel experience**. Retailers aim to build trust and enhance the smooth transition across different channels.	**Segmentation and price discrimination.** Retailers could accurately distinguish consumers who search with those who do not search.

Table WA2. Summary of Related Literature

Article	Method	Research Scope	Key Findings	Research Focus: Cross-Channel Effects	Research Focus: Performance Comparison	Research Focus: Market Descriptive
Online-Offline Integration						
Bell et al. (2017)	Empirical	Offline to online	Study the effects of showrooming, physical locations where customers can view and try products, on the omni-channel sales. They find that showrooms: (1) increase demand overall and in the online channel as well; (2) generate operational spillovers to the other channels by attracting customers who, on average, have a higher cost-to-serve; (3) improve overall operational efficiency by increasing conversion in a sampling channel and by decreasing returns; and (4) amplify these demand and operational benefits in dealing with customers who have the most acute need for the firm's products.	✓		
Cao and Li (2015)	Qualitative	Cross-channel integration	Propose a conceptual framework to explain whether and under what firm-level conditions cross-channel integration impacts firm sales growth. They find that cross-channel integration stimulates sales growth, but that firm online experience and physical-store presence weaken this effect.	✓		
Fisher et al. (2019)	Empirical	Online to offline	Study how faster delivery in the online channel affects sales within and across channels in omnichannel retailing. Online store sales increased, on average, by 1.45% per business-day reduction in delivery time, from a baseline of seven business days, and positive spillover effect to the retailer's offline stores. These effects increase gradually in the short-to-medium run as the result of higher order count.	✓		
Gallino et al. (2017)	Empirical	Cross-channel integration	Study the effects of the introduction of cross-channel functionalities on the overall sales dispersion of retailers and the implications of these effects for inventory management. On average, the contribution of the 90% lowest-selling products to total sales increased by 0.75 percentage points, increasing sales dispersion. to respond optimally to the observed increase in dispersion, the retailer would need to increase its cycle and safety inventories by approximately 2.7%.	✓		
Gu and Tayi (2017)	Analytical	Cross-channel integration	Examine consumers' cross-channel search behavior of "pseudo-showrooming," or the consumer behavior of inspecting one product at a seller's physical store before buying a related but different product at the same seller's online store, and investigates how such consumer behavior allows a multichannel seller to achieve better coordination between its online and offline arms through optimal product placement strategies.	✓		
Wang and Goldfarb (2017)	Empirical	Cross-channel substitution and complementary	Examine the drivers of substitution and complementarity between online and offline retail channels. The evidence supports the coexistence of substitution across channels and complementarity in demand. The evidence suggests that whereas online and offline channels may be substitutes in distribution, they are complements in marketing communications.	✓		

Table WA2. Summary of Related Literature (cont')

Article	Method	Research Scope	Key Findings	Research Focus: Cross-Channel Effects	Research Focus: Performance Comparison	Research Focus: Market Descriptive
Pricing in Omnichannel Operations						
Cai et al. (2019)	Analytical	Comparison of cross-channel pricing strategy	The uniform pricing strategy can be better than the price differentiation strategy when the cost saving and demand increasing are large enough or the consumers' acceptance of online channel lies in a certain interval.			✓
Cavallo (2017)	Empirical	Comparison of prices across channels	The price levels are identical about 72 percent of the time. Price changes are not synchronized but have similar frequencies and average sizes.			
Chen and Cui (2013)	Analytical	Comparison of cross-channel pricing strategy	Uniform pricing induced by consumers' concerns of fairness can actually help mitigate price competition and hence increase firms' profits if the demand of the product category is expandable. Furthermore, an individual firm may not have an incentive to unilaterally mitigate consumers' concerns of price fairness to its own branded variants, which suggests the long-run sustainability of the uniform pricing strategy.		✓	
Chen et al. (2023)	Analytical	Comparison of pricing strategy	Uniform pricing can be optimal for a monopoly retailer even though consumers have different costs for shopping online versus offline and there is no intrinsic disutility against price discrimination by consumers. In addition, when the uniform price is optimal, it can be lower than both the offline and online prices under optimal dual pricing.		✓	
Chen et al. (2020)	Analytical	Comparison of cross-channel pricing strategy	When firms have sufficiently large and nonoverlapping target segments, identity management can enable firms to extract full surplus from their targeted consumers through perfect price discrimination. Identity management can also induce firms not to serve consumers who are not targeted by either firm when the commonly nontargeted market segment is small. Thus, identity management by consumers can benefit firms and lead to lower consumer surplus and lower social welfare.		✓	
DellaVigna and Gentzkow (2019)	Empirical	Comparison of pricing strategy across locations	Most U.S. food, drugstore, and mass-merchandise chains charge nearly uniform prices across stores, despite wide variation in consumer demographics and competition.			✓
Harsha et al. (2019)	Empirical	Cross-location and cross-channel pricing optimization	Develop an integrated OCP optimization formulation to profitably coordinate prices for nonperishable products offered across channels and store locations while satisfying practical constraints on volume and price. An OCP implementation in two categories for a major retail chain projected a 7% profit lift while preserving the sales volume.			
Kireyev et al. (2017)	Analytical	Comparison of cross-location pricing strategy	Investigate the strategic forces behind the adoption (or non-adoption) of self-matching. Self-matching can dampen competition online and enable price discrimination in-store. Surprisingly, self-matching strategies can also be profitable when consumers use "smart" devices to discover online prices in stores.		✓	
Li et al. (2018)	Empirical	Comparison of cross-location pricing strategy	Under reasonable commitment mechanisms, two leading chains would benefit from employing national pricing policies, whereas a discount retailer should target prices in each local market.		✓	
Our study	Empirical	Comparison of cross-channel pricing strategy	Firms switching from channel-specific pricing to uniform pricing has an increasingly positive impact on sales over time. The trend is more pronounced for online than offline sales. The benefit of uniform pricing is driven by the reduced cross-channel search cost and increased cross-channel price rigidity.	✓	✓	

Table WA3. Definitions and Summary Statistics

Variables	Definitions	Mean	SD	Min	Max
Treat	Dummy $Treat_i$ = 1, indicating product i belongs to heavy asset mode and receive the "same price" tag	.624	.484	.000	1.000
PriceChange	Dummy $PriceChange_i$ = 1, indicating product i belongs to heavy asset mode and changed the product prices due to policy change	.356	.479	.000	1.000
Period	Dummy Periodt = 1, indicating time t is in the post-treatment period (Jun 2013 - Aug 2013)	.679	.467	.000	1.000
Period1	Dummy Period1t = 1, indicating time t is in the first quarter of the post-treatment period (Jun 2013 - Aug 2013)	.167	.373	.000	1.000
Period2	Dummy Period2t = 1, indicating time t is in the second quarter of the post-treatment period (Sep 2013 - Dec 2013)	.167	.373	.000	1.000
Period3	Dummy Period3t = 1, indicating time t is in the third quarter of the post-treatment period (Jan 2014 - Mar 2014)	.167	.373	.000	1.000
Period4	Dummy Period4t = 1, indicating time t is in the fourth quarter of the post-treatment period (Apr 2014 - Jun 2014)	.179	.384	.000	1.000
Online sales	Number of units sold for product i in online channel at time t	1.111	1.327	.000	60.000
Offline sales	Number of units sold for product i in offline channel at time t	2.525	1.967	.000	47.000
Online price	Unit price for product i in online channel at time t	1344.222	1735.733	1.000	10391.570
Offline price	Unit price for product i in offline channel at time t	1347.385	1737.959	1.000	10829.000

Table WA4. Consumer Characteristics Between Light vs. Heavy Assets

	Light Asset		Heavy Asset	
Variables	**Mean**	**SD**	**Mean**	**SD**
Age	41.334	10.636	40.970	10.447
Gender	1.678	1.008	1.682	1.007
Tenure	888.082	759.338	879.978	755.653
Membership level	1.356	1.563	1.309	1.545
Number of Consumers	55,659		105,096	

Notes. The pre-matching sample is used. 38,175 consumers who registered after the policy change are excluded.

Table WA5. Common Trend Analysis

	Pre-Matching Sample		Post-Matching Sample	
Dependent	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Week1 × Treat	.026(.037)	.006(.019)	.010(.049)	-.001(.024)
Week2 × Treat	-.023(.038)	-.027(.025)	-.040(.057)	-.019(.038)
Week3 × Treat	-.013(.029)	.007(.021)	-.022(.046)	-.020(.035)
Week4 × Treat	-.031(.031)	-.002(.021)	-.025(.045)	.008(.029)
Week5 × Treat	.029(.031)	-.037(.022)*	.040(.053)	-.012(.034)
Week6 × Treat	-.028(.034)	-.003(.020)	-.013(.054)	.031(.032)
Week7 × Treat	-.023(.033)	-.011(.022)	-.012(.048)	-.007(.032)
Week8 × Treat	-.033(.036)	-.023(.028)	-.022(.045)	-.007(.044)
Week9 × Treat	-.002(.029)	-.038(.019)**	-.012(.045)	-.013(.031)
Week10 × Treat	.033(.034)	-.047(.026)	.029(.053)	-.015(.038)
Week11 × Treat	.007(.034)	.012(.033)	.029(.053)	.027(.040)
Week12 × Treat	.022(.037)	-.010(.020)	.014(.053)	-.001(.026)
Week13 × Treat	-.026(.033)	-.026(.023)	.003(.045)	-.019(.034)
Week14 × Treat	.038(.034)	-.023(.025)	.054(.051)	-.040(.037)
Week15 × Treat	.006(.033)	.015(.021)	.002(.056)	.005(.029)
Week16 × Treat	.024(.032)	-.039(.022)*	.014(.046)	-.035(.032)
Week17 × Treat	.010(.034)	-.039(.023)*	.017(.054)	.015(.033)
Week18 × Treat	-.015(.037)	-.035(.023)	-.016(.045)	-.019(.037)
Week19 × Treat	.007(.034)	-.020(.021)	.026(.050)	-.008(.035)
Week20 × Treat	-.007(.034)	-.039(.023)*	-.002(.047)	-.028(.033)
Week21 × Treat	.013(.037)	-.006(.024)	-.004(.041)	.009(.035)
Week22 × Treat	.001(.030)	-.024(.021)	.012(.053)	-.022(.032)
Week23 × Treat	-.017(.035)	-.010(.022)	-.049(.056)	-.033(.032)
Week24 × Treat	-.019(.032)	-.042(.023)*	-.032(.049)	-.038(.037)
Sample size	323,700	323,700	164,112	164,112

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Sample is the 25 weeks of observations before treatment. The last week before treatment (Week 25) serves as the baseline. Coefficients of other covariates and post-treatment effects are not reported for parsimony. Brand-level cluster-robust SEs are reported in parentheses.

Table WA6. Cross-Product Spillover

	Model 1		Model 2	
Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post	.071(.010)***	.029(.005)***		
Post×Treat	.013(.015)	.035(.010)***		
Post1			.045(.012)***	.027(.003)***
Post2			.049(.007)***	.025(.007)***
Post3			.210(.009)***	.085(.004)***
Post4			-.020(.013)*	.020(.006)***
Post1×Treat			-.058(.019)***	-.019(.012)
Post2×Treat			-.021(.017)	.022(.012)*
Post3×Treat			.036(.014)**	.055(.011)***
Post4×Treat			.087(.021)***	.077(.013)***
Product fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	No
Sample size	164,112	164,112	164,112	164,112
Log-likelihood	-220603.262	-309107.230	-220151.012	-308899.622
AIC	445574.524	622582.460	444672.024	622169.244
BIC	452596.390	629604.326	451697.106	629194.326

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Main effects are excluded because of multicolinearity with the fixed effects. Brand-level cluster-robust SEs are reported in parentheses.

Table WA7. Rosenbaum Bounds Sensitivity Test

	Significant level		95% Confidence Interval	
Gamma	**Sig+**	**Sig-**	**CI+**	**CI-**
		Overall Treatment Effect		
Online Sales#				
1.00	**0.000**	**0.000**	**-0.0000004**	**0.0000004**
1.10	0.943	0.000	-0.0000004	0.0000004
1.20	1.000	0.000	-0.0000004	0.5000000
1.30	1.000	0.000	-0.0000004	0.5000000
Offline Sales				
1.00	0.021	0.021	-0.0000004	-0.0000004
1.10	0.043	0.000	-0.0000004	-0.0000004
1.20	**0.875**	**0.000**	**-0.0000004**	**0.0000004**
1.30	1.000	0.000	-0.0000004	0.0000004
		Treatment Effect in First Posttreatment Period		
Online Sale				
1.00	0.000	0.000	-0.0000004	-0.0000004
1.10	0.000	0.005	-0.0000004	-0.0000004
1.20	**0.000**	**0.028**	**-0.0000004**	**0.0000004**
1.30	0.000	1.000	-0.5000000	0.0000004
Offline Sales#				
1.00	0.000	0.000	-0.0000004	-0.0000004
1.10	**0.000**	**0.045**	**-0.0000004**	**0.0000004**
1.20	0.000	0.858	-0.0000004	0.0000004
1.30	0.000	1.000	-0.5000000	0.0000004
		Treatment Effect in Second Posttreatment Period		
Online Sales#				
1.00	**0.025**	**0.025**	**-0.0000005**	**0.0000005**
1.10	0.000	0.994	-0.0000005	0.0000005
1.20	0.000	1.000	-0.0000005	0.4999990
1.30	0.000	1.000	-0.5000000	0.5000000
Offline Sales#				
1.00	0.012	0.012	-0.0000005	-0.0000005
1.10	**0.093**	**0.000**	**-0.0000005**	**0.0000005**
1.20	0.954	0.000	-0.0000005	0.0000005
1.30	1.000	0.000	-0.0000005	0.0000005
		Treatment Effect in Third Posttreatment Period		
Online Sales				
1.00	0.003	0.003	-0.0000004	-0.0000004
1.10	**0.041**	**0.000**	**-0.0000004**	**0.0000004**
1.20	0.961	0.000	-0.0000004	0.0000004
1.30	1.000	0.000	-0.0000004	0.5000000
Offline Sales				
1.00	0.000	0.000	0.0000003	0.0000003
1.10	0.003	0.000	0.0000003	0.5000000
1.20	**0.937**	**0.000**	**-0.0000003**	**0.5000000**
1.30	1.000	0.000	-0.0000003	0.5000000
		Treatment Effect in Fourth Posttreatment Period		
Online Sales				
1.00	0.000	0.000	-0.0000004	-0.0000004
1.10	0.004	0.000	-0.0000004	-0.0000004
1.20	**0.935**	**0.000**	**-0.0000004**	**0.0000004**
1.30	1.000	0.000	-0.0000004	0.5000000
Offline Sales				
1.00	0.000	0.000	0.0000004	0.0000004
1.10	0.000	0.000	0.0000004	0.5000000
1.20	**0.608**	**0.000**	**-0.0000004**	**0.5000000**
1.30	1.000	0.000	-0.0000004	0.5000000

Notes. # denotes treatment effects are not significant at the 95% confidence level.

Table WA8. Intensity of Price Change

Variables	Online Sales	Offline Sales
Period1×Treat	.026(.024)	.013(.016)
Period2×Treat	.056(.023)**	.053(.016)***
Period3×Treat	.072(.019)***	.071(.017)***
Period4×Treat	.119(.025)***	.055(.015)***
Period1×PriceChange	-.030(.034)	.032(.025)
Period2×PriceChange	-.029(.032)	.016(.026)
Period3×PriceChange	.009(.028)	.034(.023)
Period4×PriceChange	.018(.029)	.089(.027)***
Period1×ΔPrice	-1.073(.136)***	-.739(.138)***
Period2×ΔPrice	-.961(.127)***	-.584(.192)***
Period3×ΔPrice	-.681(.124)***	-.565(.123)***
Period4×ΔPrice	-.689(.147)***	-.550(.146)***
Product fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Sample size	164,112	164,112
Log-likelihood	-219006.636	-307717.321
AIC	442391.272	1216738.334
BIC	449429.214	1223776.276

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Estimated coefficients of other covariates are ignored for parsimony. ΔPrice is the proportion of price adjustment due to the policy change. Brand-level cluster-robust SEs are reported in parentheses.

Table WA9. Intensity of Price Increases and Decreases

Variables	**Online Sales**	**Offline Sales**
Period1×Treat	.026(.026)	.007(.016)
Period2×Treat	.061(.024)**	.055(.016)***
Period3×Treat	.081(.020)***	.067(.017)***
Period4×Treat	.131(.025)***	.054(.014)***
Period1×PriceChange	-.030(.035)	.050(.031)
Period2×PriceChange	-.045(.034)	.009(.030)
Period3×PriceChange	-.018(.032)	.047(.030)
Period4×PriceChange	-.017(.027)	.090(.027)***
Period1×ΔPriceIncrease	-1.079(.139)***	-.900(.200)***
Period2×ΔPriceIncrease	-.858(.150)***	-.527(.222)***
Period3×ΔPriceIncrease	-.505(.169)***	-.671(.210)***
Period4×ΔPriceIncrease	-.456(.177)**	-.558(.135)***
Period1×ΔPriceDecrease	1.129(.604)*	.317(.203)
Period2×ΔPriceDecrease	1.397(.479)***	.728(.294)**
Period3×ΔPriceDecrease	1.402(.424)***	.276(.105)***
Period4×ΔPriceDecrease	1.625(.542)***	.520(.375)*
Product fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Sample size	164,112	164,112
Log-likelihood	-218999.304	-307714.738
AIC	442384.608	619815.476
BIC	449435.411	626866.279

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Main effects are excluded because of multicolinearity with the fixed effects. ΔPriceIncrease and ΔPriceDecrease are the absolute proportion of price increase or decrease, respectively. Brand-level cluster-robust SEs are reported in parentheses.

Web Appendix B: Robustness Checks

Table WB1. Robustness Checks: Alternative Sampling

	A. Full Sample				B. Daily Aggregates			
Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post×Treat	.030(.017)*	.038(.009)***			.030(.013)**	.045(.010)***		
Post1×Treat			-.023(.019)	-.028(.009)***			-.042(.019)**	-.022(.015)
Post2×Treat			.027(.015)*	.007(.011)			.000(.017)	.020(.015)
Post3×Treat			.103(.018)***	.072(.010)***			.061(.016)***	.031(.009)***
Post4×Treat			.150(.019)***	.097(.011)***			.093(.015)***	.076(.011)***
Product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	323,700	323,700	323,700	323,700	1,724,641	1,724,641	1,724,641	1,724,641
Log-likelihood	-434726.200	-606433.742	-434666.227	-606305.345	-404522.452	-690262.954	-404494.414	-690192.677
AIC	877912.400	1221327.484	877798.454	1221076.690	817504.904	1388985.908	817454.828	1388851.354
BIC	892760.304	1236175.388	892656.888	1235935.124	835426.140	1406907.144	835388.774	1406785.300
	C. Anticipation				**D. Grace Period**			
Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post×Treat	.011(.016)	.032(.010)***			.018(.016)	.040(.010)***		
Post1×Treat			-.061(.019)***	-.021(.012)			-.062(.022)***	-.017(.014)
Post2×Treat			-.024(.017)	.019(.012)			-.021(.017)	.022(.012)
Post3×Treat			.033(.014)**	.052(.011)***			.036(.014)**	.055(.011)***
Post4×Treat			.086(.022)***	.074(.013)***			.089(.021)***	.077(.013)***
Product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	155,696	155,696	155,696	155,696	155,696	155,696	155,696	155,696
Log-likelihood	-207989.932	-292112.666	-207951.630	-292076.793	-207851.856	-291834.719	-207817.256	-291805.700
AIC	420339.864	588585.332	420269.260	588519.586	420063.712	588029.438	420000.512	587977.400
BIC	427299.029	595544.497	427238.002	595488.328	427022.877	594988.603	426969.254	594946.142

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Estimated coefficients of other covariates are ignored for parsimony. Brand-level cluster-robust SEs are reported in parentheses.

Table WB2. Robustness Checks: Treatment Effects on Revenue

Variables	Online Revenue	Offline Revenue	Online Revenue	Offline Revenue
Post×Treat	.019(.049)	.075(.031)***		
Post1×Treat			-.185(.061)***	-.112(.037)***
Post2×Treat			-.078(.051)	.071(.046)
Post3×Treat			.108(.050)**	.145(.035)***
Post4×Treat			.215(.066)***	.189(.033)***
Product fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Sample size	164,112	164,112	164,112	164,112
R^2	.067	.148	.070	.148

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Revenue is log-transformed. Brand-level cluster-robust SEs are reported in parentheses.

Table WB3. Robustness Checks: Pooled Model

Variables	Sales	Sales
Post×Treat	.037(.010)***	
Post×Treat×Online	-.024(.013)**	
Post1×Treat		-.017(.012)
Post2×Treat		.025(.012)**
Post3×Treat		.057(.010)***
Post4×Treat		.078(.012)***
Post1×Treat×Online		-.043(.019)**
Post2×Treat×Online		-.046(.018)**
Post3×Treat×Online		-.025(.013)**
Post4×Treat×Online		.012(.016)
Product fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Sample size	328,224	328,224
Log-likelihood	-531796.658	-531623.973
AIC	442614.294	1067635.946
BIC	449639.376	1075350.424

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Main effects are excluded because of multicolinearity with the fixed effects. Brand-level cluster-robust SEs are reported in parentheses.

Table WB4. Robustness Checks: Linear Regressions

	Model 1: Linear				Model 2: Log-Linear			
Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post×Treat	.011(.019)	.093(.028)***			.003(.008)	.025(.007)***		
Post1×Treat			-.058(.021)**	-.036(.022)			-.031(.009)***	-.022(.009)**
Post2×Treat			-.023(.020)	.029(.021)			-.013(.008)*	.015(.010)
Post3×Treat			.040(.025)*	.049(.022)**			.017(.010)*	.046(.008)***
Post4×Treat			.082(.024)***	.064(.026)**			.037(.010)***	.057(.008)***
Product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	164,112	164,112	164,112	164,112	164,112	164,112	164,112	164,112
R^2	0.131	0.117	0.132	0.117	0.138	0.096	0.138	0.097

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Estimated coefficients of other covariates are ignored for parsimony. Brand-level cluster-robust SEs are reported in parentheses.

Table WB5. Robustness Checks: Accounting for Within-Category Heterogeneity

	Model 1 Within-Category Matching		Model 2 Interactive Fixed Effects	
Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post1×Treat	-.057(.016)***	-.019(.012)	-.063(.015)***	-.020(.012)
Post2×Treat	-.015(.016)	.007(.011)	-.025(.015)	.022(.011)**
Post3×Treat	.033(.014)**	.053(.008)***	.030(.011)***	.053(.010)***
Post4×Treat	.099(.017)***	.082(.011)***	.082(.015)***	.077(.010)***
Product fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	No	No
Category-Week fixed effects	No	No	Yes	Yes
Sample size	156,936	156,936	164,112	164,112
Log-likelihood	-212931.392	-296170.807	-218640.956	-307389.193
AIC	430232.784	596711.614	442059.912	619556.386
BIC	437215.438	603694.268	449740.882	627237.356

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. AIC = Akaike information criterion; BIC = Bayesian information criterion. Estimated coefficients of other covariates are ignored for parsimony. Brand-level cluster-robust SEs are reported in parentheses.

Table WB6. Robustness Checks: Cross-Category Matching

Variables	**Online Sales**	**Offline Sales**	**Online Sales**	**Offline Sales**
Post×Treat	.028(.013)**	.039(.010)***		
Post1×Treat			-.032(.013)**	-.008(.009)
Post2×Treat			.032(.015)**	.016(.012)
Post3×Treat			.056(.015)***	.060(.011)***
Post4×Treat			.113(.017)***	.084(.013)***
Product fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Sample size	244,608	244,608	244,608	244,608
Log-likelihood	-330591.948	-462589.880	-330553.712	-462533.717
AIC	665367.896	929363.760	665297.424	929257.434
BIC	672456.577	936452.441	672396.270	936356.280

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Estimated coefficients of other covariates are ignored for parsimony. Brand-level cluster-robust SEs are reported in parentheses.

Table WB7. Robustness Checks: Ruling Out Advertising Effects

Variables	Online Sales	Offline Sales	Online Sales	Offline Sales
Post×Treat	.010(.021)	.026(.016)		
Post×Treat×Medium	-.020(.024)	.006(.018)		
Post×Treat×Top	.014(.035)	.001(.027)		
Post1×Treat			-.049(.026)*	-.040(.017)**
Post2×Treat			-.026(.025)	.029(.016)*
Post3×Treat			.051(.022)**	.052(.018)***
Post4×Treat			.060(.034)*	.059(.021)***
Post1×Treat×Medium			-.065(.031)**	.023(.024)
Post2×Treat×Medium			-.040(.037)	.002(.021)
Post3×Treat×Medium			-.033(.028)	.001(.022)
Post4×Treat×Medium			.055(.032)*	.000(.022)
Post1×Treat×Top			.020(.046)	.021(.034)
Post2×Treat×Top			.038(.041)	-.044(.031)
Post3×Treat×Top			-.023(.034)	-.011(.029)
Post4×Treat×Top			.023(.045)	.034(.026)
Product fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Sample size	164,112	164,112	164,112	164,112
Log-likelihood	-219035.064	-307607.936	-218984.621	-307559.577
AIC	442446.128	619591.872	442375.242	619525.154
BIC	449480.855	626626.599	449458.196	626608.108

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes. Estimated coefficients of other covariates are ignored for parsimony. Brand-level cluster-robust SEs are reported in parentheses. Products fall below 33 percentile of pre-treatment sales (bottom-selling products) serve as baseline group.

Web Appendix C. Complementary Study

The experiment is pre-registered at https://aspredicted.org/N32_NN1. As our theoretical framework proposes, compared with the channel-specific pricing model, the uniform pricing model benefits consumers through the "same-price guarantee", which reduces consumers' motivation to conduct cross-channel search because the consumers could freely choose the preferred shopping channel without the concern of being price discriminated. This reduced search motivation could decrease the expected search costs. In this complementary study, we directly examine whether the consumers associate the "same-price" guarantee with lower search costs relative to the channel-specific model.

Experimental Design

We recruited 300 people (69.0% female, M_{age} = 33.37) from a Chinese online subject pool to participate in the preregistered experiment. As background information, we told participants that they wanted to buy an electronic for home use and picked a retailer with both online and offline shops available. We then randomly assigned participants to one of two conditions: *channel-specific pricing* or *uniform pricing*. We told participants in the channel-specific pricing (control) condition that, for the same product, the prices in the online and offline shops might be different. Specifically, the participants in the control group read:

> *You noticed that, for the same product, sometimes it is the retailer's online shops offer a lower product price than the retailer's offline stores, and sometimes the retailer's offline stores offer a lower product price than the retailer's online stores. You enquire a customer representative about this issue, the customer representative explains: "it is possible that the online and offline store prices of the same product are different."*

Instead, we told those in the uniform pricing (treatment) condition that the prices in the online and offline shops were consistent (You noticed that, for the same product, the online shops and offline stores of the retailer offer the same product price.). Specifically, the participants in the control group read:

> *You noticed that, for the same product, the online shops and offline stores of the retailer offer the same product price. You enquire a customer representative about this issue, the customer representative explains: "For all products, we guarantee that the online and offline store prices of the same product are exact the same."*

On seven-point scales, the participants indicated their purchase intention, perceived ease of search (opposite of search cost), and age, gender, and household income, which served as covariates. We report the measurements in Table WCD1 and group-wise summary statistics in Table WC2. To check the validity of manipulation, we asked the participants to indicate whether the prices in the online and offline shops were consistent or not for the same product.

Table WC1. Measurement Scale

Variables	Measurement	Alpha
Purchase intention	1. To what extend do you want to choose the focal retailer to buy your selected product? 2. Given the same product, to what extent would you select the focal retailer for purchase? (1 extreme unlikely, 7 extreme likely)	.89
Ease of Search	1. For the same product, it is straightforward to compare the price information between the online and offline stores. 2. It is easy to find the information regarding the product availability and prices across the online and offline stores. 3. The evaluating and selecting process of whether to shop in online or offline stores are easy. 4. Assessing the differences in product attributes and benefits between online and offline stores is hassle-free. (1 = Strongly disagree, 7 = strongly agree)	.91
Age	May I know your age	NA
Gender	Please indicate your gender (0 = Male, 1 = Female, 2 = Others)	NA
Income	May I know your annual income? (1 = Less than ￥10,000, 8 = More than ￥300,000)	NA

Table WC2. Group-Wise Summary Statistics

Variables	Observations	Mean	S.D.	Min.	Max.
Control Group					
Purchase Intention	150	4.76	1.52	1.00	7.00
Ease of Search	150	4.91	1.65	1.00	6.75
Age	150	32.10	10.15	18.00	69.00
Gender	150	0.69	0.46	0.00	1.00
Income	150	4.36	1.74	0.00	7.00
Treated Group					
Purchase Intention	150	6.18	0.62	3.50	7.00
Ease of Search	150	5.96	0.64	3.00	7.00
Age	150	34.43	10.30	17.00	78.00
Gender	150	0.69	0.47	0.00	1.00
Income	150	4.53	1.79	1.00	7.00

Results

The manipulation check shows that 94.33% of participants correctly recalled their assigned condition, suggesting a successful manipulation. In Table WC2, we report the estimation results. Model 1 shows that participants in the treatment group had a higher purchase intention ($\beta = 1.411$, $p < 0.01$) than those in the control group, and Model 2 reveals that participants in the treatment group perceived the search more easily than those in the control group ($\beta = 1.021$, $p < 0.01$). These results suggest that our empirical findings in the field study are robust to potential spillover and contamination effects. Furthermore, Model 3 shows that the ease of search serves as a partial mediator of the relationship between *Treat* and purchase intention, as both *Treat* ($\beta = .946$, $p < .01$) and ease of search ($\beta = .456$ $p < .01$) significantly affected purchase intention. For the formal mediation analysis, we adopt the PROCESS model (Model 4; Hayes 2017); the results show that the indirect effect through ease of search is positive and significant (b = 0.466, 95% CI = [0.300, 0.650]). The results confirm our theorization that consumers associate the "same-price guarantee" with lower cross-channel search cost.

Table WC3. Estimation Results for the Controlled Experiment

	Model 1	Model 2	Model 3
Variables	**Purchase intention**	**Ease of search**	**Purchase intention**
Constant	4.557(.299)***	4.764(.309)***	2.384(.356)***
Treat	1.411(.132)***	1.021(.147)***	.946(.139)***
Ease of search			.456(.062)***
Age	-.003(.006)	.004(.007)	-.004(.006)
Gender	-.195(.138)	-.360(.152)**	-.030(.137)
Income	.095(.040)**	.064(.039)*	.066(.039)*
Adj. R^2	.293	.170	.463

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Web Appendix D. Technique Details for Individual-Level Analysis

The research dataset is the same as the product-level dataset, which involves 1,110,703 individual transactions between December 2012 and July 2014. The dataset comprises 161,784 individual consumers, 1.14% of whom were newly registered after the policy change. Because the unit of analysis is the individual consumer, we aggregate each consumer's individual transactions involving products affected by uniform pricing (i.e., treatment group) separately from the transactions involving products not affected by uniform pricing (i.e., control group). To minimize sparsity concerns, for each consumer, we aggregate transactions involving the two product groups (treated and control products) into one pretreatment and two posttreatment periods, with each period lasting for six months. Specifically, for consumer i at time t, $Sales_{i1t}$ is the number of purchased products affected by the policy change, and $Sales_{i0t}$ is the number of purchased products not affected.

Table WD1. Definitions and Summary Statistics for Consumer-Level Analysis

Variables	Operationalizations	Mean	SD	Min	Max
Sales	Number of units purchased for consumer i and product group j (0 for control group products and 1 for products in treated group) at time t.	1.14	1.77	0	42
Period1	Dummy Period1t = 1, indicating time t is in first quarter of the post-treatment period (Jun 2013 - Dec 2013).	0.33	0.47	0	1
Period2	Dummy Period2t = 1, indicating time t is in second quarter of the post-treatment period (Jan 2014 - Jun 2014).	0.33	0.47	0	1
Age	Consumer self-reported age.	39.79	9.99	15	88
Gender	Consumer self-reported gender, missing = 0, male = 1, female = 2, and unknown = 3.	1.69	1.02	0	3
Tenure	The number of days since the consumer registered as a member of the retailer (negative values refer to newly registered customer).	822.81	737.05	-1236	2524
Membership level	The consumer's membership level and 0 being the lowest level and 4 being the highest level.	1.13	1.48	0	4

Table WD2. Model Selection

Latent Segment	Log-Likelihood	# of Parameters	AIC	BIC
2	-715113.82	19	1430265.64	1430341.39
3	-699614.15	27	1399282.30	1399389.95
4	-633155.39	35	1266380.79	1266520.33
5	-296681.31	43	593448.62	593620.07
6	-506623.38	51	1013348.75	1013552.10
7	-601875.84	59	1203869.68	1204104.92
8	-531398.34	67	1062930.69	1063197.82

Web Appendix E. Post-Hoc Analysis and Managerial Implications

Post-Hoc Analysis 1

In post-hoc analysis 1, we aim to uncover the cumulative effects of adopting the uniform pricing on overall sales of retailers with varying levels of online sales ratio. We first conducted additional analysis on both online sales and offline sales with the model similar to equation (2), but with varying time window for the sample. Specifically, we use all the pretreatment sample and first t posttreatment weekly sample, where $t \in [1, N]$ and N is the largest number of weeks in the posttreatment period. This approach allows us to observe the cumulative treatment effects and determine when the retailer should expect positive sales. We run the regression for N times, and the estimated treatment effects represent the cumulative treatment effects in the first n weeks ($n \leq N$) after the implementation of the policy.

After estimating the weekly cumulative treatment effects on online sales (100% pretreatment online sales ratio) and offline sales (0% pretreatment online sales ratio), we also calculate cumulative treatment effects for retailers with varying levels of online sales ratio (from 10% to 90%). The results are reported in Table WE1, and we use the odds ratio to estimate the percentage changes in product sales.

Table WE1. Cumulative Sales after Policy Change

Weeks after Policy Change	Pretreatment Online Sales Ratio										
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
1	-0.37%	-0.33%	-0.28%	-0.23%	-0.19%	-0.14%	-0.10%	-0.05%	0.00%	0.04%	0.09%
2	-1.19%	-1.37%	-1.55%	-1.73%	-1.91%	-2.09%	-2.27%	-2.45%	-2.63%	-2.81%	-2.98%
3	-1.45%	-1.76%	-2.07%	-2.38%	-2.68%	-2.99%	-3.29%	-3.60%	-3.90%	-4.20%	-4.51%
4	-2.15%	-2.34%	-2.54%	-2.74%	-2.94%	-3.14%	-3.33%	-3.53%	-3.73%	-3.92%	-4.12%
5	-2.12%	-2.41%	-2.70%	-2.98%	-3.27%	-3.55%	-3.84%	-4.12%	-4.40%	-4.69%	-4.97%
6	-1.80%	-2.08%	-2.35%	-2.63%	-2.90%	-3.17%	-3.44%	-3.72%	-3.99%	-4.26%	-4.53%
7	-2.52%	-2.77%	-3.03%	-3.28%	-3.53%	-3.78%	-4.04%	-4.29%	-4.54%	-4.79%	-5.03%
8	-2.44%	-2.74%	-3.04%	-3.33%	-3.63%	-3.93%	-4.23%	-4.52%	-4.81%	-5.11%	-5.40%
9	-2.11%	-2.40%	-2.70%	-2.99%	-3.28%	-3.57%	-3.86%	-4.15%	-4.44%	-4.73%	-5.01%
10	-1.93%	-2.27%	-2.60%	-2.94%	-3.27%	-3.61%	-3.94%	-4.27%	-4.60%	-4.93%	-5.26%
11	-1.74%	-2.10%	-2.46%	-2.82%	-3.17%	-3.53%	-3.88%	-4.23%	-4.58%	-4.93%	-5.28%
12	-1.60%	-2.01%	-2.42%	-2.83%	-3.24%	-3.64%	-4.05%	-4.45%	-4.85%	-5.25%	-5.64%
13	-1.53%	-1.90%	-2.26%	-2.63%	-2.99%	-3.35%	-3.71%	-4.07%	-4.43%	-4.79%	-5.14%
14	-1.56%	-1.91%	-2.26%	-2.60%	-2.95%	-3.29%	-3.63%	-3.98%	-4.32%	-4.66%	-4.99%
15	-1.71%	-2.00%	-2.30%	-2.59%	-2.88%	-3.16%	-3.45%	-3.74%	-4.03%	-4.31%	-4.59%
16	-1.67%	-1.93%	-2.19%	-2.44%	-2.70%	-2.95%	-3.21%	-3.46%	-3.72%	-3.97%	-4.22%
17	-1.50%	-1.81%	-2.12%	-2.43%	-2.74%	-3.05%	-3.35%	-3.66%	-3.96%	-4.27%	-4.57%
18	-1.01%	-1.37%	-1.73%	-2.09%	-2.45%	-2.81%	-3.17%	-3.52%	-3.87%	-4.23%	-4.58%
19	-0.82%	-1.19%	-1.55%	-1.91%	-2.26%	-2.62%	-2.98%	-3.33%	-3.68%	-4.04%	-4.39%
20	-0.62%	-0.99%	-1.36%	-1.73%	-2.10%	-2.47%	-2.83%	-3.20%	-3.56%	-3.92%	-4.28%
21	-0.71%	-1.08%	-1.45%	-1.81%	-2.17%	-2.53%	-2.90%	-3.25%	-3.61%	-3.97%	-4.32%
22	-0.35%	-0.77%	-1.20%	-1.62%	-2.04%	-2.46%	-2.88%	-3.30%	-3.71%	-4.12%	-4.53%
23	-0.03%	-0.45%	-0.86%	-1.28%	-1.69%	-2.10%	-2.51%	-2.92%	-3.32%	-3.73%	-4.13%
24	0.26%	-0.19%	-0.64%	-1.09%	-1.53%	-1.97%	-2.41%	-2.85%	-3.29%	-3.73%	-4.16%
25	0.29%	-0.14%	-0.57%	-0.99%	-1.42%	-1.84%	-2.26%	-2.68%	-3.10%	-3.51%	-3.93%
26	0.48%	0.03%	-0.43%	-0.88%	-1.33%	-1.78%	-2.23%	-2.67%	-3.12%	-3.56%	-4.00%
27	0.57%	0.12%	-0.33%	-0.78%	-1.22%	-1.66%	-2.11%	-2.54%	-2.98%	-3.42%	-3.85%
28	0.76%	0.31%	-0.14%	-0.58%	-1.02%	-1.47%	-1.91%	-2.34%	-2.78%	-3.21%	-3.64%
29	0.88%	0.43%	-0.01%	-0.45%	-0.88%	-1.32%	-1.75%	-2.18%	-2.61%	-3.04%	-3.47%
30	1.09%	0.65%	0.21%	-0.23%	-0.66%	-1.10%	-1.53%	-1.96%	-2.38%	-2.81%	-3.23%
31	1.26%	0.84%	0.43%	0.01%	-0.40%	-0.81%	-1.21%	-1.62%	-2.02%	-2.43%	-2.83%
32	1.29%	0.88%	0.47%	0.06%	-0.34%	-0.75%	-1.15%	-1.55%	-1.95%	-2.35%	-2.75%
33	1.28%	0.90%	0.52%	0.14%	-0.24%	-0.61%	-0.99%	-1.36%	-1.74%	-2.11%	-2.48%
34	1.37%	1.00%	0.63%	0.26%	-0.11%	-0.47%	-0.83%	-1.20%	-1.56%	-1.92%	-2.27%
35	1.54%	1.18%	0.82%	0.46%	0.11%	-0.24%	-0.60%	-0.95%	-1.30%	-1.65%	-1.99%
36	1.75%	1.41%	1.06%	0.71%	0.37%	0.03%	-0.32%	-0.66%	-1.00%	-1.33%	-1.67%
37	1.97%	1.63%	1.28%	0.94%	0.60%	0.27%	-0.07%	-0.41%	-0.74%	-1.08%	-1.41%
38	2.08%	1.74%	1.41%	1.08%	0.74%	0.41%	0.09%	-0.24%	-0.57%	-0.90%	-1.22%
39	2.11%	1.80%	1.50%	1.19%	0.89%	0.59%	0.29%	-0.01%	-0.31%	-0.61%	-0.91%
40	2.15%	1.86%	1.58%	1.30%	1.02%	0.74%	0.46%	0.18%	-0.10%	-0.38%	-0.66%
41	2.37%	2.09%	1.81%	1.54%	1.26%	0.98%	0.70%	0.43%	0.15%	-0.12%	-0.40%
42	2.57%	2.28%	2.00%	1.71%	1.43%	1.14%	0.86%	0.58%	0.29%	0.01%	-0.27%
43	2.61%	2.36%	2.11%	1.86%	1.61%	1.36%	1.11%	0.86%	0.62%	0.37%	0.12%
44	2.73%	2.48%	2.22%	1.97%	1.72%	1.47%	1.22%	0.97%	0.72%	0.47%	0.22%
45	2.71%	2.48%	2.26%	2.03%	1.80%	1.58%	1.35%	1.13%	0.91%	0.68%	0.46%
46	2.89%	2.65%	2.41%	2.18%	1.95%	1.71%	1.48%	1.25%	1.01%	0.78%	0.55%
47	2.96%	2.74%	2.51%	2.29%	2.07%	1.85%	1.63%	1.41%	1.19%	0.98%	0.76%
48	2.97%	2.77%	2.57%	2.37%	2.17%	1.97%	1.78%	1.58%	1.38%	1.19%	0.99%
49	3.15%	2.94%	2.74%	2.54%	2.33%	2.13%	1.93%	1.73%	1.52%	1.32%	1.12%
50	3.31%	3.11%	2.90%	2.70%	2.50%	2.30%	2.10%	1.90%	1.70%	1.50%	1.30%
51	3.49%	3.27%	3.05%	2.83%	2.61%	2.39%	2.17%	1.96%	1.74%	1.52%	1.31%

Notes. The simulation is conducted based on the variations of equation 2. The values in the cells represent the cumulative treatment effects from the 1st to the specific week in the posttreatment period. The cells in gray indicate the first week where the cumulative treatment effects become positive.

Post-Hoc Analysis 2

In post-hoc analysis 1, we analyze the periods of time the retailers would tolerate the overall sales loss, if the retailers take the similar approach when determining the uniform prices (i.e., medium price to maintain certain margin rate). In post-hoc analysis 2, we aim to uncover the cumulative effects of adopting the uniform pricing strategy on the product sales for retailers with different price adjustment strategy.

Similar to Post-Hoc Analysis 1, We first conducted additional analysis on both online sales and offline sales with the regression model similar to the mechanism testing regarding price adjustments (Table WA9 in Web Appendix A), but with varying time-window for the sample: We use all the pretreatment sample and first *t* quarters of the posttreatment sample, where t $\in$ [1, 4]. In other words, we run the same regression for four times, with the first regression estimating the treatment effects in the first quarter of the posttreatment period, second regression estimating the treatment effects in the first and second quarters of the posttreatment period, third regression estimating the treatment effects in the first, second, and third quarter of the posttreatment period, and fourth regression estimating the overall treatment effects.

With the four sets of the estimated coefficients, we then calculate the expected effects on online and offline sales with varying levels of price adjustments. We allow the price adjustment to range from -50% to +50% for both online and offline prices. The results are reported in Table WE2, and we use the odds ratio to estimate the percentage changes in product sales.

Table WE2. Sales Effects across Price Adjustment Levels

Posttreatment Period	**Online Price Adjustment (Proportion to Pretreatment Price)**										
	-50%	-40%	-30%	-20%	-10%	0%	+10%	+20%	+30%	+40%	+50%
1st quarter	72.7%	55.6%	40.1%	26.2%	13.7%	2.4%	-7.9%	-17.3%	-25.7%	-33.2%	-40.0%
1st and 2nd quarters	83.0%	63.5%	46.2%	30.6%	16.7%	4.3%	-5.1%	-13.7%	-21.5%	-28.7%	-35.1%
1st to 3rd quarters	100.1%	76.2%	55.1%	36.5%	20.2%	5.8%	-2.1%	-9.5%	-16.3%	-22.5%	-28.4%
Overall	118.9%	90.0%	64.9%	43.2%	24.3%	7.9%	0.6%	-6.2%	-12.6%	-18.5%	-24.0%
Posttreatment Period	**Offline Price Adjustment (Proportion to Pretreatment Price)**										
	-50%	-40%	-30%	-20%	-10%	0%	+10%	+20%	+30%	+40%	+50%
1st quarter	16.4%	13.1%	9.8%	6.7%	3.6%	0.6%	-8.4%	-16.5%	-24.0%	-30.7%	-36.9%
1st and 2nd quarters	30.3%	24.4%	18.7%	13.2%	8.0%	3.1%	-3.9%	-10.4%	-16.4%	-22.1%	-27.4%
1st to 3rd quarters	28.7%	23.4%	18.4%	13.5%	8.8%	4.4%	-2.6%	-9.1%	-15.2%	-20.9%	-26.2%
Overall	32.6%	26.5%	20.6%	15.1%	9.8%	4.7%	-2.0%	-8.4%	-14.3%	-19.8%	-25.0%

Notes. The values in the cells represent the percentages changes in sales (using odds ratio) considering the proportional price adjustment.