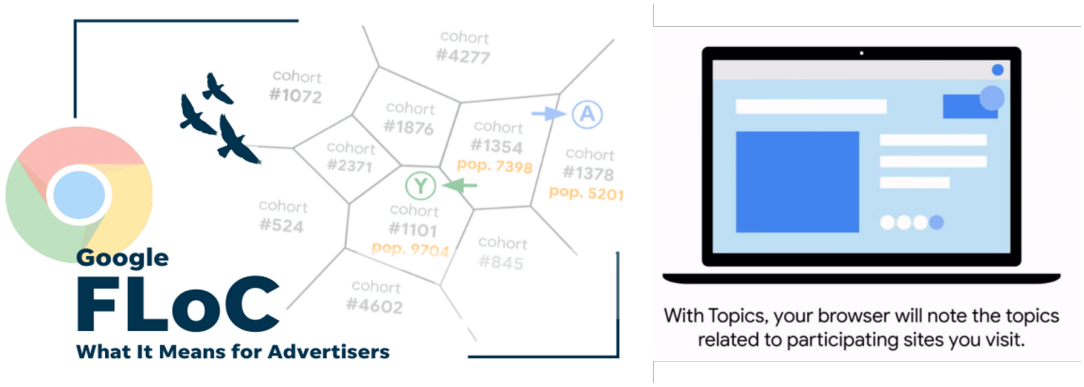
Online Appendix

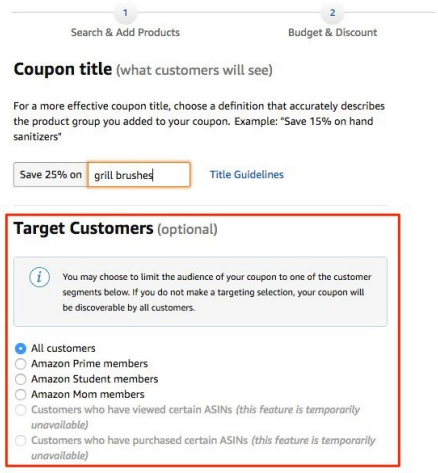
A Platform information provision in practices

A.1 Segmentation: reveal partial information about consumers for targeting

(a) Google: topics of interest



(b) Amazon: membership or history



(c) eBay: pre-defined consumer groups

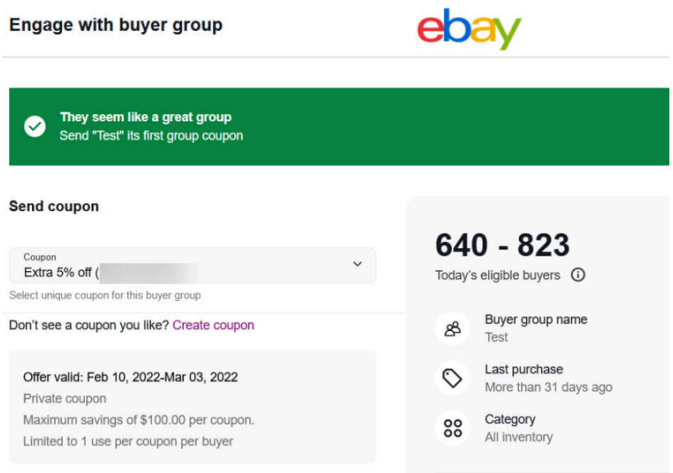


Figure A.1: Segmentation for Targeting: Google, Amazon, and eBay

Figure A.1 illustrates how platforms enable sellers (or advertisers) to target consumers in groups by providing predefined labels or segment lists. These examples suggest that information provision through segmentation is technically feasible through the platform's design of infrastructure, without the transfer of raw consumer data across business entities.

A central challenge for platforms is striking the right balance between segment granularity and privacy protection. In 2022, for example, Google replaced its fine-grained Federated Learning of Cohorts (FLoC) ini-

tiative with the broader Topics API to reduce re-identification risks and enhance user privacy, demonstrating the importance of using coarser segmentation for effective targeting.

A.2 Number of possible information designs: Derivation

Let X be a finite set consisting of n consumer types in the market. A *partition* of X can be defined as a collection of disjoint nonempty type subsets of X, whose union is X. For example, for $X = \{a, b, c\}$, there are 5 possible partitions:

$$\{\{a\},\{b\},\{c\}\}, \quad \{\{a,b\},\{c\}\}, \quad \{\{a,c\},\{b\}\}, \quad \{\{b,c\},\{a\}\}, \quad \{\{a,b,c\}\}.$$

Conceptually, each partition corresponds to a particular information design which constrains how sellers can target consumer types a, b, and c. Next, we show that the number of possible partitions, and thus information designs, depends solely on the cardinality of X— n. We denote this number as $B(n)$, which is the n-th Bell number (Bell, 1934; Rota, 1964).

Proof of the recursive formula for $B(n)$. Consider a set of $n+1$ elements, and denote the $(n+1)$-th element x. Note that for any partition of the set, element x must be in one of the subsets. There are two possibilities: First, x is in a subset by itself. In this case, the remaining n elements must be partitioned, and there are $B(n)$ ways to do this. In the second case, x is in a subset with some other elements. To count the possible partitions in this case, we can partition the n elements into k subsets ($k \in \{1, 2, ...n\}$), and add x to one of these k subsets. Therefore, we have:

$$B(n+1) = B(n) + \sum_{k=1}^{n} k \cdot S(n,k), \tag{16}$$

where $S(n,k)$ indicates the Stirling numbers of the second kind, which calculate the number of ways to partition n elements into k subsets. Through algebraic manipulation and the relationship between Stirling numbers and binomial coefficients, the formula of $B(n+1)$ can be transformed into:

$$B(n+1) = \sum_{k=0}^{n} \binom{n}{k} B(k), \text{ where } B(0) = 1. \tag{17}$$

Growth Rate of Bell Numbers. It is noteworthy that $B(n)$ grow faster than exponentially as n increases. To illustrate, we have the following Bell numbers following the recurrence formula:

$$\begin{aligned} B(4) &= 15 \\ B(5) &= 52 \\ B(6) &= 203 \\ B(7) &= 877 \\ B(8) &= 4140 \\ B(9) &= 21147 \\ B(10) &= 115975 \end{aligned} \tag{18}$$

The growth rate highlights the high-dimensional nature of the information design problem and the rising computational cost as the number of consumer types increases.

B Additional industry details and descriptive patterns

B.1 Competition outside Steam: negligible

One may wonder whether Steam competes against other major platforms. To check the relative size of Steam to its competitors, we collect search data from Google Trends to compare the number of search queries for Steam and its major competitors, Origin (developed by Electronic Arts), Epic Store (developed by Epic Games), and Uplay (developed by Ubisoft). As shown in Figure B.1, the search volume for all three competitor platforms are negligible compared to that for Steam, confirming Steam's near-monopoly position in the PC-gaming market.

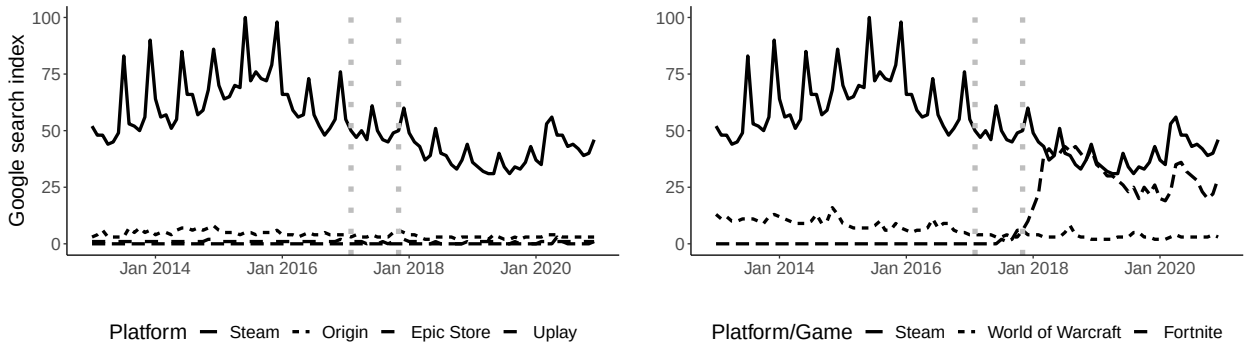


Figure B.1: Steam takes a near-monopoly position for PC-based gaming.

Note: In both figures, the gray dotted lines denote the start and end of our sample period. The vertical axis measures the Google search index, normalized by the highest value among the platforms (or games) in comparison.

We also compare the search for Steam against two major PC games outside of any platform. The first one is *World of Warcraft*, released by Blizzard Entertainment in 2004, and the second one is *Fortnite*, released by Epic Games in 2017. Both games had low search volumes during our sample period, as the craze for *World of Warcraft* had already faded, while the spike of interest in *Fortnite* had not arrived. Hence, we do not consider them as major substitutes for games inside Steam.

B.2 Tags and meta-tags

We present an example of user-generated tags in Figure B.2 and the defined Meta-tags in Table B.1.

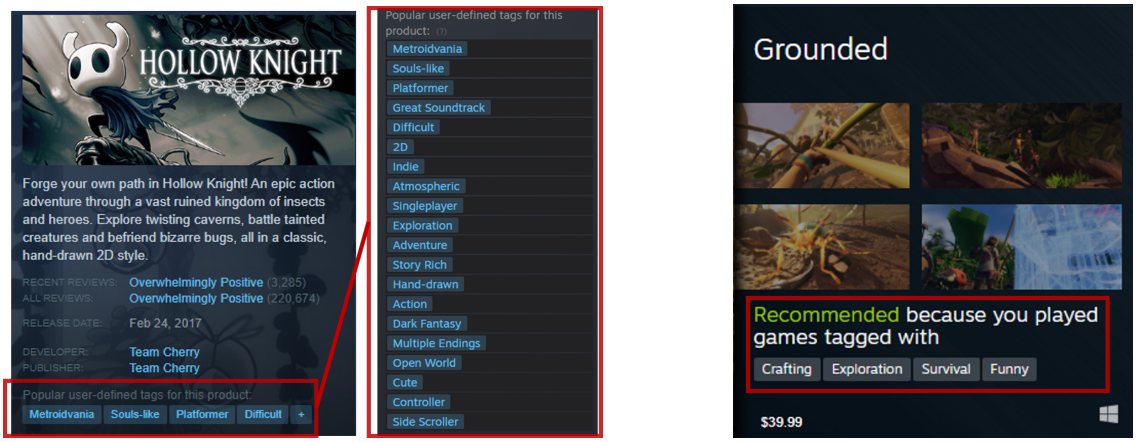


Figure B.2: Example of user-generated tags

Table B.1: Meta-tags Defined

	Meta-Tag	Number of Original Tags	Popular Original Tags
1	fantasy	25	classic, comedy, fantasy, horror, sci-fi
2	multiplayer	5	arcade, co-op, fps, mmorpg, moba
3	military	12	rts, slash, stealth, tactical, war
4	dark	20	dark, gore, nudity, sexual, violent
5	survival	17	building, crafting, management, resource, survival
6	platformer	3	isometric, platformer, tps
7	anime	7	anime, cartoon, cartoony, hentai, memes
8	team	8	city, football, sports, team, trading
9	adventure	11	agriculture, exploration, flight, pirates, space

Note: For each meta-tag, we present the top five most frequently used original tags.

B.3 Consumer Learning: negligible

One might wonder whether consumer learning plays a significant role in the video game market, especially given the nature of content goods. If consumers engage in learning— either about product quality or how well different content features match their preferences— our static demand model could misrepresent the true distribution of consumer heterogeneity. As discussed in Section 4.1, we argue that learning is minimal

in the Steam market due to the abundance of information available about game quality and the maturity of most Steam users. We further validate this claim by examining consumers' return behavior and their evolving preferences for content features over time below.

Steam offers a generous return policy, allowing consumers to return a game within two weeks of purchase (or within two days during game-specific free weekends). As we exclude all returned games from our purchase panel, we find regular returns account for only 3.8% of initial purchases, suggesting that consumers face limited uncertainty about game quality. We then analyze whether consumers change their preferences for game features over time. Specifically, for each consumer, we compare the features of their first five purchases in the sample period to those of their last five. As shown in Figure B.3, the distributions are largely similar across consumers, indicating minimal shifts in preferences and suggesting that consumer demand remains stable during our sample period.

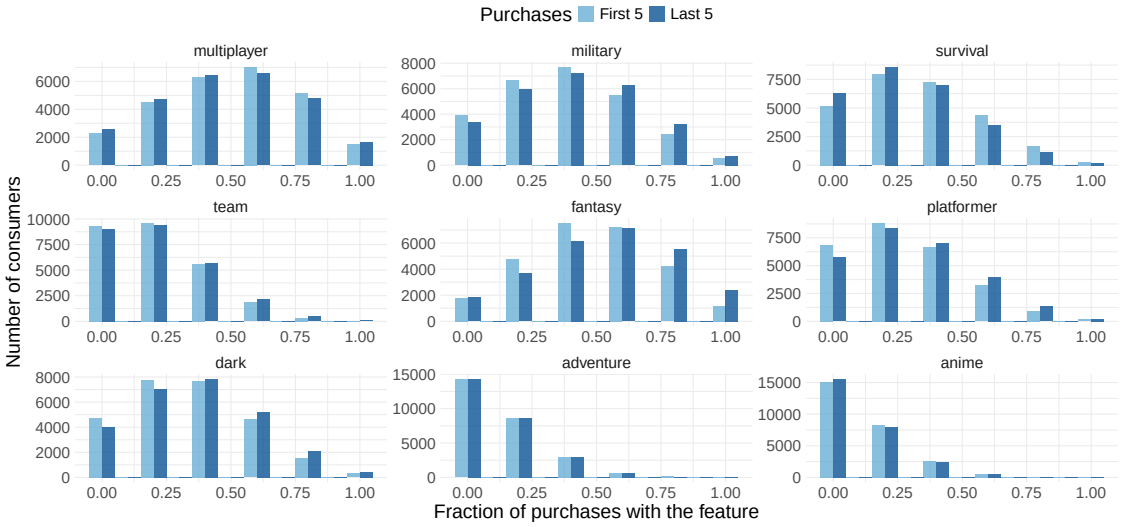


Figure B.3: What features consumers buy (first 5 vs. last 5 purchases)

B.4 Pricing patterns on Steam

We examine how typical game prices evolve over time on Steam. To capture the full pricing trajectory, we focus on the 1,434 games released between January 2015 and December 2018, tracking their price paths through December 2020 to ensure at least 24 months of observation for each title.

As shown in Figure B.4, a game's regular (list) price tends to remain stable over time. In contrast, developers frequently adjust the effective prices through discounts, with the depth of discount gradually increasing as the game ages. However, unlike the patterns observed in Nair (2007), the overall decline in effective prices is modest, with little additional change once a game is more than a year old.

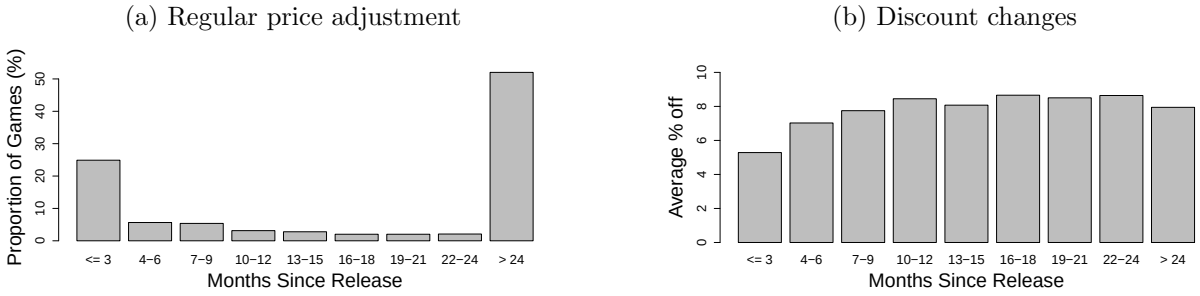


Figure B.4: Gradual price decline over time.

Price declines slowly over time. Notably, intertemporal price variation is driven primarily by discounts rather than changes in regular prices. As shown in Figure B.4a, only 25% of games adjust their regular prices within the first three months after release, while more than half never change their regular prices within the first two years. Meanwhile, although the average discount increases over time, as shown in Figure B.4b, the decline is gradual and modest in magnitude.

To further isolate within-game price changes over time, we estimate a regression of game prices on months since release, controlling for game fixed effects. Table B.2 reports results for three measures: average monthly price, lowest (effective) monthly price, and maximum monthly discount relative to the release price. All three measures show a gradual decline post-release. Average and effective prices fall by about \$0.07 per month, with discounts increasing by 0.46% per month. These modest declines suggest that consumers have limited incentives to delay purchases on Steam, in contrast to the more pronounced intertemporal pricing effects observed in the console market (Nair, 2007).

Table B.2: Effective game prices decline slowly after releases.

	Average price (\$)	Effective price (\$)	Effective discount (% off)
	(1)	(2)	(3)
Month(s) Since Release	-0.07^{***}	-0.07^{***}	0.46^{***}
	(0.001)	(0.001)	(0.005)
Game FE	Yes	Yes	Yes
Observations	137,041	137,041	137,041
R^2	0.90	0.78	0.47
Adjusted R^2	0.90	0.77	0.46
Residual Std. Error (df = 135609)	4.33	5.91	27.90
Note:			*p<0.1; **p<0.05; ***p<0.01

Identifying variations for price sensitivities. To illustrate the variation that identifies price sensitivities, Figure B.5 shows the pricing path and corresponding demand for *Hearts of Iron IV* as an example. As seen in the figure, sharp price discounts are typically followed by immediate spikes in purchases.

These purchase surges around discount events help identify consumer price sensitivity.

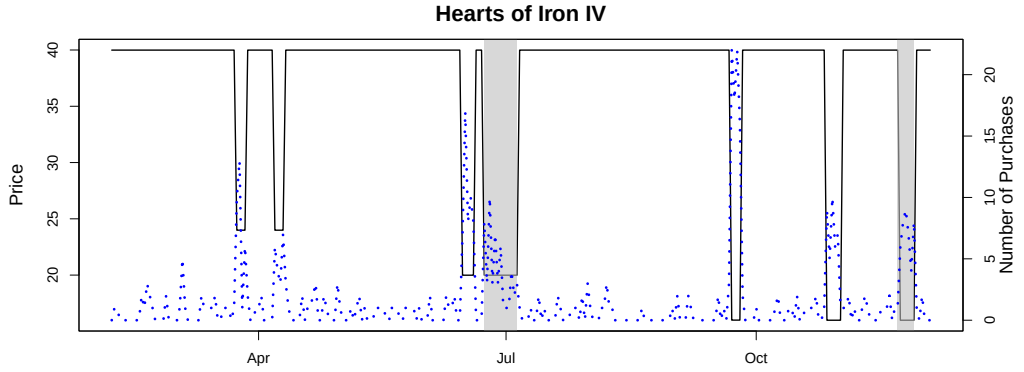


Figure B.5: Price and purchases: February 6th, 2017 to December 4th, 2017

Note: We plot the daily number of purchases among sample users against the price changes over time. The black line represents the price path, while the blue dotted lines represent the purchase path. The shaded areas represent the two major sales events on Steam — the summer sales event and the autumn sales event.

One potential concern is that our estimated price sensitivities around steep discounts may reflect inventory stockpiling-driven demand spikes, thereby biasing the coefficients downward. To address this, we test robustness by controlling for major Steam events (e.g., Summer and Autumn sales).

Table B.3 reports a reduced-form specification on the same game sample used in our structural estimation. Adding indicators for the pre-sale and during-sale weeks yields only a mild difference in the price coefficient, and both coefficients are statistically insignificant— evidence against systematic stockpiling.

Table B.3: Robustness Check: stockpiling before sales event

	log(Purchase + 1)	
	(1)	(2)
Price	-0.054^{***}	-0.051^{***}
	(0.004)	(0.004)
Pre-event		-0.036
		(0.071)
Sales-event		0.112
		(0.073)
Game-Month FE	yes	yes
Clustered S.E.	Game	Game
Observations	6,797	6,797
R^2	0.700	0.700
Adjusted R^2	0.595	0.596
Residual Std. Error	0.657 (df = 5035)	0.656 (df = 5033)
Note:		*p<0.1; **p<0.05; ***p<0.01

C Additional Model Details

C.1 Monte-Carlo Simulation

This subsection validates our demand model through Monte Carlo simulations. We consider a market with 10 video games and two consumer types—heavy (30% of the market) and light (70% of the market)—who differ in purchase intensity, usage intensity, and price sensitivity (Table C.1). Consumers make purchase decisions based on expected future usage and the additional value of expanding their game library. We simulate consumer purchase and usage behavior for 6000 consumers and 240 days, approximating our structural sample. We implement estimation for $MC = 30$.

Table C.1: Parameter Estimates from Full Sample and Later Half, with and without Usage

	True	Full Sample		Later Half		Full Sample (No usage)		Later Half (No usage)	
Parameter	Value	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Usage-game1	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game2	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game3	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game4	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game5	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game6	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game7	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game8	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game9	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
Usage-game10	1.00	1.00	(0.00)	1.00	(0.00)	–	–	–	–
γ	0.60	0.60	(0.00)	0.60	(0.00)	–	–	–	–
σ	1.00	1.0	(0.00)	1.01	(0.01)	–	–	–	–
Purchase-game1	-0.50	-0.47	(0.02)	-0.44	(0.04)	1.64	(0.01)	0.64	(0.05)
Purchase-game2	-0.50	-0.47	(0.02)	-0.43	(0.03)	1.38	(0.01)	0.77	(0.04)
Purchase-game3	-1.00	-0.97	(0.02)	-0.91	(0.03)	0.60	(0.01)	0.56	(0.04)
Purchase-game4	-1.00	-0.99	(0.02)	-0.94	(0.04)	0.70	(0.01)	0.52	(0.05)
Purchase-game5	-1.50	-1.47	(0.02)	-1.42	(0.03)	0.04	(0.01)	0.12	(0.04)
Purchase-game6	-1.50	-1.48	(0.02)	-1.43	(0.04)	0.07	(0.01)	0.18	(0.04)
Purchase-game7	-2.00	-1.98	(0.02)	-1.91	(0.04)	-0.45	(0.02)	-0.26	(0.05)
Purchase-game8	-2.00	-1.98	(0.02)	-1.92	(0.04)	-0.49	(0.02)	-0.37	(0.05)
Purchase-game9	-2.50	-2.49	(0.02)	-2.44	(0.04)	-0.96	(0.01)	-0.89	(0.06)
Purchase-game10	-2.50	-2.51	(0.02)	-2.49	(0.04)	-1.03	(0.02)	-0.96	(0.05)
α	2.00	2.01	(0.01)	2.04	(0.02)	1.68	(0.00)	1.66	(0.02)
Hetero-usage$_{\text{diff}}$	-1.00	-1.00	(0.00)	-1.00	(0.00)	–	–	–	–
Hetero-purchase$_{\text{diff}}$	-1.00	-0.99	(0.04)	-1.02	(0.09)	1.71	(0.04)	1.04	(0.09)
Hetero-alpha$_{\text{diff}}$	2.00	2.01	(0.02)	2.01	(0.04)	2.28	(0.02)	1.56	(0.04)
Fraction of type 1	0.30	0.30	(0.00)	0.30	(0.00)	0.30	(0.00)	0.07	(0.00)

Note: We simulate consumer purchase and usage behavior for 6000 consumers and 240 days, approximating our structural sample. We implement estimation for $MC = 30$ and the number of games equal to 10 to keep the simulation tractable. The type 1 consumers are the heavy type, who take 30% of the market.

Table C.1 reports the true parameter values (first column) and compares estimator performance across four scenarios: estimating on the full simulated sample versus only the latter half, each with and without modeling the usage stage. When applied to the full data path, the estimator recovers both homogeneous and heterogeneous parameters without bias. Restricting estimation to the second half—mirroring our empirical

setting, where non-empty initial game libraries could introduce biases from endogenous initial conditions—turns out to introduce only minimal bias in the recovered parameters when the usage stage is modeled. We assess whether a model estimated using only purchase-stage data can recover the true distribution of consumer types by comparing the last two columns of Table C.1. Although the estimator exhibits only minor bias when the full sample is used, the estimated distribution becomes severely distorted when relying solely on the second half of the sample. This finding highlights the potential bias of using purchase data alone for estimation, particularly given the absence of purchase history prior to the start of our sample period.

To further investigate the potential bias from the endogenous initial library, we next extend our simulations to a broader range of parameter values. Specifically, we vary two key parameters: the difference in purchase intercepts across types, which governs heterogeneity, and the baseline of purchase intercepts, which governs overall purchase activities of both types. Holding all other parameters at the values in Table C.1, we re-estimate the model using only second-half data and report the key behavioral summary statistics and resulting parameter estimates in Table C.2. We find that meaningful bias only arises in extreme cases. The bias diminishes as the difference in purchase intercepts shrinks and the low type's engagement level rises, and it remains minimal across a broad range of parameter values that imply a wide dispersion in initial libraries.

To further isolate whether it is the magnitude of heterogeneity or the baseline level of purchase intercepts that drives these results, we hold the difference in purchase intercepts at the extreme value of -5 while shifting the baseline purchase intercepts upward, reporting results in Table C.3. Again, despite persistent dispersion in initial library sizes, estimation bias remains negligible unless the low type's engagement level is extremely low, and our estimation using the second-half periods successfully recovers the true distribution of types.

Because the main sample used in our paper consists predominantly of active Steam users with nontrivial usage histories and ongoing purchase activity, it is unlikely that our empirical setting corresponds to these extreme cases. We therefore view the resulting bias as minor and unlikely to affect our conclusions qualitatively.

C.2 Demand-side: Estimation details

This subsection outlines the construction of the sub-sample used for structural estimation, presents the individual likelihood function based on observed purchases and usage behavior, and describes the selection of R through model fit comparisons.

Structural sample construction. We retain a final sample of $34,607$ active users who exhibited both positive spending and usage throughout the sample period and remained on Steam through at least November 2017. This user sample is used to construct the summary statistics of consumer behavior in Section 3. Summary statistics on seller pricing patterns, also reported in Section 3, are based on the full sample of games.

Due to computational constraints, we draw a sub-sample of users and video games for structural estima-

Table C.2: Sensitivity to Heterogeneous Purchase Parameter

	True Val	$b=-5$	$b=-4.5$	$b=-4$	$b=-3.5$	$b=-3$	$b=-2.5$	$b=-2$	$b=-1.5$	$b=-1$	$b=-0.5$	$b=0$
owned_initially (High Type)	-	2.85	2.85	2.85	2.85	2.85	2.85	2.85	2.85	2.85	2.85	2.85
owned_initially (Low Type)	-	0.01	0.02	0.03	0.04	0.07	0.11	0.18	0.28	0.41	0.59	0.79
purchases (High Type)	-	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
purchases (Low Type)	-	0.01	0.01	0.02	0.03	0.05	0.08	0.12	0.17	0.22	0.25	0.25
Usage-game1	1.00	1.01	1.01	0.94	0.77	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game2	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game3	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game4	1.00	1.01	1.01	0.95	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game5	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game6	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game7	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game8	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game9	1.00	1.01	1.01	0.94	0.77	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game10	1.00	1.01	1.01	0.94	0.77	1.00	1.00	1.00	1.00	1.00	1.00	1.00
γ	0.60	0.60	0.60	0.60	0.61	0.60	0.60	0.60	0.60	0.60	0.60	0.60
σ	1.00	1.28	1.27	1.43	0.78	0.99	1.03	1.01	1.01	1.01	1.01	1.02
Purchase-game1	-0.50	-0.42	-0.51	-0.48	-0.21	-0.47	-0.44	-0.42	-0.43	-0.44	-0.43	-0.45
Purchase-game2	-0.50	-0.47	-0.55	-0.50	-0.13	-0.48	-0.45	-0.43	-0.42	-0.43	-0.43	-0.43
Purchase-game3	-1.00	-0.83	-0.95	-0.78	-0.36	-0.94	-0.94	-0.91	-0.91	-0.91	-0.92	-0.92
Purchase-game4	-1.00	-0.86	-0.97	-0.81	-0.40	-0.97	-0.97	-0.94	-0.93	-0.94	-0.94	-0.95
Purchase-game5	-1.50	-1.36	-1.47	-1.29	-0.82	-1.45	-1.46	-1.43	-1.42	-1.42	-1.42	-1.43
Purchase-game6	-1.50	-1.35	-1.47	-1.29	-0.82	-1.45	-1.46	-1.44	-1.43	-1.43	-1.43	-1.44
Purchase-game7	-2.00	-1.82	-1.94	-1.74	-1.30	-1.94	-1.95	-1.92	-1.91	-1.91	-1.91	-1.91
Purchase-game8	-2.00	-1.83	-1.94	-1.75	-1.30	-1.94	-1.96	-1.92	-1.92	-1.92	-1.92	-1.92
Purchase-game9	-2.50	-2.33	-2.44	-2.25	-1.81	-2.44	-2.46	-2.44	-2.42	-2.44	-2.42	-2.41
Purchase-game10	-2.50	-2.41	-2.52	-2.32	-1.88	-2.52	-2.53	-2.51	-2.50	-2.49	-2.49	-2.51
α	2.00	2.11	2.10	2.35	2.51	2.04	2.04	2.04	2.04	2.04	2.04	2.04
Hetero-purchase_diff (b)	(Varying)	-5.74	-5.50	-6.19	-3.28	-2.71	-2.57	-2.02	-1.51	-1.02	-0.54	-0.05
Hetero-usage_diff	-1.00	-0.48	-0.62	-0.30	-0.56	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
Hetero-alpha_diff	2.00	2.43	2.16	1.73	1.64	2.10	2.02	2.02	2.01	2.01	2.00	2.00
Type1fraction	0.30	0.23	0.25	0.21	0.33	0.31	0.30	0.30	0.30	0.30	0.30	0.30

Note: We simulate consumer purchase and usage behavior for 6000 consumers and 240 days, approximating our structural sample. We implement estimation for $MC = 30$ and the number of games equal to 10 to keep the simulation tractable. Throughout the simulations, we only use the second half of the period to mimic the scenario where the initial library is endogenous. The type 1 consumers are the heavy type, who take 30% of the market. Across columns, we vary the difference in purchase intercepts (b) between the low type and the high type from -5 to 0, while holding all other parameters fixed at their values set in Table C.1. For each b value, we also report the key summary statistics across heterogeneous types, including the type-specific average initial library size and the average number of games purchased in the second half of the period.

Table C.3: Sensitivity to Baseline Game Intercepts

Row	True Val	$s=0$	$s=0.5$	$s=1$	$s=1.5$	$s=2$	$s=2.5$	$s=3$	$s=3.5$	$s=4$	$s=4.5$	$s=5$
owned_initially (High Type)	-	2.85	3.23	3.64	4.05	4.49	4.93	5.39	5.86	6.31	6.75	7.18
owned_initially (Low Type)	-	0.01	0.02	0.03	0.04	0.07	0.11	0.18	0.28	0.41	0.59	0.79
purchases (High Type)	-	0.65	0.74	0.85	0.97	1.12	1.26	1.41	1.55	1.68	1.80	1.88
purchases (Low Type)	-	0.01	0.01	0.02	0.03	0.05	0.08	0.12	0.17	0.22	0.25	0.25
Usage-game1	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game2	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game3	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game4	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game5	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game6	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game7	1.00	1.01	1.01	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game8	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game9	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Usage-game10	1.00	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
γ	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
σ	1.00	1.28	1.66	1.08	1.03	1.00	1.02	1.00	0.99	1.01	1.01	1.02
Purchase-game1	$-0.50+s$	-0.42	-0.22	0.53	1.02	1.54	1.98	2.52	2.99	3.47	3.96	4.44
Purchase-game2	$-0.50+s$	-0.47	-0.29	0.52	1.04	1.54	2.01	2.53	3.01	3.49	3.98	4.47
Purchase-game3	$-1.00+s$	-0.83	-0.54	0.04	0.54	1.05	1.50	2.03	2.53	3.01	3.49	3.98
Purchase-game4	$-1.00+s$	-0.86	-0.56	0.02	0.52	1.04	1.49	2.00	2.50	2.99	3.46	3.96
Purchase-game5	$-1.50+s$	-1.36	-1.06	-0.48	0.02	0.54	1.00	1.52	2.02	2.50	2.99	3.47
Purchase-game6	$-1.50+s$	-1.35	-1.04	-0.48	0.03	0.55	1.00	1.51	2.03	2.52	2.99	3.46
Purchase-game7	$-2.00+s$	-1.82	-1.49	-0.94	-0.43	0.07	0.52	1.05	1.53	2.02	2.50	2.96
Purchase-game8	$-2.00+s$	-1.83	-1.50	-0.95	-0.45	0.06	0.50	1.03	1.52	2.02	2.50	2.97
Purchase-game9	$-2.50+s$	-2.33	-1.97	-1.46	-0.96	-0.45	0.01	0.54	1.03	1.51	1.99	2.46
Purchase-game10	$-2.50+s$	-2.41	-2.06	-1.55	-1.02	-0.50	-0.03	0.51	1.00	1.50	1.98	2.45
α	2.00	2.11	2.17	2.05	2.03	2.02	2.01	2.01	2.00	2.00	2.00	1.99
Hetero-purchase_diff	-5.00	-5.74	-7.86	-5.07	-4.94	-4.81	-4.99	-4.93	-4.87	-4.92	-4.93	-4.95
Hetero-usage_diff	-1.00	-0.48	-0.09	-0.94	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
Hetero-alpha_diff	2.00	2.43	2.16	2.15	2.10	2.11	2.05	2.05	2.05	2.05	2.05	2.05
Type1fraction	0.30	0.23	0.19	0.29	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30

Note: We simulate consumer purchase and usage behavior for 6000 consumers and 240 days, approximating our structural sample. We implement estimation for $MC = 30$ and the number of games equal to 10 to keep the simulation tractable. Throughout the simulations, we only use the second half of the period to mimic the scenario where the initial library is endogenous. The type 1 consumers are the heavy type, who take 30% of the market. Across columns, we vary the purchase-stage game intercepts for both types by adding an intercept shifter (s) from 0 to 5, while holding Hetero-purchase_diff at -5 and all other parameters fixed at their values set in Table C.1. For each s value, we also report the key summary statistics across heterogeneous types, including the type-specific average initial library size and the average number of games purchased in the second half of the period.

tion. We focus on capturing competition among games that were popular either for purchases or for usage during the sample period. Thus, we select games that meet one of the following criteria: (1) they are in the top 70% of expenditure share and have more than 1% of users buying among the 34,607 active users, or (2) they are in the top 70% of timeshare and have more than 1% of players among the active users. After this step, we have a set of 170 popular games. We find 31,617 (91%) of the active users have both purchased and played at least one of the popular games.

Next, we randomly sample 6,323 (20%) of the 31,617 users for structural estimation. We further exclude one game that has fewer than 10 purchases or usage sessions among the sampled users. As a result, we include 169 popular games as inside goods (with features and prices tracked), and group all the other games into a fringe bin. On average, the inside games take up 68% of the expenditure and 75% of the playing time of a user.

Model comparison and selection. We evaluate model fit across specifications with different values of R using AIC, BIC, and quantiles of individual log-likelihoods. We find that increasing R beyond 8 yields only modest improvements in fit. Given the steep increase in the number of possible information designs as R grows, we select $R = 8$ to balance model fit and computational tractability.

Table C.4: Model Fit Comparison

	AIC	BIC	LL_i (mean)	LL_i (25 pct)	LL_i (median)	LL_i (75 pct)
Model 1	11,769,234	11,773,912	-946	-1,230	-841	-560
Model 2	11,413,259	11,418,370	-918	-1,214	-849	-537
Model 3	11,231,172	11,236,715	-903	-1,188	-826	-537
Model 4	11,129,232	11,135,208	-895	-1,171	-819	-538
Model 5	11,077,705	11,084,113	-891	-1,169	-817	-534
Model 6	11,024,452	11,031,292	-887	-1,165	-816	-524
Model 7	10,990,490	10,997,763	-884	-1,163	-815	-522
Model 8	10,951,872	10,959,577	-881	-1,164	-811	-523
Model 9	10,928,271	10,936,409	-879	-1,162	-809	-522
Model 10	10,911,232	10,919,803	-878	-1,156	-811	-517

C.3 Supply-side: Solving for the equilibrium prices.

As mentioned in Section 4.2, for each information design, we solve the static pricing equilibrium for each sampling week separately and then aggregate across weeks. This Section describes how we solve for the equilibrium prices.

In week t_w, a consumer's choice depends on her library status L_{i,t_w}. Because our platform information design does not permit targeting within the provided segment, solving for the optimal targeted prices requires an integration over consumers' libraries. We draw consumer library status from the empirical distribution when calculating $\mathbb{E}[s_{jr,t_w}] = \mathbb{E}_i[s_{ji,t_w}(L_{i,t_w})|\boldsymbol{\Theta_r}]$. Specifically, for the counterfactual targeting scenario with information sets $\boldsymbol{\mathcal{I}}$, we compute the equilibrium prices $\boldsymbol{P(\mathcal{I})}$ following three steps.

1. We calculate $\upsilon_{i,t_w}(\boldsymbol{\Theta_r}) = \mathbb{E}\Big[V_{it_w}^{usage}(L_{i,t_w-1} \cup \{j\})\Big|\boldsymbol{\Theta_r}\Big]$ for $r \in \{1, ...R\}$,$i \in \{1, ...I\}$.
2. For each type, we have $\mathbb{E}[s_{jr,t_w}] = \mathbb{E}_i\Big[s_{ji,t_w}(\upsilon_{i,t_w}(\boldsymbol{\Theta_r}))\Big]$.
3. We substitute s_{jr} in (15) with $\mathbb{E}[s_{jr,t_w}]$ to get the optimal prices.

We implement the procedure for a subset of weeks, specifically $t_w \in \{1, 9, 17, 25, 33, 41\}$, and aggregate profits across these periods. To keep the computation tractable, we use one-tenth of the consumer sample across all information designs. We confirm that this reduced sample yields the same set of equilibrium prices as the full sample, while substantially reducing computational time.

Generalized equilibrium that accommodates asymmetric information sets across sellers. We extend the Bertrand-Nash equilibrium framework in Section 4 to allow for asymmetric information sets across sellers. Let CR^f denote the information set available to seller f, and define $\mathcal{I} = \{CR^1, \ldots, CR^F\}$ as the collection of all sellers' information sets. Given $\mathcal{I}$, each seller $f \in \{1, \ldots, F\}$ solves the profit-maximization problem in equation (19), choosing prices to maximize the expected profits from its product portfolio, J_f.

$$\max_{\{\boldsymbol{P}_j(\mathcal{I})\}_{j\in J_f}} \sum_{j=1}^{J} w_{j,f} \cdot \sum_{cr\in CR^f} p_{j,cr} \cdot \Big(\overbrace{\tilde{\psi}_{cr} \cdot \sum_{r=1}^{R} \tilde{\psi}_{r|cr} \cdot s_{j,r}\big(p_{j,cr}, \boldsymbol{P_{-j}(\mathcal{I})}\big)}^{\text{expected purchases in coarsened segment } cr} \Big), \tag{19}$$

In the above, $w_{j,f}$,$\tilde{\psi}_{cr}$,$s_{j,r}$ and $s_{j,r}$ are calculated using the same specification as in Equation (14). Asymmetric information sets across sellers enter through the specification of $\mathcal{I}$. Implicitly, this generalized equilibrium concept assumes that all sellers are aware of the information sets held by their competitors.

D Additional results

D.1 Demand-side: Estimates and Interpretations

We present the demand estimates in the following order: homogeneous parameters for the usage and purchase stages, heterogeneous parameters for both stages, and game fixed effects. The left panel of Table D.1 shows that consumers exhibit significant satiation behavior and face lower time costs on weekends, during summer, and over holidays—— consistent with increased gameplay during these periods. In the purchase stage, as shown in the right panel of Table D.1, we find statistically significant positive coefficients for both pre-sale and sale event periods, suggesting these effects are not driven by inventory stockpiling behavior. Additionally, we find that the connection between the two stages, σ, is statistically significant, confirming that consumers take expected future usage into account when making purchase decisions.

Table D.1: Homogeneous parameters

parameter	estimate	s.e.
γ	3.84	0.004
c_{wkd}	-0.03	0.001
c_{smr}	-0.01	0.001
c_{hld}	-0.02	0.002

parameter	estimate	s.e.
ξ_{pre_event}	0.17	0.02
ξ_{sales_event}	0.56	0.01
σ	0.14	0.001

Note: The left panel displays estimates for the usage-stage and the right panel displays those for the purchase stage.

Table D.2 presents the game fixed effects with descending order of usage popularity, measured by the observed total number of usage sessions. Two observations stand out. First, games that are played more frequently are estimated to have higher usage-stage fixed effects, suggesting that our usage model does capture revealed consumer preferences. Second, games with higher usage-stage fixed effects are not necessarily estimated to have high purchase-stage fixed effects. The discrepancy in these two-stage fixed effects reflect consumers' different considerations when making purchase and usage decisions, underscoring the importance of including two sets of fixed effects in our model.

Table D.2: Game fixed effects

Game	**Usage**	**s.e.**	**Purchase**	**s.e.**
Football Manager 2018	1.08	0.01	-5.81	0.22
Assassin's Creed Origins	1.04	0.01	-3.29	0.20
Middle-earth: Shadow of War	1.04	0.005	-3.00	0.15
Call of Duty: WWII - Multiplayer	1.01	0.01	-4.83	0.12
Total War: WARHAMMER II	1.01	0.005	-5.32	0.15
PLAYERUNKNOWN'S BATTLEGROUNDS	1.00	0.002	-4.18	0.12
Wolfenstein II: The New Colossus	0.99	0.01	-6.37	0.15
Divinity: Original Sin 2	0.99	0.004	-2.88	0.17
fringe	0.98	0.002	-2.19	0.01
Call of Duty: WWII	0.87	0.01	-4.08	0.13
TEKKEN 7	0.86	0.01	-6.03	0.26
Tom Clancy's Ghost Recon Wildlands	0.85	0.004	-5.49	0.18
Football Manager 2017	0.84	0.005	-6.69	0.17
Friday the 13th: The Game	0.83	0.01	-6.88	0.16
Cuphead	0.82	0.01	-4.01	0.15
Hearts of Iron IV	0.81	0.004	-6.59	0.14
Black Desert Online	0.81	0.01	-6.90	0.10
For Honor	0.81	0.005	-5.65	0.14
NieR:Automata	0.80	0.01	-4.16	0.25
RimWorld	0.79	0.004	-5.59	0.16
Dead Cells	0.77	0.01	-5.86	0.11
Stellaris	0.77	0.004	-5.40	0.13
Counter-Strike: Global Offensive	0.77	0.003	-5.51	0.08
Europa Universalis IV	0.75	0.004	-7.10	0.17
Tom Clancy's Rainbow Six Siege	0.75	0.003	-6.04	0.09
Warhammer 40,000: Dawn of War III	0.74	0.01	-7.00	0.16
Prey	0.74	0.01	-5.89	0.16
Grand Theft Auto V	0.73	0.003	-3.32	0.11
DARK SOULS III	0.73	0.004	-4.36	0.15
Stick Fight: The Game	0.73	0.01	-6.06	0.10
The Binding of Isaac: Rebirth	0.72	0.004	-7.52	0.15
Total War: WARHAMMER	0.72	0.004	-5.96	0.11
Hollow Knight	0.71	0.01	-5.90	0.11
Z1 Battle Royale	0.71	0.004	-6.71	0.11
Rocket League	0.70	0.003	-6.47	0.09
Sniper Elite 4	0.69	0.01	-6.45	0.16
Conan Exiles	0.69	0.01	-6.65	0.16
Oxygen Not Included	0.68	0.01	-5.93	0.15

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Table D.2 – continued from previous page

Game	Usage	s.e.	Purchase	s.e.
theHunter: Call of the Wild	0.68	0.01	-8.24	0.15
Rising Storm 2: Vietnam	0.67	0.01	-6.69	0.11
XCOM 2	0.66	0.004	-5.85	0.14
7 Days to Die	0.66	0.005	-6.41	0.13
Factorio	0.66	0.005	-7.36	0.15
Dota 2	0.66	0.003	-7.68	0.12
Arma 3	0.64	0.003	-6.12	0.13
Stardew Valley	0.63	0.005	-5.95	0.11
The Elder Scrolls Online	0.63	0.01	-5.51	0.11
Blackwake	0.63	0.01	-7.68	0.14
Fallout 4	0.63	0.004	-4.90	0.12
Grim Dawn	0.62	0.01	-7.37	0.14
ARK: Survival Evolved	0.62	0.004	-5.35	0.12
The Witcher 3: Wild Hunt	0.61	0.004	-3.35	0.11
Dead by Daylight	0.61	0.005	-7.44	0.13
Euro Truck Simulator 2	0.61	0.005	-6.12	0.12
Warframe	0.61	0.004	-5.99	0.08
Battlerite	0.60	0.004	-5.70	0.07
Rust	0.60	0.005	-6.46	0.12
Mount and Blade: Warband	0.60	0.01	-6.78	0.14
Darkest Dungeon	0.59	0.01	-5.44	0.11
Sid Meier's Civilization VI	0.58	0.01	-5.98	0.18
Human: Fall Flat	0.57	0.02	-7.29	0.14
Kingdoms and Castles	0.56	0.02	-7.14	0.14
Paladins	0.55	0.01	-6.71	0.10
Killing Floor 2	0.55	0.01	-6.41	0.14
Path of Exile	0.53	0.01	-6.64	0.08
Bayonetta	0.53	0.02	-6.60	0.17
Slime Rancher	0.53	0.01	-7.02	0.15
Northgard	0.52	0.01	-7.52	0.13
Shadow Tactics: Blades of the Shogun	0.52	0.02	-6.58	0.17
Terraria	0.51	0.004	-6.66	0.12
Dying Light	0.51	0.01	-6.83	0.15
Golf With Your Friends	0.50	0.01	-7.29	0.12
Sid Meier's Civilization V	0.49	0.005	-6.74	0.13
Dishonored 2	0.49	0.01	-5.54	0.17
Warhammer: End Times - Vermintide	0.49	0.01	-7.26	0.11
Garry's Mod	0.48	0.004	-6.65	0.11
SMITE	0.48	0.005	-7.86	0.12
The Forest	0.46	0.01	-6.40	0.13
Planet Coaster	0.46	0.01	-4.79	0.19
DARK SOULS II: Scholar of the First Sin	0.46	0.01	-5.79	0.14
Starbound	0.45	0.01	-6.84	0.13
Borderlands 2	0.45	0.01	-6.32	0.14
The Long Dark	0.45	0.01	-6.17	0.17
Overcooked	0.45	0.02	-7.40	0.18
Mortal Kombat X	0.45	0.01	-7.40	0.13
Sleeping Dogs: Definitive Edition	0.44	0.01	-6.61	0.13
Subnautica	0.44	0.01	-5.95	0.13
Deus Ex: Mankind Divided	0.43	0.01	-7.26	0.16
Team Fortress 2	0.43	0.01	-7.56	0.13
Just Cause 3	0.43	0.01	-4.82	0.12
Rise of the Tomb Raider	0.43	0.01	-4.63	0.15
Cities: Skylines	0.42	0.01	-5.74	0.13
The Elder Scrolls V: Skyrim	0.42	0.005	-6.33	0.16
Middle-earth: Shadow of Mordor	0.40	0.01	-5.39	0.08
Tabletop Simulator	0.40	0.01	-6.56	0.13
War Thunder	0.40	0.01	-7.13	0.10
DOOM	0.39	0.01	-5.42	0.11
Mad Max	0.38	0.01	-7.34	0.16
Batman: Arkham Knight	0.38	0.01	-6.88	0.16
The Witness	0.37	0.02	-4.94	0.14
DiRT Rally	0.36	0.02	-6.49	0.16
SimplePlanes	0.36	0.02	-8.70	0.23
Wolfenstein: The New Order	0.35	0.01	-7.40	0.12
PAYDAY 2	0.34	0.005	-4.67	0.07
Verdun	0.33	0.01	-8.47	0.20
Hyper Light Drifter	0.33	0.02	-6.95	0.15
Ori and the Blind Forest: Definitive Edition	0.32	0.02	-5.90	0.13
Age of Empires II (2013)	0.31	0.01	-7.67	0.15
Offworld Trading Company	0.30	0.03	-7.40	0.16
Borderlands: The Pre-Sequel	0.29	0.01	-5.58	0.18
Insurgency	0.29	0.01	-6.93	0.09

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Table D.2 – continued from previous page

Game	Usage	s.e.	Purchase	s.e.
Ultimate Chicken Horse	0.28	0.02	-7.25	0.17
Don't Starve Together	0.28	0.01	-6.30	0.11
SUPERHOT	0.25	0.02	-6.53	0.13
Hand of Fate	0.25	0.02	-6.82	0.14
Titan Quest Anniversary Edition	0.24	0.01	-7.65	0.14
Warhammer 40,000: Eternal Crusade	0.22	0.02	-7.88	0.12
Plague Inc: Evolved	0.22	0.02	-8.27	0.15
INSIDE	0.22	0.03	-6.94	0.14
South Park: The Stick of Truth	0.21	0.02	-5.52	0.16
Kingdom: New Lands	0.20	0.03	-7.51	0.17
Left 4 Dead 2	0.20	0.01	-6.30	0.10
Sniper Elite 3	0.18	0.02	-7.71	0.16
Poly Bridge	0.17	0.02	-8.06	0.22
Metro 2033 Redux	0.17	0.02	-7.45	0.12
Layers of Fear	0.14	0.04	-7.20	0.17
This War of Mine	0.14	0.01	-7.09	0.13
Alien: Isolation	0.14	0.02	-7.69	0.17
Lords Of The Fallen	0.13	0.03	-7.13	0.15
Unturned	0.12	0.01	-7.07	0.10
Borderlands GOTY	0.12	0.01	-6.84	0.14
Rising Storm/Red Orchestra 2 Multiplayer	0.11	0.01	-6.68	0.10
SpeedRunners	0.10	0.02	-8.42	0.20
Galactic Civilizations III	0.09	0.03	-7.34	0.17
Undertale	0.09	0.02	-7.32	0.17
Metro: Last Light Redux	0.07	0.02	-7.74	0.13
Saints Row IV	0.07	0.01	-6.56	0.13
Shadow Warrior	0.05	0.02	-5.40	0.08
Portal 2	0.04	0.01	-5.33	0.09
Dungeons 2	0.03	0.03	-5.74	0.10
Beholder	0.03	0.03	-7.50	0.15
Outlast	0.02	0.02	-5.23	0.09
Killer is Dead	0.02	0.04	-6.00	0.09
Killing Floor	0.01	0.01	-5.65	0.10
Mirage: Arcane Warfare	-0.005	0.04	-5.42	0.09
Chivalry: Medieval Warfare	-0.07	0.01	-5.72	0.10
Sid Meier's Civilization III: Complete	-0.07	0.02	-6.40	0.09
Ashes of the Singularity: Escalation	-0.08	0.05	-6.01	0.17
The Witcher 2: Assassins of Kings Enhanced Edition	-0.08	0.02	-5.98	0.11
RIVE	-0.08	0.07	-7.29	0.17
Jotun: Valhalla Edition	-0.09	0.03	-4.91	0.08
BioShock Infinite	-0.09	0.01	-6.34	0.13
Tomb Raider	-0.11	0.02	-6.79	0.14
Fallout	-0.12	0.03	-5.63	0.08
BioShock Remastered	-0.13	0.02	-7.43	0.18
Guns of Icarus Online	-0.14	0.02	-6.97	0.10
Brtal Legend	-0.21	0.03	-6.01	0.10
The Walking Dead	-0.22	0.03	-6.41	0.15
Sanctum 2	-0.22	0.03	-6.16	0.09
The Bureau: XCOM Declassified	-0.24	0.04	-5.64	0.08
Starpoint Gemini 2	-0.25	0.04	-5.20	0.12
Psychonauts	-0.30	0.04	-7.12	0.16
Outland	-0.30	0.04	-6.55	0.10
Saints Row 2	-0.34	0.03	-6.17	0.08
Monaco	-0.43	0.05	-9.26	0.25
Portal	-0.46	0.02	-7.14	0.13
Left 4 Dead	-0.49	0.03	-7.65	0.13
Serious Sam Fusion 2017 (beta)	-0.58	0.06	-5.17	0.07
Dear Esther: Landmark	-0.93	0.12	-6.19	0.11
Alan Wake's American Nightmare	-1.12	0.09	-6.70	0.12

Moreover, Tables D.3 and D.4 reveal notable discrepancies across consumer types, particularly in overall engagement. For example, Type 7 consumers generally enjoy playing games but are less likely to make purchases and are more price sensitive compared to other types. We also observe meaningful variation in preferences for specific game features.

Table D.3: Usage-stage heterogeneity ($\boldsymbol{\lambda}$)

Parameter	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
fraction	12%	13%	10%	19%	6%	9%	11%	19%
any	0	0.13	-0.41	-0.75	-0.57	0.08	0.29	-0.44
	-	(0.008)	(0.008)	(0.010)	(0.007)	(0.005)	(0.006)	(0.007)
multiplayer	0	0.003	-0.041	-0.037	0.135	-0.029	-0.002	-0.103
	-	(0.005)	(0.005)	(0.007)	(0.004)	(0.003)	(0.004)	(0.005)
military	0	-0.045	-0.109	-0.012	0.068	-0.004	-0.129	-0.052
	-	(0.004)	(0.005)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
survival	0	-0.029	0.179	-0.009	-0.040	0.059	-0.169	-0.055
	-	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)	(0.005)
team	0	-0.14	0.13	0.12	0.24	0.17	0.07	-0.07
	-	(0.004)	(0.005)	(0.007)	(0.004)	(0.003)	(0.004)	(0.006)
fantasy	0	-0.32	0.31	-0.21	0.26	0.16	-0.10	-0.08
	-	(0.004)	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
platformer	0	-0.093	-0.002	0.316	0.143	-0.165	-0.052	0.101
	-	(0.003)	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)	(0.004)
dark	0	0.06	-0.28	-0.19	0.05	-0.06	-0.06	-0.06
	-	(0.004)	(0.005)	(0.007)	(0.004)	(0.003)	(0.003)	(0.007)
adventure	0	-0.20	-0.19	-0.28	0.23	-0.07	-0.13	-0.07
	-	(0.005)	(0.006)	(0.010)	(0.003)	(0.004)	(0.004)	(0.005)
anime	0	-0.09	-0.54	-0.17	0.13	-0.22	-0.13	0.01
	-	(0.006)	(0.010)	(0.013)	(0.005)	(0.005)	(0.005)	(0.007)
fringe	0	-0.75	-0.47	-0.47	0.37	-0.17	-0.43	-0.07
	-	(0.007)	(0.009)	(0.011)	(0.007)	(0.005)	(0.005)	(0.007)

Interpreting $\hat{\delta}_j$, $\hat{\boldsymbol{\lambda}}$, and $\hat{\boldsymbol{\alpha}}_r$. Although we do not fully disentangle the underlying channels that are discussed in Section 4.2, we explore whether consumer learning is reflected in $\hat{\delta}_j$, $\hat{\boldsymbol{\lambda}}_r$, and $\hat{\boldsymbol{\alpha}}_r$. Figure D.1 plots each game's purchase-stage fixed effect against its usage-stage fixed effect. If post-purchase learning drove the purchase-stage effect, we would expect games with low usage (and thus more learning potential) to exhibit higher purchase-stage fixed effects, reflecting the overestimation of game quality at the point of purchase. Instead, we observe only a weak overall correlation and a slight positive correlation among the most frequently played games. This pattern is more consistent with Steam's recommendation algorithm, which amplifies popular games in consideration.

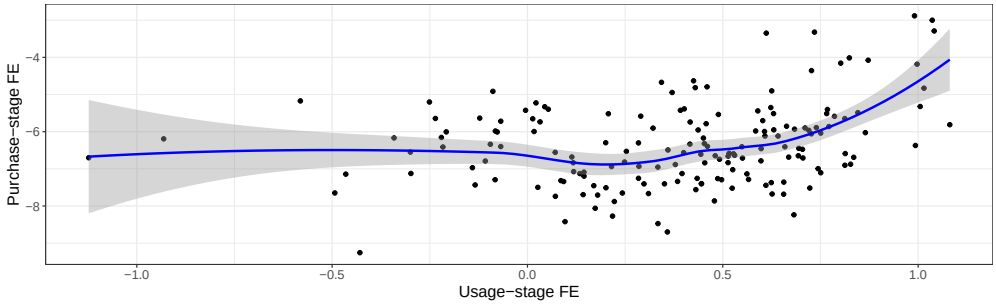


Figure D.1: Correlation between two-stage FEs: η_j and δ_j

Additionally, across consumer types, we find that stronger feature preferences correlate weakly with more negative price sensitivities. This pattern again aligns with algorithmic recommendations, which amplifies

Table D.4: Purchase-stage heterogeneity

(a) Intercepts for meta-tags ($\boldsymbol{\beta}$)

Parameter	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
any	0	-1.8	-2.0	-2.4	-0.7	-1.0	-0.8	-0.7
	-	(0.1)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	(0.1)
multiplayer	0	0.59	0.64	0.49	0.06	0.35	0.31	-0.06
	-	(0.10)	(0.12)	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)
military	0	0.112	-0.121	0.344	0.089	0.191	0.020	0.009
	-	(0.09)	(0.11)	(0.10)	(0.10)	(0.10)	(0.08)	(0.07)
survival	0	0.7	0.6	0.4	0.2	0.3	0.3	0.2
	-	(0.09)	(0.11)	(0.09)	(0.10)	(0.09)	(0.08)	(0.07)
team	0	0.42	0.25	0.25	0.12	0.27	0.50	0.06
	-	(0.10)	(0.12)	(0.10)	(0.11)	(0.10)	(0.09)	(0.08)
fantasy	0	-0.12	-0.15	-0.05	0.15	-0.07	-0.07	-0.04
	-	(0.09)	(0.11)	(0.09)	(0.11)	(0.10)	(0.08)	(0.07)
platformer	0	0.2	0.1	0.5	0.1	0.2	0.2	0.1
	-	(0.09)	(0.11)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)
dark	0	-0.13	-0.08	-0.42	-0.23	-0.20	-0.11	-0.10
	-	(0.09)	(0.11)	(0.09)	(0.10)	(0.10)	(0.08)	(0.07)
adventure	0	-0.021	0.004	-0.151	-0.148	-0.195	-0.200	-0.208
	-	(0.11)	(0.13)	(0.11)	(0.11)	(0.11)	(0.09)	(0.08)
anime	0	0.24	-0.03	0.36	-0.08	-0.14	0.03	0.07
	-	(0.1)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	(0.1)
fringe	0	0.8	0.7	0.8	0.1	0.4	0.4	0.1
	-	(0.1)	(0.2)	(0.1)	(0.2)	(0.2)	(0.1)	(0.1)

(b) Price sensitivities ($\boldsymbol{\alpha}$)

Parameter	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
any	-0.090	-0.081	-0.083	-0.048	-0.087	-0.102	-0.093	-0.088
	(0.0048)	(0.0091)	(0.0106)	(0.0090)	(0.0100)	(0.0100)	(0.0084)	(0.0077)
multiplayer	0.0280	0.0054	0.0024	0.0034	0.0258	0.0234	0.0213	0.0247
	(0.0026)	(0.0050)	(0.0056)	(0.0049)	(0.0052)	(0.0053)	(0.0046)	(0.0040)
military	0.036	0.033	0.056	0.022	0.028	0.034	0.035	0.035
	(0.0026)	(0.0051)	(0.0059)	(0.0050)	(0.0052)	(0.0054)	(0.0046)	(0.0041)
survival	0.0098	-0.0088	-0.0055	0.0030	0.0053	0.0054	0.0064	0.0071
	(0.0026)	(0.0048)	(0.0054)	(0.0048)	(0.0052)	(0.0050)	(0.0044)	(0.0040)
team	0.00035	-0.00399	-0.00283	-0.00516	-0.00297	-0.00686	-0.01038	-0.00209
	(0.0027)	(0.0050)	(0.0055)	(0.0050)	(0.0055)	(0.0053)	(0.0046)	(0.0043)
fantasy	-0.0040	-0.0104	-0.0192	-0.0316	-0.0119	-0.0184	-0.0131	-0.0064
	(0.0027)	(0.0049)	(0.0055)	(0.0049)	(0.0055)	(0.0052)	(0.0046)	(0.0042)
platformer	-0.011	-0.017	-0.015	-0.032	-0.017	-0.016	-0.014	-0.013
	(0.0025)	(0.0045)	(0.0051)	(0.0046)	(0.0048)	(0.0048)	(0.0042)	(0.0038)
dark	0.011	0.026	0.027	0.035	0.022	0.032	0.025	0.016
	(0.0026)	(0.0050)	(0.0057)	(0.0050)	(0.0055)	(0.0053)	(0.0046)	(0.0042)
adventure	0.00535	-0.00713	-0.00276	-0.01176	0.00015	-0.00143	0.00278	0.00980
	(0.0027)	(0.0056)	(0.0060)	(0.0054)	(0.0053)	(0.0058)	(0.0048)	(0.0041)
anime	-0.00088	-0.04381	-0.02524	-0.03524	-0.00791	-0.02223	-0.01465	-0.00303
	(0.0049)	(0.0095)	(0.0094)	(0.0083)	(0.0082)	(0.0097)	(0.0076)	(0.0066)

games matching individual tastes in the purchase-stage consideration, rather than with learning behavior about potential match value with the features. Taken together, the pattern of estimates $\hat{\delta}_j$, $\hat{\boldsymbol{\lambda}}_{\boldsymbol{r}}$, and $\hat{\boldsymbol{\alpha}}_{\boldsymbol{r}}$ is closely aligned with the recommendation algorithm instead of consumer learning.

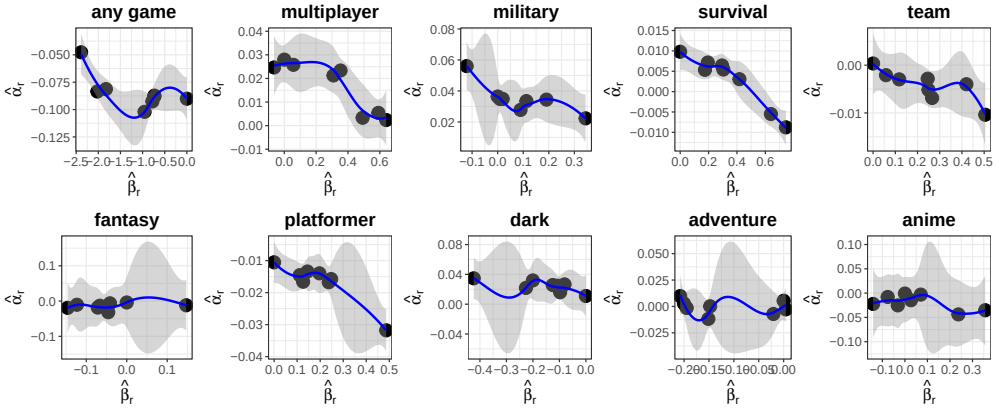


Figure D.2: Correlation between purchase tastes and sensitivity: β_r and α_r

Implied price elasticities and substitution: additional details. Figure 5.4 reveals substantial heterogeneity in consumers' own-price elasticities across games. One concern is that using the raw elasticities as a similarity metric may overweight discrepancies in games with larger dispersion in elasticities, thereby impacting the effectiveness of the resulting segmentation in increasing profits. Therefore, Figure D.3 visualizes a rescaled elasticity pattern across consumers toward games. For each game j, we compute $\tilde{\eta}jj^r = -\eta jj^r / \max_r |\eta^r_{jj}|$ so that the most price-elastic type for each game has a relative elasticity of 1 and all others lie between 0 and 1. This normalization adjusts for game-specific differences in price sensitivity and reveals how the ranking of "strong" versus "weak" markets varies by game title. In Section 6, we use the rescaled elasticity measure as an alternative metric to capture demand similarity across consumer types.

In the meantime, Table D.5 highlights heterogeneity in substitution patterns across consumer types. For each type, we report the average diversion ratio from a focal game to all other inside goods. The results show meaningful variation in substitution behavior, most strikingly among Type 1 consumers, the most engaged type, who shift a large share of their purchases to alternative games when a focal title is removed.

Table D.5: Diversion ratios to inside goods: across consumer types

	Type1	Type2	Type3	Type4	Type5	Type6	Type7	Type8
Fraction	12%	13%	10%	19%	6%	9%	11%	19%
Diversion Ratio	0.30	0.11	0.09	0.07	0.18	0.16	0.20	0.17

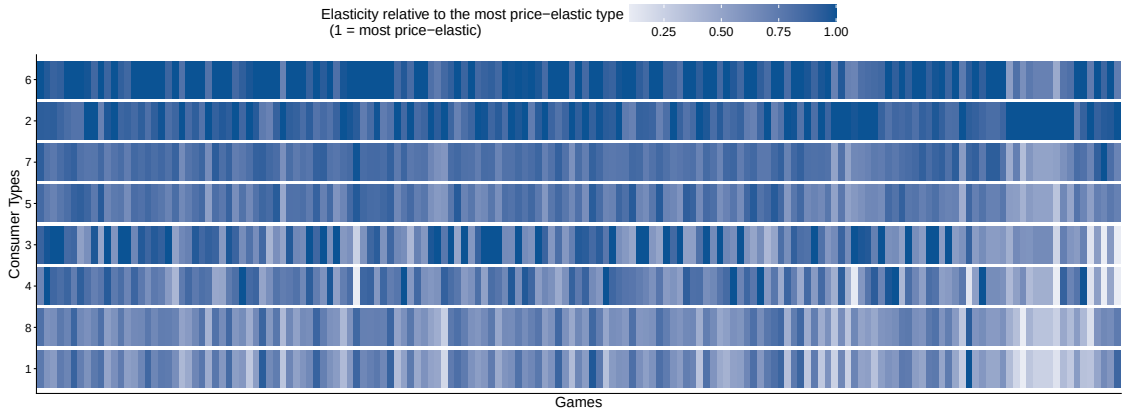


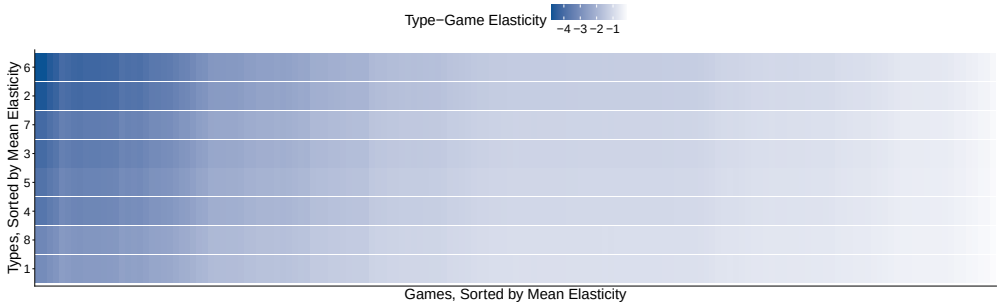
Figure D.3: Rescaled own elasticities across games and consumer types.

Note: We evaluate all price elasticities at the observed prices. For visualization, we re-scale game-type price elasticities by computing $\tilde{\eta}^r_{jj} = \eta^r_{jj} / \max_r |\tilde{\eta}^r_{jj}|$. The darker a tile is, the more price-sensitive the type is towards the game. We sort the types by their mean elasticity (across games) and sort the games by their market-level elasticities.

D.2 Supply-side: Generalization

Alternative consumer heterogeneity patterns. Figure D.4 illustrates the two distinct heterogeneity patterns uncovered in the decomposition exercise (Section 6.3), while Table D.6 compares the coarse segmentation formed using optimal information design and the demand-based heuristics under the two counterfactual demand scenarios.

(a) Vertical heterogeneity: elasticity toward games



(b) Horizontal heterogeneity: elasticity toward games

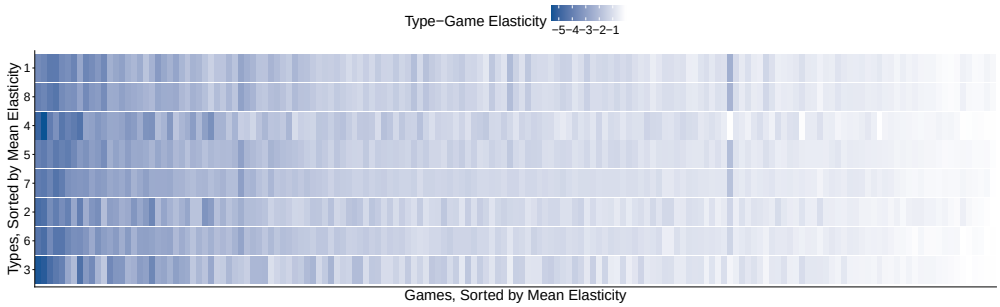


Figure D.4: Alternative demand: vertical versus horizontal heterogeneity

Table D.6: Heterogeneity decomposition: Vertical versus Horizontal

(a) Vertical (full-info profit gain: 1.56%)

Coarse-n	Heuristic	Profit gain	Optimal	Profit gain
$n = 2$	{1,4,5,8},{2,3,6,7}	1.04%	{1,8},{2,3,4,5,6,7}	1.3%
$n = 7$	{1,8},{2},{3},{4},{5},{6},{7}	1.51%	{1},{2},{3},{4,7},{5},{6},{8}	1.58%

(b) Horizontal (full-info profit gain: 1.08%)

Coarse-n	Heuristic	Profit gain	Optimal	Profit gain
$n = 2$	{1},{2,3,4,5,6,7,8}	0.34%	{1,5,7,8},{2,3,4,6}	0.59%
$n = 7$	{1},{2,7},{3},{4},{5},{6},{8}	0.98%	{1},{2},{3},{4},{5,7},{6},{8}	1.07%

Evidently, even under one-dimensional heterogeneity, profit gaps persist across varying levels of granularity. Specifically, when consumer differences are purely vertical (i.e., engagement and price sensitivity)— that is, a scenario where the sellers are aligned in targeting "strong" and "weak" markets, the elasticity-based heuristics fail to approximate the optimal design. Moreover, comparison between Table 6.1 and Table D.6 suggests that the optimal "Coarse 2" design under both dimensions of heterogeneity (6.2) reflects pooling in the vertical distinction, while the finer optimal "Coarse 7" reflects pooling in the horizontal distinction.

Other objectives: consumer welfare by type. Table D.7 reports changes in consumer welfare by type. Relative to the uniform-pricing benchmark, total welfare gains arise primarily from lower prices for the more price-elastic types. Moreover, the optimal "Coarse 2" segmentation delivers larger welfare improvements than the heuristic "Coarse 2" by implementing price cuts that benefit a greater share of consumers, while imposing only modest price increases on the remainder of the market.

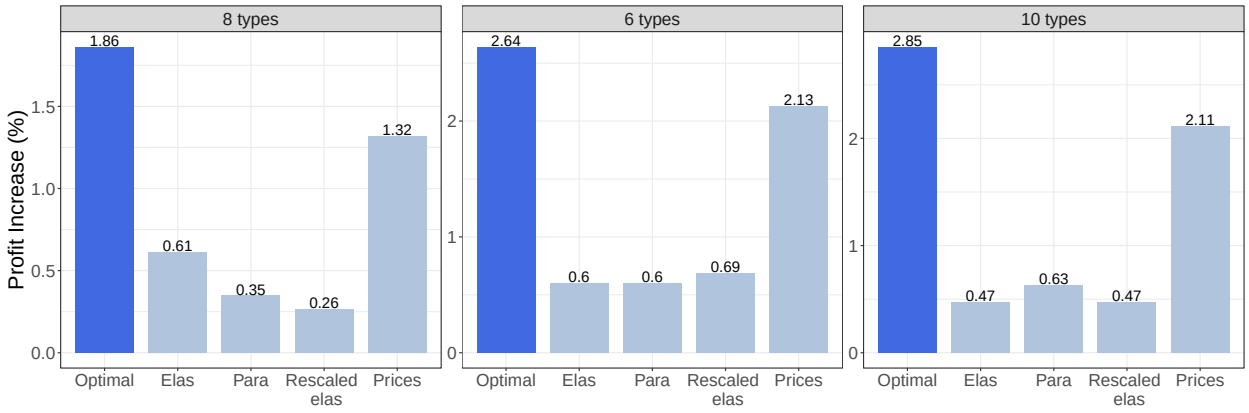
Table D.7: Changes in Price and Consumer Surplus by Type across Information Designs

	Heuristic Coarse-2		Optimal Coarse-2		Full-info	
Type	ΔPrice(%)	ΔCS	ΔPrice(%)	ΔCS	ΔPrice(%)	ΔCS
1	-4.2	-6	-29.9	8	-34.5	22
2	73.8	-26	38.4	-19	73.8	-20
3	-6.8	-6	27.1	-19	25.9	-1
4	-13.1	-6	49.3	-19	16.7	6
5	-3.2	-6	14.9	-19	4.1	-4
6	-5.9	-6	23.6	-19	45.3	-23
7	-6.6	-6	25.8	-19	19.9	-10
8	-7.2	-6	-49.9	8	-40.3	14

Alternative number of types. We further show that the profit gaps between the equilibrium-based optimal design and demand-based heuristic design are robust to the choice of the number of latent types

(R). We re-estimate demand assuming $R = 6$ and $R = 10$, and reproduce the comparison as shown in Figure 6.2. As shown in Figure D.5, the equilibrium-based optimal design consistently outperforms various demand-based heuristics with more or fewer types assumed.

Figure D.5: Profit gaps: alternative heuristics and alternative R



Note: This figure compares the profit increases achieved by various heuristic approaches under different numbers of latent types (R) with $n = 2$. We use three different heuristics to cluster consumers into coarsened segments: their own-price elasticities across games ("Elas"), the full vector of utility parameters ("Para"), and the rescaled own-price elasticities relative to each game's most elastic type ("Rescaled elas"). We also include a heuristic based on full-information equilibrium prices ("Prices"). The left, middle, and right panels show results under the estimated demand distributions with $R = 8$ (our main specification), $R = 6$, and $R = 10$, respectively.