Online Appendix For "Consumer Transportation Costs and the Value of E-commerce: Evidence from the Dutch Apparel Industry"

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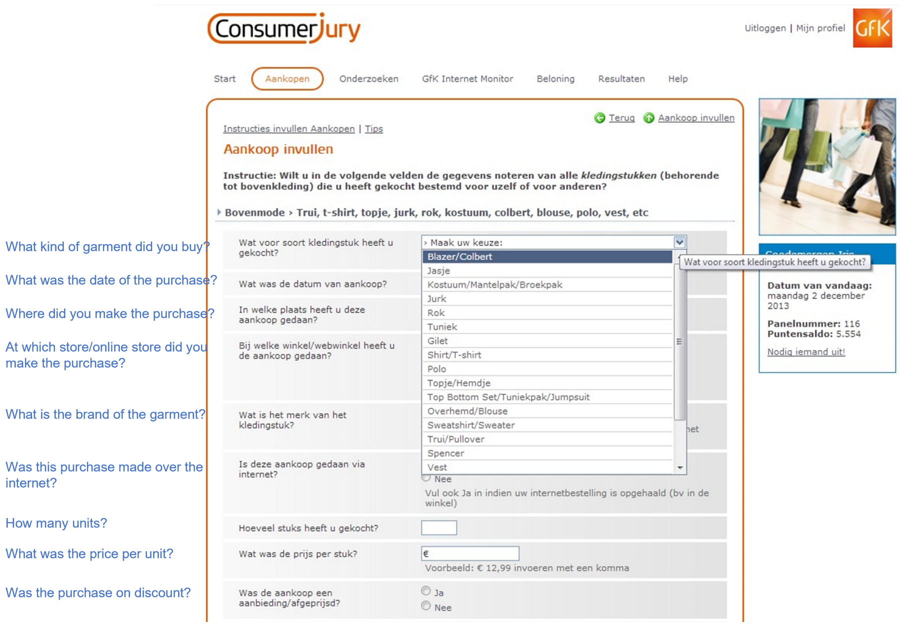
A Online-diary interface of the JURY panel



Appendix Figure A.1: Online-diary design of the JURY panel

Notes: This screenshot illustrates the online diary design of the JURY panel. The left-most texts are Google translations to the questions. The screenshot is taken in February, 2013.

B Construction of the price index

We construct prices indices at the chain-month level to measure overall price levels across products. One way to construct this index is to simply compute the average purchase price in a given chain-month. However, we only observe price conditional on purchase, and one might worry about a selection problem on *who* purchases the product, as well as on unobserved characteristics of the product purchased. We proceed to construct a price index that is net of these unobserved demand shifters. In particular, we observe *whether* a purchased product is on a price discount, along with its price. We will leverage this data advantage to project price variations into discount frequency and depth variations. The underlying assumption of our approach is that the same discounts are offered to all consumers shopping for products of the same characteristic, and thus, discounts are exogenous to unobserved demand shocks conditional on individual-chain fixed effects and observed demographics and product characteristics. Meanwhile, this assumption is less likely to hold for the purchase price because the price itself is selected by the individual shopper.

To implement this idea, we first estimate two hedonic regressions, of price and discount incidence on year y, month-of-the-year m, observed product characteristics, consumer demographic variables, and consumer-chain fixed effects. For consumer i who purchases item r at chain j in month t, we specify

$$\log\left(\text{price}_{ijrt}\right) = p_{j0} + \tau^0_{jy(t)} + \tau^0_{jm(t)} + \left(\tau^1_{jy(t)} + \tau^1_{jm(t)}\right) \cdot \text{discount}_{ijrt} + x^p_{jr}\beta^p_1 + z^p_{it}\beta^p_2 + \alpha^p_{ij} + \omega_{ijrt} \tag{B.1}$$

where the dummies $\tau^0_{jy(t)}$ and $\tau^0_{jm(t)}$ capture year and month level variations in the regular price for chain j, and the dummies $\tau^1_{jy(t)}$ and $\tau^1_{jm(t)}$ capture year- and month variations in discount depth. Note that these effects are net of observed product characteristics x^p_{jr} (brand and product type), observed demographics z^p_{it}, and consumer-chain fixed effects α^p_{ij}. Similarly, we also estimate

$$\text{discount}_{ijrt} = d_{j0} + \eta_{jy(t)} + \eta_{jm(t)} + x^d_{jr}\beta^d_1 + z^d_{it}\beta^d_2 + \alpha^d_{ij} + \upsilon_{ijrt} \tag{B.2}$$

to obtain $\eta_{jy(t)}$ and $\eta_{jm(t)}$ as year- and month-of-the-year variations in the discount frequency. Estimating both Equation (B.1) and (B.2), we then construct the price index as

$$\log\left(P_{jt}\right) = \hat{p}_{j0} + \hat{\tau}^1_{jy(t)} \times \hat{\eta}_{jy(t)} + \hat{\tau}^1_{jm(t)} \times \hat{\eta}_{jm(t)} \tag{B.3}$$

where we explicitly concentrate on only the chain-average price level $\hat{p}_{j0}$ and the over-time variations in discount depth and discount frequency.

C Do store locations and price discounts target local consumer demographics?

To identify consumers' distance sensitivity, the key assumption is that, within the coverage area of a store, consumers are dispersed and the store cannot locate precisely to target individual consumer characteristics or unobserved demand (beyond targeting the demographics and unobserved demand of an area). Recall that we show in Section 3 that those who are close to a newly-entered store do not exhibit a different time trend to shop at the chain, compared to those who are further away from the store, supporting this identifying assumption. We now complement this exercise and demonstrate that the store's location indeed does not target observed demographics beyond the broad demographics in a region.

We first take a 30% random sample of the balanced individual-level data at the individual-chain-month level (i.e. including no-purchase occasions). We combine this sample with 4-digit zip code level average income and total population (from 2007 to 2014), which we obtain from the census. This exercise brings us to a balanced panel where we can examine whether the presence of the chain in the consumer's local zip code (5-digit zip code) is explained by the consumer's demographics or the demographics of a broader area. Denote $\bar{\text{inc}}_{jt}$ as a measure of the average income of the chain's customer base, here constructed as expenditure-weighted average income from the purchase panel. We now estimate

$$100 \times \text{store\_in\_zip5}_{ijt} = b_0 \text{hhinc}_{it} + b_1 \text{hhinc}_{it} \times \bar{\text{inc}}_{jt} + b_2 \text{zipinc}_{m(i)t} + b_3 \text{zipinc}_{m(i)t} \times \bar{\text{inc}}_{jt} + \delta_{ij} + \lambda_{jt} + \varepsilon_{ijt} \tag{C.4}$$

where $\text{store\_in\_zip5}_{ijt}$ indicates 1 if the closest store of j to a given consumer i is in the same five-digit zip code as the consumer, hhinc_{it} is the household income of i and $\text{zipinc}_{m(i)t}$ is the average household income in the 4-digit zip code of i, $m(i)$. If the chain selectively enters into markets (4-digit zip codes) with local income matching its typical clientele, we should expect b_3 to be positive. In addition, if the chain further targets granular clusters of consumers within the 4-digit zip code, one should expect b_1 to be positive.

We present the estimates in the first column of Table C.1. We find that given the set of controls, store location is correlated with the interaction between 4-digit zip code level income and the income of the chain's clientele, but the correlation is small in magnitude. Suppose Chain A caters to customers with an average of €40,000 annual income and Chain B's customers have an income of €20,000. When the average income of a market grows by €1,000, the positive coefficient $\hat{b}_3$ suggests that Chain A will be more likely to enter in this market than Chain B – consistent with the conjecture that chains selectively enter into markets that are similar to their own clientele. However, compared to Chain B, Chain A is $20 \times 1 \times \hat{b}_3 = 20 \times 0.000053 = 0.0011$ percentage points more likely to enter this market, or 0.4% relative to the baseline entry probability at 0.25 percent-

Appendix Table C.1: Targeting of store location and price discounts

	store in zip5	discount
household income	0.001093***	-0.088312
	(0.000)	(0.093)
... X clientele income	-0.000036***	0.001237
	(0.000)	(0.003)
average zip4 income	-0.007005***	-0.271892
	(0.001)	(0.193)
... X clientele income	0.000053***	0.009949*
	(0.000)	(0.006)
zip4 population	0.013308***	0.132689
	(0.002)	(0.139)
individual-chain FE	Yes	Yes
chain-year FE	Yes	Yes
month FE	Yes	Yes
R-squared	0.96	0.37
observations	15923662	566730

Notes: Column 1 reports regression results of Equation (C.4). Column 2 focuses on the sample of consumer purchases and reports whether discounts are targeted to local income, using the same set of controls as Equation (C.4). The dependent variables are percentage points and the income variables are in thousand euros.

age points. This estimate suggests that store locations do target to the average local income but the degree of targeting is negligible.

More importantly, we find that store locations do not target individual income within the local 4-digit zip code market. For a given consumer, her income increasing by €1,000 will predict that she is 0.3% *less* likely to be close to Chain A, the high-end chain. Where the sign might be counter-intuitive, we note that the magnitude of this effect is economically negligible. We conclude that we do not find evidence that store locations target to changes in customer income within a 4-digit zip code.

We further examine whether discounts are targeted to local markets in a similar way. We take the sample of consumer purchases and estimate whether a purchase contains a product on discount, on the same set of variables and fixed effects as Equation (C.4). We find that an increase in the average income of the 4-digit zip code is associated with fewer discounts: A €1,000 increase in the average income predicts 0.27 *percentage point* decrease in the share of discount (and it is statistically insignificant), or 0.5% relative to the 47 percentage point baseline discount level. Similarly, the interaction with chain's clientele characteristics also return a small effect. Further, given the average income at the 4-digit zip code level, individual consumer income and its interaction with the chain's clientele do not predict the share of discount this consumer purchases in a statistically or economically significant way. We find no sign of targeted price discounts.

D Additional descriptive statistics

Diversity of retail formats. Table D.1 shows summary statistics at the consumer-chain-month level, using the full (unbalanced) sample and taking into account consumer-months without purchase. We examine, for the overall sample and then by retail format, the frequency of shopping incidence, expenditure given the incidence, frequency of shopping online, and shopping distance if the consumer shops offline. Consumers travel further for branded chains (e.g. H&M) and for specialty stores (e.g. The Shoe Factory). The share of online sales are higher for branded chains and department stores.

Appendix Table D.1: Summary of expenditure, variety, channel, and shopping distance

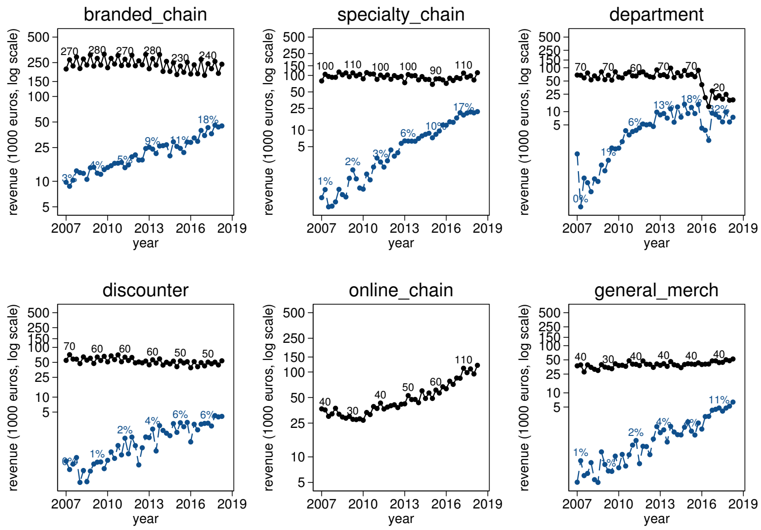
	branded	department	discounter	general	online	specialty	all formats
purchase offline	0.141	0.035	0.092	0.091	0.000	0.057	0.292
purchase online	0.016	0.003	0.002	0.003	0.032	0.005	0.055
number of chains purchased from	4.603	0.205	1.125	0.511	1.228	2.148	9.922
expenditure if purchase	62.725	59.674	22.307	17.207	67.233	60.609	21.562
distance of offline purchase	10.521	9.329	3.226	4.564	0.000	26.081	1.573
observations (HH-chain-year-month)	1,111,402	1,111,402	1,111,402	1,111,402	1,111,402	1,111,402	1,111,402

Notes: This table reports offline and online incidence at the monthly level, expenditure given shopping incidence, number of distinct chains shopped at, and shopping distance if the consumer shops offline.

Growth of e-commerce across retail formats. Figure D.1 presents the growth of total and online expenditure across retail formats. One finds that while all formats growth in the total online expenditure (except for department stores, which saw exit of a major player in 2016), the within-format growth rate of online expenditure is lower than the total growth rate. This contrast is explained by the composition change across formats – in particular, online chains take an increasingly significant role.

Choice of variety. We examine the number of chains a consumer purchases from, and the composition of expenditure among these chains, in each trip and within various time windows. Table D.2 shows the average number of chains a consumer purchases from and the share of expenditure at the top chain, on the unit of analysis of consumer-date, consumer-month, and consumer-quarter. We find that there are limited multi-chain visits within a shopping date: 87.5% trips are only associated with purchasing from one chain and the top chain takes 96% expenditure on that day.

Over a wider time frame, however, we do observe that the consumer purchases from more than one chain: 42% of months and 59% of quarters with positive expenditure are associated with at least two chains. Aggregating across time, only 13% consumers ever bought from only one chain. This indicates significant choice of variety chosen by the consumer, but importantly not on the same date.



Appendix Figure D.1: Growth of e-commerce by format

Note: See note of Figure 3.

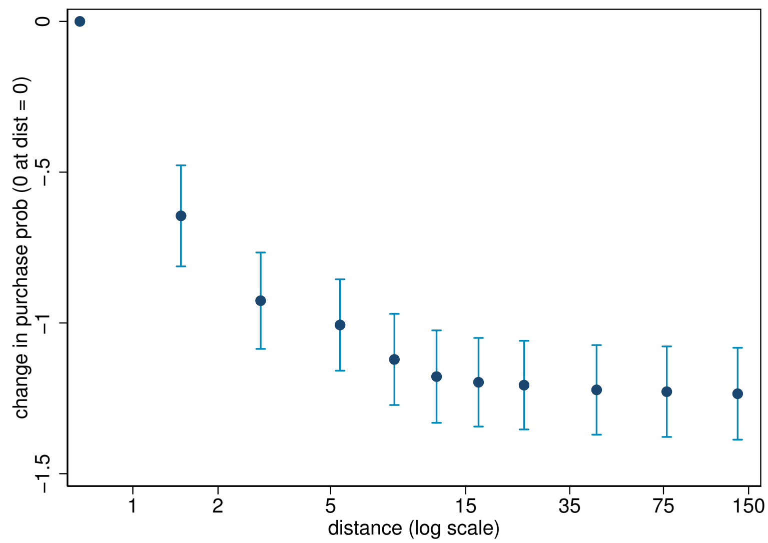
Appendix Table D.2: Choice of variety in various time window definitions

	same day	same month	same quarter	entire sample
purchase from 1 chain	0.868	0.575	0.575	0.139
purchase from 2 chains	0.106	0.231	0.231	0.092
purchase from 3 chains	0.020	0.102	0.102	0.066
purchase from 4+ chains	0.006	0.093	0.093	0.703
expd. share, chain of highest expd.	0.954	0.827	0.827	0.387
observations	551,214	355,718	355,718	23,976

Notes: Number of distinct chains the HH purchases from, conditional on making a purchase in a given time window.

E Additional results of the effect of distance

Flexible functional form. We present a flexible specification on the effect of distance. We estimate Equation (3) with the same set of control variables, but with a series of distance bins to capture the effect of distance in a flexible way. We find that the shape of the effect is concave, with the marginal effect of distance decreasing the further a consumer is away from the store. In addition, we find that the $\log(D_{ijt}+1)$ specification is almost exactly correct when the consumer is within 15km of the store, which is a range with the majority of offline purchases (See Figure 4). Beyond this range, the marginal effect of distance further declines.



Appendix Figure E.1: Heterogeneous marginal effect of $\log(D_{ijt}+1)$

Note: This figure visualizes the estimates of a more flexible distance-sensitivity regression. The x-axis presents distance bins that are rescaled to the $\log(D+1)$ specification, and the y-axis is the marginal effect of distance for each bin.

The effect of distance by-format. We present estimation results of Equation (3) separately by retail format. While we find significant heterogeneity in the sensitivity to distance across retail formats, we consistently find no evidence that offline and online channels are net substitutes or complements.

Appendix Table E.1: Sensitivity to distance (Y is purchase × 100): Full table

Panel A: sensitivity to own distance: offline demand

	offline: branded	discounter	gen. merch.	specialty
log(dist + 1)	-0.161***	-0.861***	-1.012***	-0.145***
	(0.012)	(0.069)	(0.208)	(0.021)
consumer-chain FE	Yes	Yes	Yes	Yes
chain-year FE	Yes	Yes	Yes	Yes
choice set FE	Yes	Yes	Yes	Yes
R-squared	0.16	0.17	0.19	0.09
observations	27139763	4076745	2446991	11939507

Panel B: sensitivity to own distance: online demand

	online: branded	discounter	gen. merch.	specialty
log(dist + 1)	0.003	-0.001	-0.005	-0.006
	(0.003)	(0.007)	(0.026)	(0.005)
consumer-chain FE	Yes	Yes	Yes	Yes
chain-year FE	Yes	Yes	Yes	Yes
choice set FE	Yes	Yes	Yes	Yes
R-squared	0.13	0.08	0.12	0.07
observations	27139763	4076745	2446991	11939507

Notes: Panel A presents the sensitivity of the consumer's shopping trip to offline chain choice to the distance to the chain's nearest store. The results are presented by retail formats: branded chains, department stores, discounters, general merchandisers, and specialty chains. Panel B presents the sensitivity of online shopping trips to the distance to the closest store. conditions on existing users, i.e. household has purchased from the focal chain before.

F Implementation detail of the structural model

F.1 Parameterization of random coefficients

Heterogeneity in chain-channel effects in the quantity-choice stage and the chain-channel choice stage, ρ_{ij} and δ_{ijc}, are specified as a combination of fixed effects and random chain effects: $\rho_{ij} = \bar{\rho}_j + \sigma_{j,1}\nu_{ij,1}$ and $\delta_{ijc} = \bar{\delta}_{jc} + \sigma_{j,2}\nu_{ij,2}$, $j = 1, ..., 20$, where $\nu_{ij,1}$ and $\nu_{ij,2}$ are IID standard normal draws.

We model the heterogeneity in the utility curvature σ_i, transportation costs β_i, and Poisson arrival rates λ_i, using demographic effects and log normal random effects, as follows

$$\begin{pmatrix} \sigma_i \\ \beta_i \\ \lambda_i \end{pmatrix} = \begin{pmatrix} \sigma \cdot \exp(Z_i\omega_1 + \sigma_1\nu_{i1}) \\ \beta \cdot \exp(Z_i\omega_2 + \sigma_2\nu_{i2}) \\ \lambda \cdot \exp(Z_i\omega_3 + \sigma_3\nu_{i3}) \end{pmatrix}, \tag{F.5}$$

with ν_{ik} being standard normal draws. Demographic variables Z_i include age bins (cutoff at 40 years old), gender, net monthly income bins (cutoff at 2,500 per month), plus a bin for consumers who do not report net income.

Next, we model the heterogeneous responses to X_{ijc}, which are time-invariant characteristics that include an intercept, online dummy, brand concentration, and the log average distance:

$$\begin{pmatrix} \gamma_{i1} \\ \gamma_{i2} \\ \gamma_{i3} \\ \gamma_{i4} \\ \theta_{i1} \\ \theta_{i2} \\ \theta_{i3} \\ \theta_{i4} \end{pmatrix} = \begin{pmatrix} Z_i\omega_4 \\ Z_i\omega_5 + \sigma_5\nu_{i5} \\ Z_i\omega_6 + \sigma_6\nu_{i6} \\ \bar{\gamma}_4 + Z_i\omega_7 \\ Z_i\omega_8 \\ Z_i\omega_9 + \sigma_9\nu_{i9} \\ Z_i\omega_{10} + \sigma_{10}\nu_{i10} \\ \bar{\theta}_4 + Z_i\omega_{11} \end{pmatrix}. \tag{F.6}$$

Most random coefficient terms in $\gamma_{i\cdot}$ and $\theta_{i\cdot}$ have mean zero because the baseline is absorbed by chain-channel fixed effects. The only exception is the the log average distance terms, γ_{i4} and θ_{i4}, because the baseline is identified from cross-sectional variation in the average distance between consumer and chains.

F.2 Derivation of the likelihood function

We demonstrate the derivation of the density function of consumer expenditure, $E_{ijc\tau}$.

First, from equation (17), one arrives at

$$\mu_{ijc\tau} := g\left(E_{ijc\tau}\right) = \frac{1}{\sigma}\log\left(\frac{\alpha_{1i}}{\sigma}\right) + \frac{1-\sigma}{\sigma}\log\left(E_{ijc\tau}\right) + \log\left(P_{jt}\right) - X_{jc}\theta_i - \rho_j - \eta_{ct}. \tag{F.7}$$

Then, use the $g(\cdot)$ function from above as a tranformation-of-variable between expenditure $E_{ijc\tau}$ and the marginal utility shock $\mu_{ijc\tau}$, and we have

$$\begin{aligned} f_e\left(E_{ijc\tau}|i\right) &= \Pr\left(j,c|\tau,i\right)\cdot f_e^{+}\left(E_{ijc\tau}\right) \\ &= \Pr\left(j,c|\tau,i\right)\cdot f_\mu\left(g\left(E_{ijc\tau}\right)\right)\frac{\partial g\left(E_{ijc\tau}\right)}{\partial E_{ijc\tau}} \\ &= \Pr\left(j,c|\tau,i\right)\cdot f_\mu\left(\frac{1}{\sigma}\log\left(\frac{\alpha_{1i}}{\sigma}\right) + \frac{1-\sigma}{\sigma}\log\left(E_{ijc\tau}\right) + \log\left(P_{jt}\right) - X_{jc}\theta_i - \rho_j - \eta_{ct}\right)\cdot\left(\frac{\partial\frac{1-\sigma}{\sigma}\log\left(E_{ijc\tau}\right)}{\partial E_{ijc\tau}}\right) \\ &= \Pr\left(j,c|\tau,i\right)\cdot\phi\left(\frac{\frac{1}{\sigma}\log\left(\frac{\alpha_{1i}}{\sigma}\right) + \frac{1-\sigma}{\sigma}\log\left(E_{ijc\tau}\right) + \log\left(P_{jt}\right) - X_{jc}\theta_i - \rho_j - \eta_{ct}}{\sigma_\mu}\right)\cdot\left(\frac{1-\sigma}{\sigma}\frac{1}{E_{ijc\tau}}\right)\cdot\frac{1}{\sigma_\mu}, \end{aligned} \tag{F.8}$$

where the last line applies another transformation of variable from $g\left(E_{ijc\tau}\right)$ to $\frac{g\left(E_{ijc\tau}\right)}{\sigma_\mu} = \mu/\sigma_\mu$, which is standard normal.

F.3 Computation of the price equilibrium

In section 4.2, we infer costs and markups by assuming that the first-order condition is correct on average, or $\frac{1}{T_j}\sum_t \frac{\partial\Pi_{jt}}{\partial P_{jt}} = 0$, where T_j is the number of months chain j stays in the sample. Take derivatives on profit Π_{jt}, defined by equation (23), one arrives at

$$\frac{1}{T_j}\sum_{t=1}^{T_j}\left(\frac{\partial Q_{jt}}{\partial P_{jt}}\left(P_{jt}\cdot(1-0.09) - \mathrm{mc}_j\right) + (1-0.09)\,Q_{jt}\right) = 0, \tag{F.9}$$

where

$$\frac{\partial Q_{jt}}{\partial P_{jt}} = \sum_{c=0,1} \int_i \mathbb{E} \left[\sum_{\tau=1}^{\bar{\tau}_{it}} \left(\frac{\partial q_{ijc\tau}}{\partial P_{jt}} \Pr(j,c|\tau,i) + \frac{\partial \Pr(j,c|\tau,i)}{\partial P_{jt}} q_{ijc\tau} \right) |\Theta_i \right] dF(\Theta_i). \tag{F.10}$$

In the above equation, the derivative on quantity conditional on purchase comes from the closed-form quantity demand function (equation (13)). That is,

$$\begin{aligned} \frac{\partial q_{ijc\tau}}{\partial P_{jt}} &= -\frac{1}{1-\sigma_i} \left(\frac{\sigma_i \Psi_{ijc\tau}}{P_{jt}} \right)^{\frac{1}{1-\sigma_i}} P_{jt}^{-1} \\ &= -\frac{1}{1-\sigma_i} \frac{q_{ijc\tau}}{P_{jt}}. \end{aligned} \tag{F.11}$$

On the other hand, the logit choice probability's derivative is:

$$\begin{aligned} \frac{\partial \Pr(j,c|\tau,i)}{\partial P_{jt}} &= \Pr(j,c|\tau,i)\left(1-\Pr(j,c|\tau,i)\right) \frac{\partial \tilde{w}_{ijc\tau}}{\partial P_{jt}} \\ &= \Pr(j,c|\tau,i)\left(1-\Pr(j,c|\tau,i)\right) \left(-\frac{\sigma_i}{1-\sigma_i} \left(\Psi_{ijc\tau} \frac{\left(q_{ijc\tau}\right)^{\sigma_i}}{P_{jt}} - q_{ijc\tau} \right) \right), \end{aligned} \tag{F.12}$$

where the second line follows the definition of $\tilde{w}_{ijc\tau}$, the indirect utility that drives chain-channel choice, in equation (14).

Equations (F.9)–(F.12) give a closed-form solution to the marginal costs of each chain, mc_j. In counterfactual simulations, we take these costs as given and solve for new equilibrium prices under each scenario, outlined by Table 6.

G Additional figures and tables

Appendix Table G.1: Sample selection

	fraction of sample
chain identity not missing	0.644
individual location not missing	0.999
individual never moved	0.831
all of the above	0.531
observations	2,267,772

Notes: This table reports our sample selection criteria.

Appendix Table G.2: Store-entry effect on offline shopping incidence

	distance change 5-20km	1-5km	0.1-1km	0-0.1km	no store entry (placebo)
post entry	0.445***	0.347***	0.199***	0.079	0.021**
	(0.038)	(0.035)	(0.043)	(0.050)	(0.006)
pre trend	-0.004**	-0.003*	-0.005**	-0.007**	-0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)
post trend	-0.004**	-0.002	-0.003	-0.006**	-0.007***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)
R-squared	0.15	0.15	0.15	0.15	0.16
observations	1,135,074	1,361,960	813,099	473,821	27,299,660

Notes: This table shows estimates of Equation (4) of the main paper, focusing on consumer-chain pairs where the closest store is within 20 km of the consumer at the start of the sample, and where the chain builds a store and reduces its distance to the customer. We divide the sample into groups where the entry has different impact on the travel distance of the customer. Column 1-4 examines customer-chain pairs where the distance change at entry is 5-20 km, 1-5 km, 0.1-1 km, and 0-0.1 km. Finally, the last column presents a placebo test where we focus on consumer-chain pairs where no store entry or exits are relevant, and we hypothetically assign a "store entry date" for each of such pairs.

Appendix Table G.3: Additional parameter estimates for the structural model

	ρ_j		chain choice: offline		online		scale of RC	
branded chain 1	1.306	0.026	-2.950	0.051	-8.197	0.119	0.645	0.021
branded chain 2	1.085	0.027	-3.901	0.064	-7.611	0.109	-0.746	0.035
branded chain 3	1.687	0.031	-4.566	0.070	-8.807	0.138	0.203	0.045
branded chain 4	1.927	0.034	-6.050	0.108	-8.870	0.139	1.241	0.059
branded chain 5	1.427	0.032	-4.861	0.071	-10.005	0.201	0.087	0.063
branded chain 6	1.584	0.034	-4.935	0.080	-9.944	0.233	0.267	0.066
branded chain 7	0.616	0.027	-3.648	0.073			-0.918	0.058
other branded chains	1.895	0.027	-2.648	0.053	-7.395	0.103	0.561	0.019
department store 1	1.284	0.026	-3.087	0.056	-7.895	0.126	-0.664	0.027
department store 2	2.205	0.032	-6.001	0.102	-10.069	0.158	1.243	0.048
discounter 1	-0.135	0.024	-3.574	0.057			0.825	0.029
discounter 2	1.602	0.034	-5.286	0.070	-10.584	0.233	1.070	0.071
other discounters	0.207	0.021	-2.594	0.047	-9.161	0.168	0.912	0.021
general merch. 1	0.310	0.026	-2.967	0.064	-8.213	0.127	0.669	0.025
other general merch.	0.071	0.024	-2.929	0.047	-8.486	0.163	-0.934	0.021
online chain 1	1.760	0.034			-7.088	0.110	0.613	0.066
online chain 2	2.003	0.037			-7.167	0.114	0.439	0.068
other online chains	1.565	0.029			-5.064	0.100	-0.859	0.026
specialty chain 1	1.052	0.024	-4.132	0.057	-9.175	0.160	0.325	0.046
other specialty chains	2.076	0.028	-2.014	0.052	-7.181	0.101	0.303	0.016

Appendix Table G.4: Average price elasticity matrix

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)	(M)	(N)	(O)
(A) branded chain 1	-2.16	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
(B) branded chain 2	0.01	-2.12	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
(C) branded chain 3	0.01	0.01	-2.26	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
(D) branded chain 4	0.01	0.01	0.01	-2.44	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01
(E) branded chain 5	0.00	0.00	0.00	0.00	-2.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(F) branded chain 6	0.00	0.00	0.00	0.00	0.00	-2.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(G) branded chain 7	0.00	0.00	0.00	0.00	0.00	0.00	-2.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(H) department store 1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-2.18	0.01	0.01	0.01	0.01	0.01	0.01	0.01
(I) department store 2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-2.75	0.00	0.01	0.00	0.01	0.01	0.01
(J) discounter 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.93	0.00	0.00	0.00	0.00	0.00
(K) discounter 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-2.25	0.00	0.00	0.00	0.00
(L) general merch. 1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-1.96	0.01	0.01	0.01
(M) online chain 1	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	-2.50	0.02	0.00
(N) online chain 2	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.02	-2.59	0.00
(O) specialty chain 1	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	-2.20

Notes: Average (across consumers and time) price elasticity between pairs of chains. Each cell in the table represents the percent-change in purchase incidence to the *column* chain, in response to a percent-change in the price of the *row* chain.

Appendix Table G.5: Structural estimates without random coefficients (and robustness checks)

	main spec.	std err	full sample	std err	w/ 2nd distance	std err	less flex ctrl	std err
utility curvature (σ)	0.066	0.003	0.058	0.001	0.067	0.003	0.072	0.003
$\theta\times$ age>45	-0.017	0.005	-0.008	0.001	-0.017	0.004		
$\theta\times$ female	-0.039	0.005	-0.031	0.001	-0.017	0.005		
$\theta\times$ high income	0.086	0.005	0.068	0.001	-0.040	0.005		
$\theta\times$ inc missing	0.049	0.005	0.050	0.001	0.086	0.005		
$\theta\times$ online $\times$ age>45	-0.005	0.010	-0.015	0.003	-0.005	0.010	0.019	0.009
$\theta\times$ online $\times$ female	-0.026	0.009	0.002	0.002	-0.026	0.009	-0.056	0.008
$\theta\times$ online $\times$ high income	0.016	0.009	0.008	0.003	0.016	0.009	0.066	0.009
$\theta\times$ online $\times$ inc missing	0.071	0.011	0.019	0.003	0.072	0.011	0.081	0.010
$\theta\times$ brand HHI $\times$ age>45	-0.055	0.009	-0.011	0.002	-0.055	0.009	-0.044	0.008
$\theta\times$ brand HHI $\times$ female	0.059	0.009	0.053	0.003	0.060	0.009	-0.013	0.008
$\theta\times$ brand HHI $\times$ high income	-0.042	0.008	-0.007	0.002	-0.042	0.008	0.044	0.008
$\theta\times$ brand HHI $\times$ inc missing	-0.052	0.009	-0.004	0.003	-0.053	0.010	-0.006	0.008
$\theta\times$ log(avg distance+1)	-0.017	0.004	-0.013	0.001	0.252	0.033		
$\theta\times$ log(avg distance+1) $\times$ age>45	0.027	0.003	0.020	0.001	0.049	0.005		
$\theta\times$ log(avg distance+1) $\times$ female	-0.002	0.002	-0.005	0.001	0.027	0.003		
$\theta\times$ log(avg distance+1) $\times$ high income	-0.005	0.003	-0.003	0.001	-0.002	0.002		
$\theta\times$ log(avg distance+1) $\times$ inc missing	-0.009	0.003	-0.002	0.001	-0.005	0.003		
scale of μ	0.836	0.003	0.841	0.001	0.835	0.003	0.839	0.003
arrival rate of choice occasions (λ)	1.029	0.025	0.980	0.008	1.029	0.025	0.947	0.023
log(distance+1) (β)	-0.335	0.021	-0.246	0.007	-0.346	0.021	-0.411	0.014
log(second distance+1)					0.047	0.008		
age>45	0.527	0.039	0.546	0.012	0.279	0.035		
female	0.906	0.034	0.850	0.011	0.525	0.039		
high income	-0.292	0.034	-0.327	0.011	0.906	0.034		
inc missing	-0.251	0.040	-0.303	0.013	-0.291	0.034		
$\beta\times$ age>45	0.129	0.020	0.004	0.007	0.137	0.020	0.044	0.010
$\beta\times$ female	0.115	0.020	-0.001	0.006	0.121	0.020	0.106	0.009
$\beta\times$ high income	-0.015	0.021	0.010	0.007	-0.010	0.021	0.016	0.010
$\beta\times$ inc missing	-0.237	0.026	-0.026	0.008	-0.233	0.026	-0.033	0.011
online $\times$ age>45	-0.489	0.096	-0.302	0.029	-0.492	0.096	-0.759	0.087
online $\times$ female	0.478	0.088	0.087	0.028	0.473	0.087	0.425	0.085
online $\times$ high income	-0.029	0.090	-0.079	0.029	-0.032	0.090	-0.564	0.089
online $\times$ inc missing	-0.491	0.102	-0.047	0.031	-0.495	0.102	-0.575	0.095
brand HHI $\times$ age>45	0.032	0.049	-0.183	0.016	0.030	0.049	-0.015	0.040
brand HHI $\times$ female	0.219	0.047	0.209	0.016	0.218	0.047	0.859	0.040
brand HHI $\times$ high income	0.446	0.045	0.270	0.015	0.446	0.045	-0.121	0.037
brand HHI $\times$ inc missing	0.320	0.052	0.205	0.017	0.322	0.052	0.076	0.043
log(avg distance+1)	0.291	0.035	0.132	0.011	-0.002	0.000		
log(avg distance+1) $\times$ age>45	-0.399	0.030	-0.250	0.010	-0.251	0.040		
log(avg distance+1) $\times$ female	-0.196	0.026	-0.016	0.009	-0.403	0.030		
log(avg distance+1) $\times$ high income	-0.032	0.027	0.022	0.009	-0.200	0.026		
log(avg distance+1) $\times$ inc missing	0.256	0.033	0.045	0.010	-0.036	0.027		

Notes: The first column presents structural estimates without individual random coefficients, using the same estimation sample as the main model. The second column uses the full sample. The third column uses the estimation sample but also allows consumer store choices to depend on her distance to the second-closest store ("second distance"). The fourth column presents the estimates of a restrictive specification where we take away controls that resemble cross-sectional variation between consumers (i.e., baseline demographics, log average distance, and the interaction between the two sets of variables).

Appendix Table G.6: Gains from e-commerce and decomposition (year 2018)

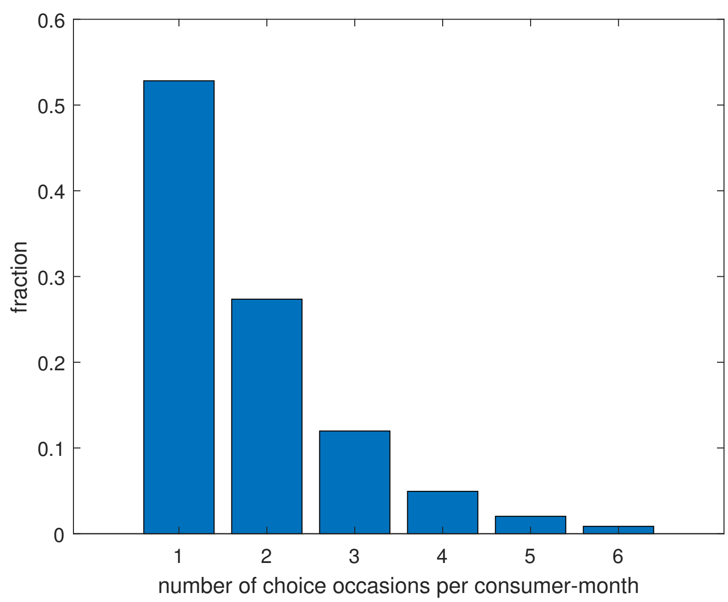
	mean surplus (euros)	(std err)	25%	(std err)	75%	(std err)
equiv. variations: remove all online	469.39	7.22	294.82	5.37	596.79	9.48
... from transport. costs	208.86	4.15	90.00	0.00	270.00	4.74
... from online-only rtl.	142.72	4.16	68.51	4.11	186.00	9.09
... from online channel of existing rtl.	111.38	3.33	60.00	2.43	150.00	2.69
... from price changes	6.44	0.50	2.50	0.00	10.00	0.81

Notes: These tables present the decomposition of welfare gains from e-commerce, focusing on year 2018. Mean consumer surplus is the average equivalent variation, $\bar{\Delta}_{iy}$, for each individual i and for $y = 2018$.

Appendix Table G.7: Changes in equilibrium prices from taking away e-commerce (year 2018)

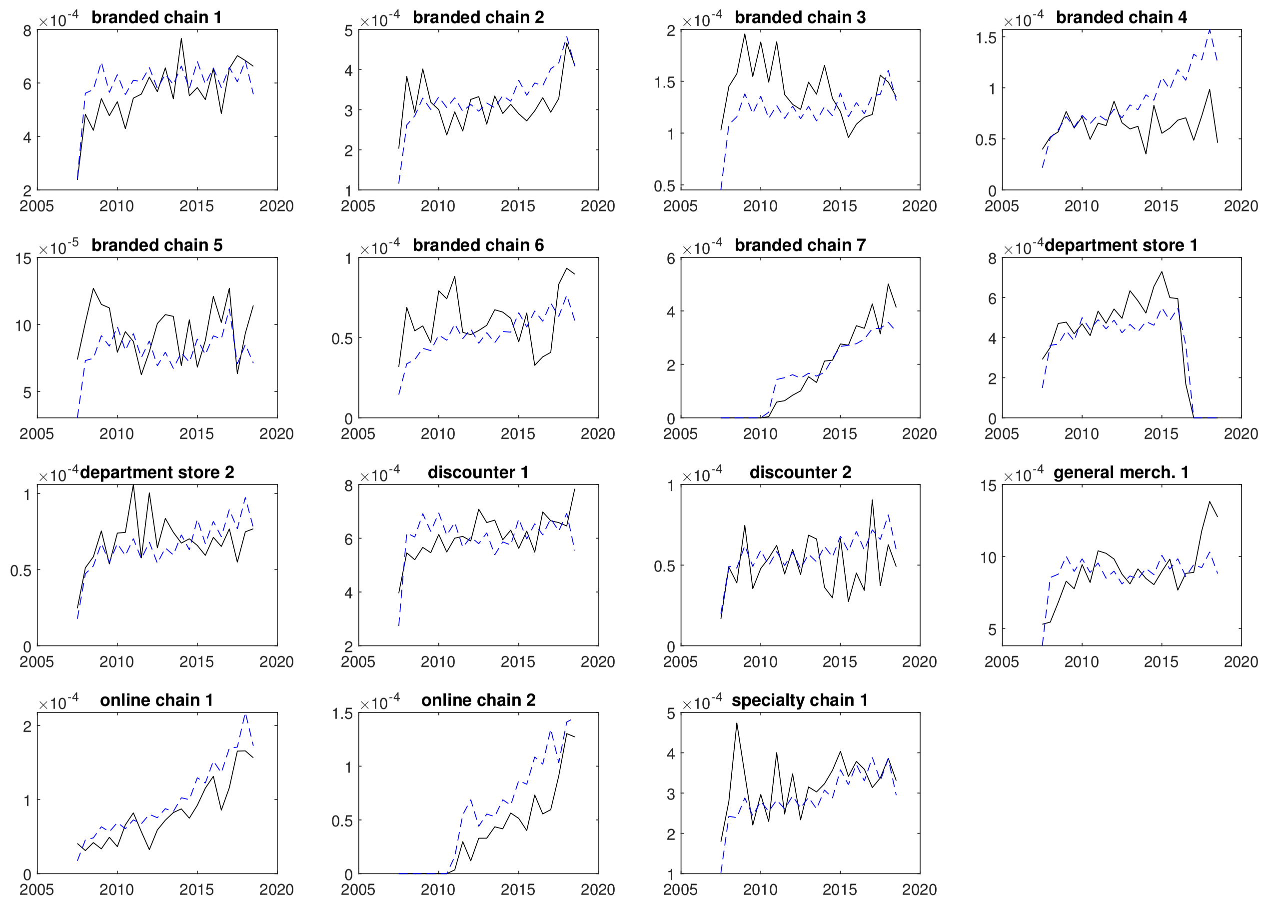
	mean	(std err)	std	(std err)
price change: all online	0.01	0.00	0.01	0.00
... from transport. costs	0.00	0.00	0.00	0.00
... from online-only rtl.	0.00	0.00	0.00	0.00
... from online channel of existing rtl.	0.01	0.00	0.01	0.00

Notes: Counterfactual changes in equilibrium prices when e-commerce is taken away, focusing on year 2018.



Appendix Figure G.1: Distribution of choice occasions

Notes: Distribution of choice occasions across consumers.



Appendix Figure G.2: Observed and model-predicted quantity

Notes: This figure reports observed (in solid) and simulated (in dash) expected per-customer purchase quantity for each chain over time.