E-Companion–Online Appendix

A. Subsample Analysis with Lead Time Less than or Equal to 60 Days

We limit our sample to those orders with lead times less than or equal to 60 days to exclude those possible highly customized products, which significantly delay lead time. We repeat our main analyses of testing the three hypotheses. The results are shown in Tables 9, 10a, and 10b, which are consistent with those reported in the main paper.

Table 9: Lead Time Elasticity

Variable	Model 1 Estimated by 2SLS
ln*AVGLEADTIME*	–0.034*** (0.008)
ONLINE	0.372** (0.145)
CATALOG	0.118 (0.150)
ONLINE ×ln*AVGLEADTIME*	–0.198** (0.072)
CATALOG ×ln*AVGLEADTIME*	–0.068* (0.028)
Control Variables	
ln*CATLEADTIME*	–0.003 (0.022)
ln*PRICE*	–0.063*** (0.007)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	362,182
Adj. R^2	0.730

Notes. Robust standard errors clustered at the product category–day level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Moderating Effects of Popular and Niche Products and Experience and Search Goods

(a) Moderating Effects of Popular and Niche Products

Variable	ABC
ln*AVGLEADTIME*	–0.033*** (0.008)
ONLINE	–0.020 (0.059)
CATALOG	–0.009 (0.030)
ONLINE ×ln*AVGLEADTIME*	–0.006* (0.003)
CATALOG ×ln*AVGLEADTIME*	–0.005* (0.002)
B	0.024* (0.011)
C	0.052*** (0.014)
B ×ln*AVGLEADTIME*	–0.018** (0.007)
C ×ln*AVGLEADTIME*	–0.021*** (0.006)
B ×*ONLINE*	0.059 (0.129)
C ×*ONLINE*	–0.090 (0.070)
B ×*CATALOG*	–0.016 (0.090)
C ×*CATALOG*	0.104 (0.144)
B ×ln*AVGLEADTIME* ×*ONLINE*	–0.022* (0.011)
C ×ln*AVGLEADTIME* ×*ONLINE*	–0.047 (0.038)
B ×ln*AVGLEADTIME* ×*CATALOG*	–0.016* (0.008)
C ×ln*AVGLEADTIME* ×*CATALOG*	–0.052** (0.019)
Control Variables	
ln*CATLEADTIME*	–0.012 (0.021)
ln*PRICE*	–0.76*** (0.015)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	362,182
Adj. R^2	0.734

Notes. Robust standard errors clustered at the product category–day level in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

(b) Moderating Effects of Experience and Niche Goods

Variable	Experiential
ln*AVGLEADTIME*	–0.034* (0.013)
ONLINE	–0.026 (0.052)
CATALOG	–0.018 (0.011)
ONLINE ×ln*AVGLEADTIME*	–0.004* (0.002)
CATALOG ×ln*AVGLEADTIME*	–0.003* (0.001)
EXPERIENTIAL	–0.073* (0.033)
EXPERIENTIAL ×ln*AVGLEADTIME*	–0.009 (0.017)
EXPERIENTIAL×*ONLINE*	0.369 (0.294)
EXPERIENTIAL ×*CATALOG*	0.156* (0.079)
EXPERIENTIAL ×ln*AVGLEADTIME* ×*ONLINE*	–0.179 (0.149)
EXPERIENTIAL ×ln*AVGLEADTIME* ×*CATALOG*	–0.080* (0.040)
Control Variables	
ln*CATLEADTIME*	–0.072 (0.056)
ln*PRICE*	–0.051* (0.025)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	362,182
Adj. R^2	0.732

Notes. Robust standard errors clustered at the product category–day level in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

B. Subsample Analysis Excluding Products Prone to Customization

We consult with our industry data provider to generate a list of product categories that are prone to customization, which may delay the lead time, and exclude them from our full sample. They are bedroom, wardrobe, bookcase, dresser, chest, living room, mirror, showcase, and office furniture. We then replicate our main analyses on this subset of products to test the three hypotheses. The results are shown in Tables

11, 12a, and 12b and are consistent with those reported in the main paper. That is, the showroom channel makes customers less sensitive to lead time than both online and catalog channels. Furthermore, customers are less sensitive to lead time when purchasing niche products in the showroom than in either the online or catalog channel, and customers are more sensitive to lead time when purchasing experiential products from the catalog or online than at the showroom because they require more touch and feel than non-experiential ones.

Table 11: Lead Time Elasticity

Variable	Model 1 Estimated by 2SLS
ln*AVGLEADTIME*	–0.034*** (0.009)
ONLINE	0.308* (0.123)
CATALOG	0.034 (0.210)
ONLINE ×ln*AVGLEADTIME*	–0.167** (0.062)
CATALOG ×ln*AVGLEADTIME*	–0.025** (0.009)
Control Variables	
ln*CATLEADTIME*	–0.036 (0.033)
ln*PRICE*	–0.058*** (0.010)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	273,543
Adj. R^2	0.766

Notes. Robust standard errors clustered at the product category–day level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Moderating Effects of Popular and Niche Products and Experience and Search Goods

(a) Moderating Effects of Popular and Niche Products

Variable	ABC
ln*AVGLEADTIME*	–0.033** (0.011)
ONLINE	–0.008 (0.058)
CATALOG	–0.036 (0.026)
ONLINE ×ln*AVGLEADTIME*	–0.008* (0.003)
CATALOG ×ln*AVGLEADTIME*	–0.010** (0.003)
B	0.017 (0.015)
C	0.047*** (0.011)
B ×ln*AVGLEADTIME*	–0.015 (0.008)
C ×ln*AVGLEADTIME*	–0.017** (0.006)
B ×*ONLINE*	0.018 (0.141)
C ×*ONLINE*	–0.083 (0.097)
B ×*CATALOG*	–0.015 (0.123)
C ×*CATALOG*	0.154 (0.123)
B ×ln*AVGLEADTIME* ×*ONLINE*	–0.001* (0.000)
C ×ln*AVGLEADTIME* ×*ONLINE*	–0.043 (0.052)
B ×ln*AVGLEADTIME* ×*CATALOG*	–0.013* (0.006)
C ×ln*AVGLEADTIME* ×*CATALOG*	–0.084** (0.031)
Control Variables	
ln*CATLEADTIME*	–0.041 (0.032)
ln*PRICE*	–0.72*** (0.017)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	273,543
Adj. R^2	0.768

Notes. Robust standard errors clustered at the product category–day level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(b) Moderating Effects of Experience and Niche Goods

Variable	Experiential
ln*AVGLEADTIME*	–0.033* (0.013)
ONLINE	–0.019 (0.059)
CATALOG	–0.041** (0.013)
ONLINE ×ln*AVGLEADTIME*	–0.001* (0.000)
CATALOG ×ln*AVGLEADTIME*	–0.014* (0.006)
EXPERIENTIAL	–0.074 (0.041)
EXPERIENTIAL ×ln*AVGLEADTIME*	–0.004 (0.021)
EXPERIENTIAL×*ONLINE*	0.173 (0.347)
EXPERIENTIAL ×*CATALOG*	0.255* (0.122)
EXPERIENTIAL ×ln*AVGLEADTIME* ×*ONLINE*	–0.084 (0.180)
EXPERIENTIAL ×ln*AVGLEADTIME* ×*CATALOG*	–0.133* (0.062)
Control Variables	
ln*CATLEADTIME*	–0.046 (0.036)
ln*PRICE*	–0.071*** (0.009)
SKU Effects	Yes
ZIP Code Effects	Yes
Day Effects	Yes
No. of observations	273,543
Adj. R^2	0.768

Notes. Robust standard errors clustered at the product category–day level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C. Propensity Score, Covariate Balance Test, and Results

We match ZIP codes in one channel with the ZIP codes in another channel using ZIP code level economic and demographic attributes, namely–*Average Age of Household Head, University Degree, Household Size, Home Ownership,* and *Residential Building Status*. We provide the definition of these variables and their descriptive statistics in Table 13. These variables are known to influence channel choice and purchasing behaviors (Bhatnagar and Ratchford, 2004; Fox et al., 2004). Through these variables, we seek to match ZIP codes across two channels with similar demographic characteristics and socioeconomic status.

Table 13: Demographic Variable Definition and Descriptive Statistics

Variable	Description	Min	Max	Mean	Std. Dev.
Average Age of Household Head	Average age (in years) of household head.	34.27	65.14	45.24	2.47
University Degree	Percentage of population in the ZIP code with a university degree.	0.01	0.37	0.15	0.06
Household Size	Average number of members in household.	1.34	2.47	2.40	0.268
Home Ownership	Percentage of home ownership in the ZIP code as opposed to being leased.	0.16	0.98	0.71	0.07
Residential Building Status	Percentage of residential buildings in the ZIP code with "excellence" status.	0.00	1.00	0.34	0.16

We estimate the propensity score by using a logistic regression model in which an indicator for channel selected is regressed on the observed covariates. We then obtain the propensity score from the predicted probability, which ranges between 0 and 1. We choose to use one-to-one matching with replacement because this option can often decrease bias by using ZIP codes in one channel that look similar to ZIP codes in another channel multiple times (Guo and Fraser, 2014). Moreover, when matching with replacement, the order in which the ZIP codes are matched does not matter (Stuart, 2010). Our derived sample is based on the lower count of two channels. For example, the online channel has 15,498 observations, while the showroom channel has 334,802 observations. Therefore, a matching procedure carried out for the online and showroom channel will result in a derived sample of 15,498 matched observations.

To validate the effectiveness of our matching procedure, we compare the average values of each covariate, prior to matching and after matching, by conducting a t-test of mean difference. Tables 14 through 16 demonstrate that our matching procedure effectively matches two groups at a time. The t-statistic values in the *before matching* column are all statistically significant at the 0.05 level, suggesting the means of the two groups are statistically different. However, the t-statistic values in the *after matching* column are all statistically nonsignificant, which suggests that our propensity score matching procedure manages to balance the means of the two matched groups.

Table 14: Propensity Score Covariate Balance Test (Online and Showroom Channels)

	Before Matching			After Matching		
	Online	Showroom	t-statistic	Online	Showroom	t-statistic
Average Age of Household Head	45.75	45.18	–28.26	45.75	45.75	0.18
University Degree	0.16	0.15	–13.66	0.16	0.16	0.04
Household Size	2.41	2.40	–4.42	2.41	2.41	–0.02
Home Ownership	0.71	0.71	–2.76	0.71	0.71	0.00
Residential Building Status	0.35	0.34	–8.45	0.35	0.36	–0.78

Table 15: Propensity Score Covariate Balance Test (Catalog and Showroom Channels)

	Before Matching			After Matching		
	Catalog	Showroom	t-statistic	Catalog	Showroom	t-statistic
Average Age of Household Head	45.67	45.18	–33.31	45.67	45.67	0.07
University Degree	0.15	0.15	–10.78	0.15	0.155	–0.20
Household Size	2.40	2.40	0.00	2.40	2.40	–0.53
Home Ownership	0.71	0.71	8.91	0.71	0.71	–0.03
Residential Building Status	0.34	0.34	7.85	0.34	0.34	–0.27

Table 16: Propensity Score Covariate Balance Test (Online and Catalog Channels)

	Before Matching			After Matching		
	Online	Catalog	t-statistic	Online	Catalog	t-statistic
Average Age of Household Head	45.75	45.67	–3.26	45.75	45.75	–0.37
University Degree	0.16	0.15	–4.70	0.16	0.16	–1.32
Household Size	2.41	2.40	–3.47	2.41	2.41	1.48
Home Ownership	0.71	0.71	–7.87	0.71	0.71	1.65
Residential Building Status	0.35	0.34	–12.22	0.35	0.36	–0.57

The three columns in Table 17 present the results of the comparisons between showroom and online, showroom and catalog, and catalog and online, respectively. The coefficients of $\ln AVGLEADTIME$ are all significant and negative (-0.020, -0.018, and -0.007). They are consistent with our main results that suggest lead time inhibits sales volume in the showroom (Columns 1 and 2) and the catalog (Column 3) channels. In addition, the coefficients of the interaction terms are significant and negative (−0.023, −0.126) in Columns 1 and 2. They support our main finding that the showroom makes consumers less sensitive to lead time than either the online or catalog channel. The interaction term turns out to be nonsignificant in Column 3 (–0.042), which is also consistent with the results in Table 3. We find that the catalog channel's lead time sensitivity is statistically indistinguishable from the online channel's.

Table 17: Propensity Score Matching Estimates

Variable	(1) Showroom vs. Online	(2) Showroom vs. Catalog	(3) Catalog vs. Online
ln*AVGLEADTIME*	–0.020*** (0.001)	–0.018*** (0.002)	–0.007* (0.003)
ONLINE	–0.070 (0.225)		–0.095 (0.126)
CATALOG		–0.300 (0.214)	
ONLINE ×ln*AVGLEADTIME*	–0.023* (0.011)		–0.042 (0.053)
CATALOG ×ln*AVGLEADTIME*		–0.126* (0.061)	
Control Variables			
ln*CATLEADTIME*	–0.086 0.068)	–0.093 (0.077)	–0.129 (0.133)
ln*PRICE*	–0.298*** (0.057)	–0.265*** (0.016)	–0.174* (0.073)
SKU Effects	Yes	Yes	Yes
ZIP Code Effects	Yes	Yes	Yes
Day Effects	Yes	Yes	Yes
No. of observations	15,498	30,092	15,498
Adj. R^2	0.7185	0.7322	0.790

Notes. Robust standard errors clustered at the product category–day level in parentheses.
Showroom channel is the base in Columns 1 and 2 and in Column 3, catalog channel is the base.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

D. Results of Subsample Analyses for Single-Item Orders, Comparable Products Across Channels, and Home Delivery Orders

Table 18 shows the results of the subsample analyses based on single-item orders, comparable products across channels, and home delivery orders. As can be seen, the coefficients of ln*AVGLEADTIME* are all statistically significant and negative (–0.027, –0.038 and –0.022). The interaction terms with *CHANNEL* are also all significantly negative, consistent with our main results in Table 3. All of these results support our finding that the showroom channel makes consumers less sensitive to lead time than both the online and catalog channels.

Table 18: Subsample Regression Estimates

Variable	(1) Estimated by 2SLS (Single-Item Order)	(2) Estimated by 2SLS (Common Products)	(3) Estimated by 2SLS (Home Delivery)
ln*AVGLEADTIME*	–0.027* (0.011)	–0.038*** (0.009)	–0.022*** (0.005)
ONLINE	0.354 (0.207)	0.392** (0.135)	0.163 (0.129)
CATALOG	0.108 (0.094)	0.013 (0.287)	0.046 (0.106)
ONLINE ×ln*AVGLEADTIME*	–0.187*** (0.005)	–0.213** (0.066)	–0.088*** (0.004)
CATALOG ×ln*AVGLEADTIME*	–0.062* (0.030)	–0.013* (0.005)	–0.032*** (0.003)
Control Variables			
ln*CATLEADTIME*	–0.011 (0.012)	–0.060 (0.043)	–0.014 (0.022)
ln*PRICE*	–0.063*** (0.005)	–0.016*** (0.002)	–0.068*** (0.012)
SKU Effects	Yes	Yes	Yes
ZIP Code Effects	Yes	Yes	Yes
Day Effects	Yes	Yes	Yes
No. of observations	272,253	226,463	332,955
Adj. R^2	0.736	0.773	0.750

Notes. Robust standard errors clustered at the product category–day level in parentheses.
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

E. Consumer-Order Level Analysis

We use a consumer-level Heckman selection model as a robustness check to address customers' self-selecting channels further. The consumer-level analysis also allows us to control for additional confounding factors, such as the mode of fulfillment. The serious shortcoming of a consumer-level analysis is its vulnerability given the potential censoring bias from customers who find the lead time to be long and, therefore, decide not to make the purchase.[17] Hence, we use the SKU–ZIP code–day level study as our main analysis and the consumer-level analysis as a robustness check. Our consumer-level model has the following

[17] We thank the anonymous associate editor for raising this excellent point and providing a helpful suggestion.

specification:

$$
\begin{aligned}
\ln SALES_{ghk} \quad = \quad & \zeta_{0h} + \Lambda_0 \ln LEADTIME_{ghk} + \tau_k CHANNEL_{gh} \\
& + \tau_k \ln LEADTIME_{ghk} \times CHANNEL_{gh} + \zeta_1 \ln CATLEADTIME^c_g + \zeta_2 FULFILLMENTMODE_g \\
& + \zeta_3 \ln STOREAGE_g + \zeta_4 ABC^c_g + \sum_g SKU_g \cdot \nu_g + \sum_t WEEK_t \cdot \Psi_t + \varepsilon_{ghk}.
\end{aligned} \tag{6}
$$

The dependent variable is ln$Sales_{ghk}$, representing the amount (in EUR) that consumer h spends on order g in channel k. Independent variable ln*LEADTIME* is the natural logarithm of order g's lead time. Independent variable *CHANNEL* has the same definition as the main analysis. As before, we specify channel $k = s$ (showroom) as our base. For the control variables, consumer fixed effects ζ_{0h} control for consumer heterogeneity. The lead time of other products in the category $CATLEADTIME^c$ adjusts for substitution effect. We adapt this variable previously defined in Model 3 in Section 6.3 to the order-level analysis. In particular, for single-item orders, we compute the average lead time of other single-item orders within the same product category as the focal order's SKU during the week it was transacted to generate variable $CATLEADTIME^c$ (77% of our sample are single-item orders). For multi-item orders, we calculate the average lead time of other orders with the same combination of product categories as the focal order's during the week it was transacted. For example, for a focal order with three SKUs, each from a different product category, we compute the average lead time of other orders that have the items only from all of the three identical categories. Besides, variable $FULFILLMENTMODE$ is an indicator that equals 1 if order g was fulfilled by a warehouse pick up, and 0 otherwise. Consumers can only choose one fulfillment mode for the entire order. Variable $STOREAGE$ captures the number of years the showroom store (where the order was placed or nearest to the consumer's address) was in operation. Similar to $CATLEADTIME^c$, we adapt the *ABC* variable previously defined in the aggregate-level analysis (Model 3) to the order-level analysis. We set ABC^c to be the ABC classification of the SKU in the order for single-item orders. For multi-item orders, we compute the weighted average value based on each SKU's contribution to the total order sales amount. A Class A SKU is assigned a value of 1, a Class B SKU a 2, and a Class C SKU a 3. Then, we compute the weighted average value for each multi-item order and assign ABC^c = A if the average is closest to 1, ABC^c = B if the value is closest to 2, and ABC^c = C if the value is closest to 3.[18] We set ABC^c = A as the base in all model estimations. We also include SKU fixed effects to adjust for unobserved product heterogeneity in each order and weekly fixed effects to control for temporal shocks (e.g., seasonality).[19] Moreover, we use cluster-robust standard errors at the consumer province (i.e., the province where the consumer resides) level for robust estimation.

We adopt both the 2SLS IV approach explained in Section 5.2 and a Heckman selection method (Heckman, 1976, 1979) to address the channel selection bias. For the Heckman model, we follow Lee's generalized approach (Lee, 1983) to obtain the channel-specific correction term ratio (λ) from a first-stage multinomial logit model of channel selection. The model is specified as

$$Pr(CHANNEL_{gh} = k) = exp(\mathbf{X}_{ghk}\pi)/[exp(\mathbf{X}_{gho}\pi) + exp(\mathbf{X}_{ghs}\pi) + exp(\mathbf{X}_{ghc}\pi)], \quad (7)$$

where $k = o$, s and c, and $\mathbf{X}_{gh}$ and π denote the vector of variables in the selection model and their corresponding coefficients, respectively. The variables $\mathbf{X}_{gh}$, expounded in the extant literature that are likely to influence a consumer's channel choice, include average product price (in EUR) in order g placed by consumer h, an indicator of whether or not consumer h is a high spender (her total expenditures of all transactions greater than sample median of EUR 718); distance between consumer h and the nearest showroom store; ZIP code level economic and demographic controls (*Average Age of Household Head, University Degree, Household Size, Home Ownership,* and *Residential Building Status*); and week factors $WEEK_g$ (Fox et al., 2004; Bhatnagar and Ratchford, 2004; Zentner et al., 2013; Gallino et al., 2017; Lim et al., 2021).

Let $F(\mathbf{X}_{gh}\pi)$ be a logistic distribution function to predict the probabilities of each channel given $\mathbf{X}_{gh}\pi$ and the transformation $J = \Phi^{-1}F$. We then compute the correction term ratio in the first stage as follows:

[18] For example, an order has two SKUs, comprising a Class A SKU with a retail price of 100 EUR and a Class B SKU with a retail price of 200 EUR. Then, the weighted average value would be 1.67 ([(100 EUR×1) + (200 EUR×2)]/300). Since 1.67 is closest to 2, this order will be assigned ABC = B.

[19] For multi-item orders, we control for the unique combination of the SKU fixed effects.

$$\hat{\lambda_{gh}} = \lambda(\mathbf{X}_{gh}\hat{\pi}) = \frac{\phi(J(\mathbf{X}_{gh}\hat{\pi}))}{F(\mathbf{X}_{gh}\hat{\pi})}. \quad (8)$$

where $\phi(.)$ is the probability density function of a standard normal. In the second stage, we bring the computed ratio into Model 6 as an additional control variable of consumers' channel selection decision.

Table 19 presents the results. Similar to our main results shown in Table 3, the IVs correct the biased estimation of ln*LEADTIME* downwards from 0.189 (Column 1) to −0.214, and −0.163 (Columns 2 and 3). The coefficients of the interaction terms between lead time and channels are significantly negative (–0.049 and –0.060 in Column 1, –0.507 and –0.393 in Column 2, and –0.275 and –0.087 in Column 3), again corroborating our main finding that showroom demand is less sensitive to lead time than either the online or catalog demand.

Table 19: Consumer-Order Level Lead Time Elasticity Estimates

Variable	(1) Estimated by OLS	(2) Estimated by 2SLS	(3) Estimated by 2SLS + Heckman
ln*LEADTIME*	0.189*** (0.005)	–0.214*** (0.007)	–0.163*** (0.007)
ONLINE	–0.258*** (0.026)	0.646* (0.271)	0.478 (0.318)
CATALOG	–0.260*** (0.023)	0.394 (0.204)	0.035 (0.178)
ONLINE ×ln*LEADTIME*	–0.049*** (0.013)	–0.507*** (0.136)	–0.275* (0.130)
CATALOG ×ln*LEADTIME*	–0.060*** (0.013)	–0.393*** (0.106)	–0.087* (0.041)
Control Variables			
ln$CATLEADTIME^c$	–0.209*** (0.026)	–0.181*** (0.027)	–0.175*** (0.024)
FULFILLMENTMODE	–0.317*** (0.023)	–0.284*** (0.019)	–0.231*** (0.018)
STOREAGE	–0.004** (0.001)	–0.004*** (0.001)	–0.005 (0.007)
$ABC^c = B$	0.033** (0.010)	–0.070*** (0.014)	0.037** (0.012)
$ABC^c = C$	0.059** (0.018)	–0.112*** (0.026)	–0.048 (0.020)
$\hat{\lambda}$			1.844*** (0.089)
Consumer Effects	Yes	Yes	Yes
Week Effects	Yes	Yes	Yes
Product Effects	Yes	Yes	Yes
No. of observations	390,548	390,548	390,548
Adj. R^2	0.423	0.562	0.531

Notes. Robust standard errors clustered at the consumer province level in parentheses.

** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

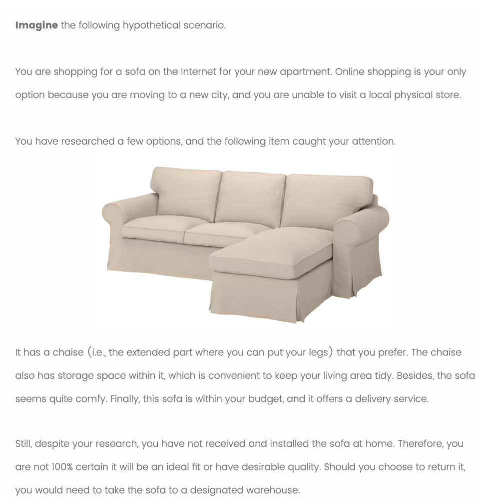
F. Online Experiment on the Effects of Information Precision on Anxiety and Purchase Intent

F.1 Participants. We recruited 200 participants from Amazon Mechanical Turk and offered for $1.00 for their participation. We chose the sample size of 200 participants to capture 50 observations per condition. One participant who did not complete all tasks as instructed was dropped from the sample, resulting in a final dataset of 199 participants. In this sample, the average age is 35.5 years old, and approximately 35.18% of the participants are females. In addition, 84% of the participants have at least a bachelor's degree. 51.26% definitely have purchased a sofa, while 35.68% may have purchased a sofa.

F.2 Design and procedure. At the beginning of the experiment, we told the participants to read a hypothetical online shopping scenario carefully and answer the questions. We then randomly assigned the participants into either a full information condition or a limited information condition (Figure 2). Both conditions asked the participants to imagine that they were shopping for a sofa on the Internet for their new apartment. They were asked to evaluate the same sofa. The difference is the amount of information about the sofa provided to the participants.

Figure 2: Screenshots of the Scenarios

(a) Full Information Condition



(b) Limited Information Condition

After that, we asked the participants to rate, “To what extent is the information provided sufficiently precise for you to evaluate the furniture’s quality and fit?” on a sliding scale from 0 (Not at all) to 100 (Very much so). We used this input to measure information precision, one of the variables reported in Table 7 of the main paper.

We then randomly manipulated the lengths of delivery time. Specifically, we informed half of the participants that the the sofa could be delivered in one week (i.e., fast delivery condition), and the other half that the delivery could take eight weeks (i.e., slow delivery condition). In both conditions, before telling the participants their manipulated delivery times, we had primed them with a prior expectation of two weeks, so that the participants could distinguish the long or short delivery times. We also conveyed the possibility of a further delay.

After the delivery time manipulation, we used the six-item Short-form Spielberger State-Trait Anxiety Inventory (“STAI”) (Marteau and Bekker, 1992) instrument to measure anxiety. In particular, we took the averages of the three anxiety inputs (i.e., tense, upset, worried) and the three calm inputs (i.e., calm, relaxed, content) separately. We subtracted the anxiety level from the calm level to calculate the final Anxiety variable. Figure 3 shows the six questions.

Figure 3: STAI Questions


Given the delivery time and product information, please rate the extent to which the following emotions would describe your feelings while waiting for the sofa.

	Not at all	Somewhat	Moderately so	Very much so
I would feel tense.	○	○	○	○
I would feel calm.	○	○	○	○
I would feel upset.	○	○	○	○
I would feel relaxed.	○	○	○	○
I would feel content.	○	○	○	○
I would feel worried.	○	○	○	○

We subsequently asked the participants to rate, “Given all the product information and the delivery time, how likely are you to purchase this product?” on a sliding scale from 0 (Not at all likely) to 100 (Very likely). With this input, we constructed the Purchase Intent variable examined in Table 7 of the main paper.

Finally, we collected some demographic information including age, gender, education background, and past experience with purchasing a sofa as control variables to isolate the effects of information precision and delivery time.

G. Proofs of Propositions 1 and 2

Proof of Proposition 1

Proof. Denote $n^*(\xi_s) = \arg\max_n P(n, \xi_s)$, given ξ_s. Thus, we have $n^* = n^*(\xi_s)$ and $\tilde{n}^* = n^*(\tilde{\xi}_s)$. Note that for any $n_1, n_2, \xi_{s1}, \xi_{s2}$, where $n_1 > n_2, \xi_{s1} > \xi_{s2}$, we have $P(n_1, \xi_{s1}) - P(n_1, \xi_{s2}) = (\xi_{s1} - \xi_{s2})\frac{m_s D n_1}{\pi r}\int_0^{\frac{\pi r}{n_1}} \alpha(x)dx \geq (\xi_{s1} - \xi_{s2})\frac{m_s D n_2}{\pi r}\int_0^{\frac{\pi r}{n_2}} \alpha(x)dx = P(n_2, \xi_{s1}) - P(n_2, \xi_{s2})$, where the inequality is because $\alpha(x) \geq 0$ is decreasing in x (and thus the function $F(n) = n\int_0^{\frac{\pi r}{n}} \alpha(x)dx$ is increasing in n). Therefore, $P(n, \xi_s)$ has increasing difference in (n, ξ_s). Since $0 > w_s > w_o = \tilde{w}_s$, we have $\xi_s > \tilde{\xi}_s$. Then, by Topkis's monotonicity theorem (Topkis, 1998), we have $n^*(\xi_s) \geq n^*(\tilde{\xi}_s)$ for $\xi_s > \tilde{\xi}_s$, that is, $n^* \geq \tilde{n}^*$. □

Proof of Proposition 2

Proof. Note that $\pi^{(1)} - \pi^{(2)} = m_s(1-\alpha_s)[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ - m_o(1-\alpha_o)[D_o - (Q-D_s)^+ - (D_o-Q)^+]^+$. Next, we show that $[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ = [D_o - (Q-D_s)^+ - (D_o-Q)^+]^+$.

If $Q \geq D_s + D_o$, then $[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ = [D_o - (Q-D_s)^+ - (D_o-Q)^+]^+ = 0$. If $Q < D_s + D_o$, then:

- If $D_o < D_s$, then:
  - If $Q < D_o < D_s$, then $[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ = [D_o - (Q-D_s)^+ - (D_o-Q)^+]^+ = Q$.
  - If $D_o < Q < D_s$, then $[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ = [D_o - (Q-D_s)^+ - (D_o-Q)^+]^+ = D_o$.
  - If $D_o < D_s < Q$, then $[D_s - (Q-D_o)^+ - (D_s-Q)^+]^+ = [D_o - (Q-D_s)^+ - (D_o-Q)^+]^+ = D_s + D_o - Q$.
- If $D_s < D_o$, then:

- If $Q < D_s < D_o$, then $[D_s - (Q - D_o)^+ - (D_s - Q)^+]^+ = [D_o - (Q - D_s)^+ - (D_o - Q)^+]^+ = Q$.
- If $D_s < Q < D_o$, then $[D_s - (Q - D_o)^+ - (D_s - Q)^+]^+ = [D_o - (Q - D_s)^+ - (D_o - Q)^+]^+ = D_s$.
- If $D_s < D_o < Q$, then $[D_s - (Q - D_o)^+ - (D_s - Q)^+]^+ = [D_o - (Q - D_s)^+ - (D_o - Q)^+]^+ = D_s + D_o - Q$.

Thus, we always have $[D_s - (Q - D_o)^+ - (D_s - Q)^+]^+ = [D_o - (Q - D_s)^+ - (D_o - Q)^+]^+$. As a result, $\pi^{(1)} - \pi^{(2)} = [m_s(1 - \alpha_s) - m_o(1 - \alpha_o)][D_s - (Q - D_o)^+ - (D_s - Q)^+]^+$. Therefore, the sign of $\pi^{(1)} - \pi^{(2)}$ is the same as the sign of $m_s(1 - \alpha_s) - m_o(1 - \alpha_o)$. This concludes the result. □