

WEB APPENDIX

A Zhihu Interface

The screenshot displays the Zhihu profile of user 张佳玮 (Zhang Jiawei). The profile header includes a profile picture, a cover image, and the user's name. Below the header, there are navigation tabs for 'All Activities', 'Answers', 'Questions', 'Articles', 'Columns', 'Ideas', 'Collections', and 'Follows'. The 'All Activities' tab is selected, showing a list of the user's past activities in chronological order. The activities include articles, answers, and questions. The first activity is an article titled '梅西倒钩梅开二度，内马尔的从容自如：巴黎新阵新气象?' (Messi's backflip goal opens his second account, Neymar's calm and confident: Paris's new lineup and new atmosphere?). The second activity is an answer to a question titled '如果没有和石秀绑定，光凭自己能力杨雄够资格进天罡吗?' (If not bound with Shi Xiu, is Yang Xiong qualified to enter the Tiantang based on his own abilities?). The third activity is a question titled '为什么《笑傲江湖》中，华山派只有岳不群夫妇二人夫妻店?' (Why, in 'The Smiling Proud in Wonderland', is the Huashan Sect only a couple's shop with岳不群 and his wife?). The right sidebar shows the user's statistics, including '认证信息' (Verification Information), '优秀答主、新知答主' (Excellent Contributor, New Contributor), '知乎收录' (Zhihu Collection), '获得 8,804,942 次赞同' (Received 8,804,942 likes), '参与 17 次公共编辑' (Participated in 17 public edits), '出版作品' (Published Works), '#Followees' (130), '#Followers' (3,455,724), and '#Lives held' (12).

张佳玮 公号：张佳玮写字的地方 User Name

动态 回答 4,194 提问 0 文章 1,333 专栏 1 想法 723 收藏 0 关注

他的动态

All the past activities by the user (in time order)

发表了文章 2022-08-06 18:02

梅西倒钩梅开二度，内马尔的从容自如：巴黎新阵新气象?

张佳玮 2021 新知答主

103 人赞同了该文章

法甲开局，巴黎圣日耳曼开门红，5比0克萊蒙。内马尔一球三助攻。梅西两球一助攻——包括一个凌空倒钩。35岁了，第86分钟，背门凌空倒钩。（好像是他生涯第一个倒钩进球？）上周巴黎4比0南特拿了法国超级杯，... 阅读全文

赞同了回答 2022-08-06 12:47

如果没有和石秀绑定，光凭自己能力杨雄够资格进天罡吗?

顾兰端 剩下的惟有沉默而已

133 人也赞同了该回答

当然能了。水浒传里吹嘘好汉武艺常用的形容手法就是“百十人近身不得”，反过来说就是任你武功如何惊天动地，被近身了也照样熄火。武松强吧，空手打死老虎，三五百斤石头当篮球玩，不也是阴沟里翻船，被飞虎大将军和张府八骠骑轻松拿下，甚至连手里的器械都用不出来。武松听得这话，提着梢棒，大踏步，直赶入花园里去寻时，一周遭不见。复翻身却...

赞同了问题 2022-08-05 07:44

为什么《笑傲江湖》中，华山派只有岳不群夫妇二人夫妻店?

张佳玮 2021 新知答主

522 人赞同了该回答

类似的问题：为什么衡山派掌门那么神秘莫测？为什么泰山派是几个师叔挟制一个掌门？为什么嵩山派是一个大师兄带好几个师弟？为什么恒山派是三师姐独尊？..... 如果存心挖下去，可以找出每个门派的隐藏内幕。但其实有另一种可能：金庸先生写小说时，没想着专门给华山派设置不同的体制。可能宁中则就是为了故事情节的角色。比起营造世界观，可... 阅读全文

认证与成就

认证信息 体育盐究员

优秀答主、新知答主

文学、篮球 话题

2021 新知答主

知乎收录 412 个回答、155 篇文章

编辑推荐、知乎圆桌、知乎周刊和知乎日报收录

获得 8,804,942 次赞同

获得 1,111,234 次喜欢、2,331,874 次收藏、183 次专业认可

参与 17 次公共编辑

出版作品

历史与传奇

历史的细节里，常蕴含着我们意想不到的传奇。...

2 条评论

#Followees

关注了 130

#Followers

关注者 3,455,724

我关注的人中有 31 人最近关注了他

#Lives held

举办的 Live 12

关注的话题 0

关注的专栏 1

关注的问题 4,042

关注的收藏夹 0

Figure A1: Example of User Profile Page

Title: Things to consider when choosing a restaurant



Figure A2: Example of a Live Event

Note: This figure illustrates the interface of a Live event. During the livestream, the creator will give a real-time talk via voice, text, and picture messages. The creator can also respond to questions raised by the audience.

B Price Comparison Across Comparable Content Platforms

To the best of our knowledge, Zhihu Live was the largest livestreaming platform of its kind during our study period, while competing platforms remained relatively small. We identified four comparable platforms in China that may compete with Zhihu Live, including Himalaya FM, Dedao, Lychee Live, and Qianliao Live. In the summer of 2016, we conducted a survey of event prices on these five platforms by randomly scraping 100 paid events from each platform. The descriptive statistics for these prices are presented in Table B1. To ensure comparability across platforms, we standardize the price to USD per 30 minutes of content. The results show that paid events hosted on Zhihu generally had higher price points compared to similar events on competing platforms.

Table B1: Price Comparison (Unit:
USD per 30 minutes of content)

Platform	Mean	Median	Std.
Zhihu Live	1.83	1.97	1.36
Himalaya FM	0.85	0.58	0.79
Dedao	0.50	0.38	0.37
Lychee Live	1.84	0.71	4.20
Qianliao Live	0.48	0.42	0.43

C Robustness Checks: OLS Estimation

Table C2: OLS Estimation: Inclusion of Additional Controls

Dependent Variable: $\ln(\text{Demand})$	Category-specific Time Trends (1)	Period-specific Covariate Effects (2)
<i>Key Independent Variables</i>		
<i>Post</i>	−2.384*** (0.142)	−2.386*** (0.891)
$\ln(\text{Price})$	−1.163*** (0.065)	−1.177*** (0.060)
$\text{Post} \times \ln(\text{Price})$	0.329*** (0.041)	0.381*** (0.085)
<i>Event Characteristics</i>		
ExposureDuration	0.005 (0.048)	0.029 (0.035)
SeatLimit	−0.094* (0.055)	−0.070*** (0.027)
Advertisement	0.532*** (0.101)	0.686*** (0.111)
Rating	0.482*** (0.033)	0.443*** (0.037)
Holiday	−0.505*** (0.143)	−0.358*** (0.129)
<i>Creator Profile in QA Community</i>		
Follower	0.127*** (0.047)	0.117*** (0.042)
Followee	−0.001 (0.023)	0.039 (0.028)
Answer	0.033 (0.029)	0.037 (0.032)
Upvote	0.376*** (0.082)	0.356*** (0.099)
Downvote	0.205*** (0.064)	0.184*** (0.062)
Thank	0.005 (0.121)	−0.046 (0.108)
Unhelpful	−0.412*** (0.129)	−0.318** (0.125)
Badge	−0.042 (0.083)	−0.117 (0.081)
TenureQA	0.101*** (0.033)	0.090*** (0.030)
Celebrity	0.850*** (0.208)	1.182*** (0.190)
<i>Creator Profile in Zhihu Live Market</i>		
NumPastEvent	−0.147*** (0.051)	−0.193*** (0.043)
AvgPastSales	0.309*** (0.063)	0.255*** (0.055)
AvgPastRating	0.066* (0.037)	0.057* (0.033)
TenureMarket	−0.013 (0.053)	0.032 (0.050)
Invitation	0.076 (0.142)	0.122 (0.127)
Category fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Category $\times$ Time fixed effects	Yes	No
<i>Post</i> $\times$ Category fixed effects	No	Yes
<i>Post</i> $\times$ Time fixed effects	Yes	Yes
<i>Post</i> $\times$ Event and creator characteristics	No	Yes
R ²	0.585	0.502
Num. obs.	4,598	4,598

Note: Each event contributes one observation for the pre-period and one for the post-period, resulting in a total of $2,299 \times 2 = 4,598$ observations. Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C3: OLS Estimation: Separate Pre- and Post-Period Regressions

Dependent Variable	No Controls		Full Controls		Exclusion of Rating	
	$\ln(\text{Demand}_{Pre})$ (1)	$\ln(\text{Demand}_{Post})$ (2)	$\ln(\text{Demand}_{Pre})$ (3)	$\ln(\text{Demand}_{Post})$ (4)	$\ln(\text{Demand}_{Pre})$ (5)	$\ln(\text{Demand}_{Post})$ (6)
<i>Key Independent Variables</i>						
$\ln(\text{Price})$	-0.989*** (0.066)	-0.707*** (0.068)	-1.177*** (0.057)	-0.795*** (0.063)	-1.194*** (0.059)	-0.795*** (0.063)
<i>Event Characteristics</i>						
ExposureDuration			0.029 (0.033)	-0.037 (0.033)	0.063* (0.034)	0.063* (0.034)
SeatLimit			-0.070*** (0.026)	-0.057** (0.028)	-0.070*** (0.026)	-0.070*** (0.026)
Advertisement			0.686*** (0.105)	0.422*** (0.117)	0.714*** (0.109)	0.714*** (0.109)
Rating			0.443*** (0.035)	0.495*** (0.038)		
Holiday			-0.358*** (0.122)	-0.425*** (0.135)	-0.340*** (0.126)	-0.340*** (0.126)
<i>Creator Profile in QA Community</i>						
Follower			0.117*** (0.040)	0.097** (0.044)	0.110*** (0.041)	0.110*** (0.041)
Followee			0.039 (0.026)	0.010 (0.029)	0.041 (0.027)	0.041 (0.027)
Answer			0.037 (0.030)	0.016 (0.033)	0.037 (0.031)	0.037 (0.031)
Upvote			0.356*** (0.094)	0.439*** (0.104)	0.399*** (0.097)	0.399*** (0.097)
Downvote			0.184*** (0.059)	0.157** (0.065)	0.172*** (0.061)	0.172*** (0.061)
Thank			-0.046 (0.102)	-0.061 (0.113)	-0.098 (0.105)	-0.098 (0.105)
Unhelpful			-0.318*** (0.119)	-0.362*** (0.132)	-0.291** (0.123)	-0.291** (0.123)
Badge			-0.117 (0.077)	-0.145* (0.085)	-0.042 (0.079)	-0.042 (0.079)
TenureQA			0.090*** (0.028)	0.079** (0.031)	0.096*** (0.029)	0.096*** (0.029)
Celebrity			1.182*** (0.180)	0.354* (0.199)	1.112*** (0.186)	1.112*** (0.186)
<i>Creator Profile in Zhihu Live Market</i>						
NumPastEvent			-0.193*** (0.041)	-0.084* (0.045)	-0.227*** (0.042)	-0.227*** (0.042)
AvgPastSales			0.255*** (0.052)	0.354*** (0.057)	0.264*** (0.054)	0.264*** (0.054)
AvgPastRating			0.057* (0.031)	0.009 (0.035)	0.099*** (0.032)	0.099*** (0.032)
TenureMarket			0.032 (0.047)	-0.034 (0.053)	0.027 (0.049)	0.027 (0.049)
Invitation			0.122 (0.120)	0.044 (0.133)	0.198 (0.124)	0.198 (0.124)
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.090	0.045	0.461	0.352	0.421	0.421
Num. obs.	2,299	2,299	2,299	2,299	2,299	2,299

Note: Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

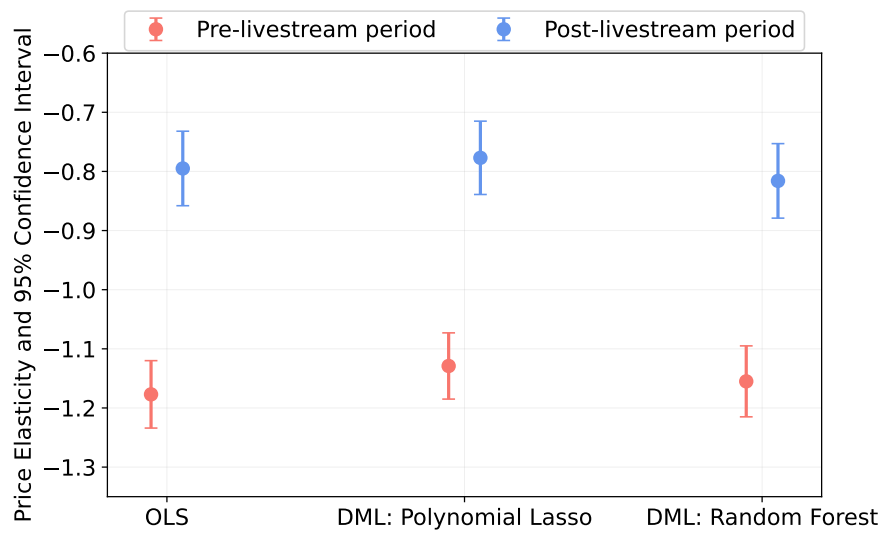


Figure C3: Comparing Estimated Price Elasticities across Functional Forms

Note: We compare the OLS estimates (Columns (3) and (4) of Table C3) with the DML estimates for the pre- and post-periods. For DML, we consider two candidate models for nuisance estimation: Lasso and Random Forest.

D Double Machine Learning

Double Machine Learning (DML) (Chernozhukov et al., 2018) is a method for estimating treatment effects when potential confounders/controls are either too many (high-dimensional) or their effects on the treatment and outcome cannot be satisfactorily modeled by parametric functions.

Consider the following partially linear regression (PLR) models:

$$Y = \theta T + g(X) + \varepsilon, \quad \mathbb{E}[\varepsilon|X] = 0 \quad (9)$$

$$T = f(X) + \eta, \quad \mathbb{E}[\eta|X] = 0 \quad (10)$$

where Y is the outcome variable (e.g., demand), T is the treatment variable (e.g., price), and X is the (high-dimensional) confounding covariates. Our goal is to estimate the average treatment effect θ .

We can rewrite the partially linear equations as

$$Y - \mathbb{E}[Y|X] = \theta(T - \mathbb{E}[T|X]) + \varepsilon. \quad (11)$$

Thus, if we can estimate the conditional expectation functions (both of which are pure predictive tasks): $q(X) = \mathbb{E}[Y|X]$ ²⁷ and $f(X) = \mathbb{E}[T|X]$, then we can compute the residuals: $\tilde{Y} = Y - q(X)$ and $\tilde{T} = T - f(X) = \eta$, which are subsequently related by the equation: $\tilde{Y} = \theta\tilde{T} + \varepsilon$. Consequently, estimating θ is a final regression problem, i.e.,

$$\hat{\theta} = \operatorname{argmin}_{\theta \in \Theta} \mathbb{E}[(\tilde{Y} - \theta\tilde{T})^2]. \quad (12)$$

The main advantage of DML is that it can achieve fast estimation rates and asymptotic normality on the second stage estimate $\hat{\theta}$, even if the first stage estimates on $q(X)$ and $f(X)$ are only $N^{1/4}$ consistent, due to the robustness provided by Neyman orthogonality and cross-fitting. This robustness is beneficial because it allows the final estimator for θ to perform well, even if the nuisance parameters $g(\cdot)$ and $f(\cdot)$ are not correctly specified or suffer from bias induced by regularization and over-fitting (Chernozhukov et al., 2018; Ellickson, Kar, and Reeder III, 2022).

We implement DML to estimate price elasticity separately for the pre- and post-periods, considering two

²⁷Note that we do not estimate $g(\cdot)$ directly, but the conditional expectation of Y given X , denoted as $q(X) = \mathbb{E}[Y|X]$.

candidate models for nuisance estimation: Lasso and Random Forest. For Lasso, we include quadratic terms for continuous covariates to capture potential non-linearity. We use grid search with cross-validation to select optimal hyper-parameters for the first-stage models, evaluated based on Mean Squared Error (MSE). For Lasso, we focus on selecting the optimal regularization parameter, α , which controls the strength of the penalty applied to the model's coefficients. For Random Forest, we tune key parameters, including `n_estimators` (the number of trees), `max_depth` (the maximum depth of each tree), `min_samples_leaf` (the minimum number of samples required at each leaf node), and `max_features` (the maximum number of features considered at each split). All 2,299 observations are used for this tuning process. The selected hyper-parameters are then passed to the DML framework to perform the first-stage estimation.

E Robustness Checks: IV Estimation

Table E4: IV Estimation: Alternative Embedding Technique and Instrument Construction Method

Dependent Variable: $\ln(\text{Demand})$	Alternative Embedding Method (1)	Alternative IV: Avg. Similar Event Price (2)
<i>Key Independent Variables</i>		
<i>Post</i>	−2.560*** (0.865)	−2.568*** (0.860)
$\ln(\text{Price})$	−1.277*** (0.122)	−1.255*** (0.099)
$\text{Post} \times \ln(\text{Price})$	0.495*** (0.155)	0.503*** (0.130)
<i>Event Characteristics</i>		
ExposureDuration	−0.001 (0.025)	−0.003 (0.025)
SeatLimit	−0.063*** (0.019)	−0.063*** (0.019)
Advertisement	0.547*** (0.080)	0.551*** (0.079)
Rating	0.469*** (0.026)	0.469*** (0.026)
Holiday	−0.395*** (0.091)	−0.393*** (0.091)
<i>Creator Profile in QA Community</i>		
Follower	0.110*** (0.030)	0.108*** (0.030)
Followee	0.024 (0.020)	0.024 (0.020)
Answer	0.026 (0.022)	0.027 (0.022)
Upvote	0.396*** (0.070)	0.397*** (0.070)
Downvote	0.172*** (0.044)	0.171*** (0.044)
Thank	−0.052 (0.076)	−0.053 (0.076)
Unhelpful	−0.341*** (0.089)	−0.340** (0.089)
Badge	−0.130** (0.057)	−0.131** (0.057)
TenureQA	0.084*** (0.021)	0.084*** (0.021)
Celebrity	0.781*** (0.137)	0.773*** (0.136)
<i>Creator Profile in Zhihu Live Market</i>		
NumPastEvent	−0.134*** (0.032)	−0.137*** (0.031)
AvgPastSales	0.303*** (0.039)	0.304*** (0.039)
AvgPastRating	0.035 (0.024)	0.034 (0.024)
TenureMarket	−0.004 (0.036)	−0.002 (0.036)
Invitation	0.092 (0.091)	0.087 (0.090)
Category fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
$\text{Post} \times \text{Time}$ fixed effects	Yes	Yes
R^2	0.498	0.498
Num. obs.	4,598	4,598

Note: Column (1) uses OpenAI’s pre-trained embedding models to construct the IV. Column (2) uses the average price of the three most similar events as the IV. Each event contributes one observation for the pre-period and one for the post-period, resulting in a total of $2,299 \times 2 = 4,598$ observations. Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E5: IV Estimation: Inclusion of Additional Controls

Dependent Variable: $\ln(\text{Demand})$	Category-specific Time Trends (1)	Period-specific Covariate Effects (2)	Event Embeddings (3)
<i>Key Independent Variables</i>			
<i>Post</i>	-2.565*** (0.826)	-2.590*** (0.903)	-2.565*** (0.817)
$\ln(\text{Price})$	-1.205*** (0.109)	-1.311*** (0.114)	-1.420*** (0.106)
$\text{Post} \times \ln(\text{Price})$	0.500*** (0.132)	0.582*** (0.161)	0.500*** (0.131)
<i>Event Characteristics</i>			
<i>ExposureDuration</i>	0.002 (0.027)	0.037 (0.035)	-0.009 (0.024)
<i>SeatLimit</i>	-0.094*** (0.021)	-0.070** (0.027)	-0.051*** (0.018)
<i>Advertisement</i>	0.539*** (0.085)	0.663*** (0.113)	0.711*** (0.077)
<i>Rating</i>	0.482*** (0.028)	0.442*** (0.037)	0.454*** (0.025)
<i>Holiday</i>	-0.503*** (0.097)	-0.369*** (0.129)	-0.394*** (0.088)
<i>Creator Profile in QA Community</i>			
<i>Follower</i>	0.123*** (0.037)	0.126*** (0.043)	0.120*** (0.029)
<i>Followee</i>	-0.001 (0.021)	0.039 (0.028)	0.003 (0.019)
<i>Answer</i>	0.034 (0.024)	0.036 (0.032)	0.050** (0.022)
<i>Upvote</i>	0.378*** (0.077)	0.349*** (0.099)	0.427*** (0.068)
<i>Downvote</i>	0.204*** (0.049)	0.188*** (0.062)	0.126*** (0.042)
<i>Thank</i>	0.004 (0.084)	-0.040 (0.108)	-0.166** (0.073)
<i>Unhelpful</i>	-0.411*** (0.100)	-0.322** (0.125)	-0.235*** (0.085)
<i>Badge</i>	-0.043 (0.063)	-0.114 (0.081)	-0.101* (0.056)
<i>TenureQA</i>	0.101*** (0.023)	0.089*** (0.030)	0.055*** (0.021)
<i>Celebrity</i>	0.836*** (0.148)	1.223*** (0.192)	0.898*** (0.132)
<i>Creator Profile in Zhihu Live Market</i>			
<i>NumPastEvent</i>	-0.152*** (0.035)	-0.180*** (0.044)	-0.139*** (0.030)
<i>AvgPastSales</i>	0.310*** (0.043)	0.253*** (0.055)	0.209*** (0.037)
<i>AvgPastRating</i>	0.064** (0.026)	0.063* (0.034)	0.025 (0.023)
<i>TenureMarket</i>	-0.010 (0.039)	0.024 (0.050)	0.045 (0.035)
<i>Invitation</i>	0.067 (0.101)	0.149 (0.128)	0.089 (0.087)
Category fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Category $\times$ Time fixed effects	Yes	No	No
$\text{Post} \times$ Category fixed effects	No	Yes	No
$\text{Post} \times$ Time fixed effects	Yes	Yes	Yes
$\text{Post} \times$ Event and creator characteristics	No	Yes	No
Event embeddings	No	No	Yes
R ²	0.585	0.501	0.552
Num. obs.	4,598	4,598	4,598

Note: Each event contributes one observation for the pre-period and one for the post-period, resulting in a total of $2,299 \times 2 = 4,598$ observations. Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E6: IV Estimation: Separate Pre- and Post-Period Regressions

Dependent Variable	Full Controls		Exclusion of Rating
	$\ln(Demand_{Pre})$ (1)	$\ln(Demand_{Post})$ (2)	$\ln(Demand_{Pre})$ (3)
<i>Key Independent Variables</i>			
$\ln(Price)$	-1.311*** (0.108)	-0.729*** (0.120)	-1.289*** (0.112)
<i>Event Characteristics</i>			
ExposureDuration	0.037 (0.033)	-0.041 (0.037)	0.069** (0.035)
SeatLimit	-0.070*** (0.026)	-0.057** (0.028)	-0.070*** (0.027)
Advertisement	0.663*** (0.107)	0.433*** (0.118)	0.697*** (0.110)
Rating	0.442*** (0.035)	0.496*** (0.038)	
Holiday	-0.369*** (0.122)	-0.419*** (0.135)	-0.348*** (0.126)
<i>Creator Profile in QA Community</i>			
Follower	0.126*** (0.040)	0.093** (0.045)	0.116*** (0.042)
Followee	0.039 (0.026)	0.010 (0.029)	0.041 (0.027)
Answer	0.036 (0.030)	0.017 (0.033)	0.036 (0.031)
Upvote	0.349*** (0.094)	0.443*** (0.104)	0.394*** (0.097)
Downvote	0.188*** (0.059)	0.155** (0.065)	0.174*** (0.061)
Thank	-0.040 (0.102)	-0.064 (0.113)	-0.093 (0.106)
Unhelpful	-0.322*** (0.119)	-0.360*** (0.132)	-0.294** (0.123)
Badge	-0.114 (0.077)	-0.146* (0.085)	-0.040 (0.080)
TenureQA	0.089*** (0.028)	0.079** (0.032)	0.095*** (0.029)
Celebrity	1.223*** (0.182)	0.333* (0.202)	1.141*** (0.189)
<i>Creator Profile in Zhihu Live Market</i>			
NumPastEvent	-0.180*** (0.042)	-0.091* (0.046)	-0.217*** (0.043)
AvgPastSales	0.253*** (0.052)	0.355*** (0.057)	0.262*** (0.054)
AvgPastRating	0.063** (0.032)	0.006 (0.035)	0.103*** (0.033)
TenureMarket	0.024 (0.048)	-0.030 (0.053)	0.021 (0.049)
Invitation	0.149 (0.122)	0.031 (0.135)	0.217* (0.126)
Category fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R ²	0.460	0.352	0.421
Num. obs.	2,299	2,299	2,299

Note: Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. Event characteristics and creator profiles in both the Q&A community and the Zhihu Live market are omitted for ease of tabulation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F Mechanisms

F.1 Word-of-mouth Information

One important source of word-of-mouth information is the ratings and reviews submitted by consumers upon livestream completion. Across all events, consumers submitted a total of 77,956 ratings and 29,652 text reviews, with each event receiving an average of 35 ratings and 13 reviews. The average rating across events is 4.43 (S.D. = 1.01) and the average review length is 18.20 words (S.D. = 24.30). Table F7 presents ten randomly drawn reviews from our data.

Table F7: Examples of Reviews

No.	Review Content
1	Very comprehensive and packed with useful information.
2	The delivery isn't very fluent, and there isn't much substance to it.
3	Awesome.
4	There's a lot of practical information, and it's all very concise. Maybe because I already have some background knowledge, it wasn't too hard for me to grasp.
5	The voice was a bit soft, but the presentation was professional and well-targeted; however, there were some issues with pacing.
6	The explanation was very vivid and detailed.
7	The foundational theory is decent, but I feel it didn't quite meet my expectations. For example, the section on forgetfulness didn't offer any effective solutions or relevant theories.
8	It was clear that the presenter put a lot of thought into it, spent a great deal of time preparing, and was well-prepared, with clear logic and precise delivery. For me, this was definitely a live session that I found extremely beneficial.
9	Great! This livestream focused more on methodology. I suggest offering more specific livestreams on different topics in the future, such as academic sessions or business sessions... Looking forward to it!
10	Takeaways: I need to dive deeper into this and put more effort into learning the foundational knowledge required... Anyway... since I want to become a tech expert... I just have to keep evolving! I thought the instructor did a great job... Applause!!!

To assess whether reviews provide meaningful information about content quality, we conduct the following text analyses. First, we extract the most frequently occurring phrases from reviews across all events. The top-5 phrases include “live,” “content,” “teacher,” “learned,” and “practical,” suggesting a strong focus on learning and content quality. Second, we apply BERTopic (Grootendorst, 2022), a transformer-based topic modeling technique that extracts semantically coherent topics from text. Table 11 in Section 5 presents the keywords associated with the top-3 topics, which consistently center on content quality, information, and learning. Taken together, these findings support that consumer reviews provide useful quality-related information for prospective buyers in the post-period.

As a supplementary check, we examine review linguistic styles using Linguistic Inquiry and Word Count

(LIWC) (Boyd et al., 2022). Reviews in our sample score relatively high on the Authenticity dimension (mean = 61.8, on a scale of 0 to 99), suggesting that the reviews are generally expressed in a personal and natural manner.

F.2 Heterogeneity across Creators and Content Category

Table F8: IV Estimation: Heterogeneity by Consumer Follow Status (Intersection Group)

Dependent Variable	$\ln(\text{Demand}^{NF})$ (1)	$\ln(\text{Demand}^F)$ (2)
$\ln(\text{Price})$	-1.136*** (0.102)	-0.613*** (0.098)
<i>Post</i>	-2.354*** (0.831)	-2.289*** (0.793)
$\text{Post} \times \ln(\text{Price})$	0.415*** (0.133)	0.326** (0.127)
Event characteristics	Yes	Yes
Creator characteristics	Yes	Yes
Category fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
$\text{Post} \times \text{time fixed effects}$	Yes	Yes
R^2	0.498	0.443
Num. obs.	4,598	4,598

Note: Each event contributes one observation for the pre-period and one for the post-period, resulting in a total of $2,299 \times 2 = 4,598$ observations. Time fixed effects refer to event start week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. Event characteristics and creator profiles in both the Q&A community and the Zhihu Live market are omitted for ease of tabulation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F9: IV Estimation: Heterogeneity by Creator Reputation and Content Category (Intersection Group)

Event Segments	Dependent Variable: $\ln(Demand)$								
	Non-recipient (1)	Recipient (2)	F^1 (3)	F^2 (4)	F^3 (5)	F^4 (6)	F^5 (7)	Soft (8)	Hard (9)
$\ln(Price)$	-1.101*** (0.128)	-1.012*** (0.181)	-1.188*** (0.347)	-1.372*** (0.291)	-0.483** (0.218)	-1.371*** (0.225)	-1.363*** (0.165)	-1.180*** (0.154)	-1.000*** (0.141)
$Post$	-2.585 (1.668)	-2.513*** (0.830)	-3.219*** (1.205)	-2.422** (1.113)	-2.802** (1.135)	-2.057** (1.038)	-3.341*** (1.067)	-2.693 (1.646)	-2.274** (0.939)
$Post \times \ln(Price)$	0.537*** (0.173)	0.376** (0.188)	0.749 (0.471)	0.842** (0.399)	0.467* (0.278)	0.385 (0.297)	0.469** (0.187)	0.621*** (0.200)	0.271 (0.177)
Event characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Creator characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Post \times$ time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.506	0.664	0.656	0.570	0.557	0.579	0.669	0.510	0.554
Num. obs.	3,778	820	920	920	920	919	919	2,498	2,100

Note: F^g ($g \in \{1, 2, 3, 4, 5\}$) is the segment of events within the g th quantile range of $Follower_{it}$. Within each segment, every event contributes one observation for the pre-period and one for the post-period. Time fixed effects refer to event streaming week and day-of-week fixed effects. We standardize all continuous covariates to ensure comparability of coefficients. Event characteristics and creator profiles in both the Q&A community and the Zhihu Live market are omitted for ease of tabulation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

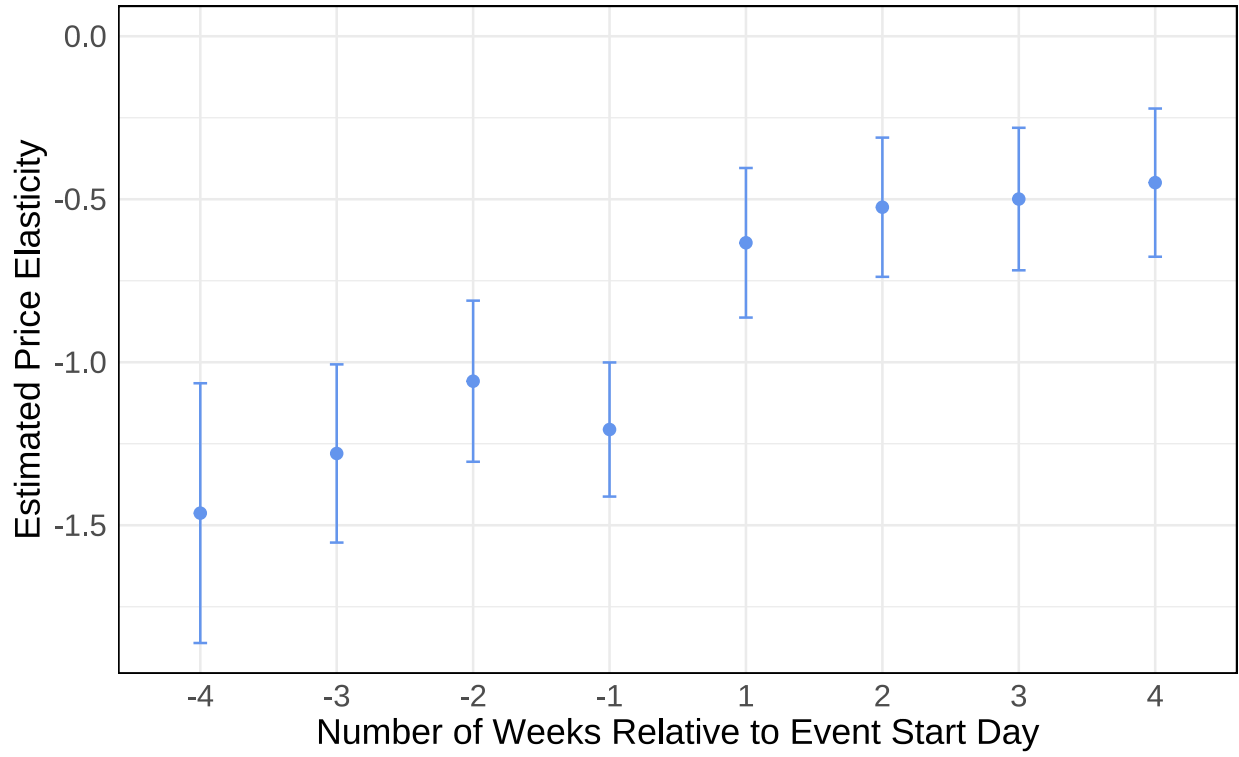


Figure F4: Price Elasticity Over Number of Weeks to Event Start Day

Note: Week -1 (1) refers to the seven-day period immediately before (after) the event start date, inclusive of the start day. Week -2 (2) denotes the seven days preceding (following) Week -1 (1), and so on.