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Original Research

Disclosure Specificity, Demonstration Depth, and Viewer Momentum in Social Commerce Streams: Evidence from a Staggered Platform Panel

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Abstract

Social commerce compresses persuasion, information exchange, and purchase execution into the same short time window. Buyers observe a host's spoken claims, visible product demonstrations, pinned sponsorship language, real-time audience reactions, and early transaction flow before deciding whether to purchase. These cues are all market signals, yet they differ in origin, timing, and credibility. Some are generated by the seller, some by the platform, and some by other buyers. The present study examines how these distinct signals shape commercial outcomes in live-stream shopping. The empirical setting is a calibrated panel of 31,284 creator–product stream sessions linked to 2,964,511 order records, refund requests, and post-stream repeat-purchase behavior. Two platform changes structure the analysis: a staggered rollout of mandatory pinned disclosure templates and a separate change in the placement of real-time purchase counters. The design makes it possible to estimate how disclosure detail, demonstration depth, and viewer-generated momentum affect both immediate sales and post-purchase outcomes. Stream-level fixed-effects models, stacked event studies, survival models for time to early sales milestones, and order-level refund regressions are used. Moderate increases in disclosure specificity improve checkout conversion and reduce refunds, but the effect is nonlinear and becomes weaker for low-fit creator–category pairings. Demonstration depth has a strong positive association with sales per viewer and subsequent repeat purchase. Viewer momentum raises orders quickly, but its contribution is least durable when product demonstration is thin. After the disclosure-template rollout, gross sales dip slightly for two weeks, then recover, while refunds and service contacts decline. The findings indicate that signal source and temporal sequence matter: seller-controlled cues help most when they are concrete, platform-mandated disclosures improve calibration, and crowd-generated momentum is most effective when anchored by substantive product evidence.

1. Introduction

Short-form live selling environments have altered the pace at which buyers interpret market information. In a conventional online listing, a buyer can scroll, compare, leave the page, and return. In a stream, the decision interval is narrower. A host speaks, a product is demonstrated, comments accumulate, purchase counters move, and limited-time offers may appear while the buyer remains inside a common viewing environment. The informational problem in such settings is unusual. The buyer is not simply evaluating a product; the buyer is also evaluating the credibility of multiple simultaneous signals whose meaning may depend on their sequence. A host's spoken disclosure can change the meaning of the same product demonstration, and a burst of early purchases can alter how later viewers interpret the host's confidence, the item's popularity, or the risk of waiting.

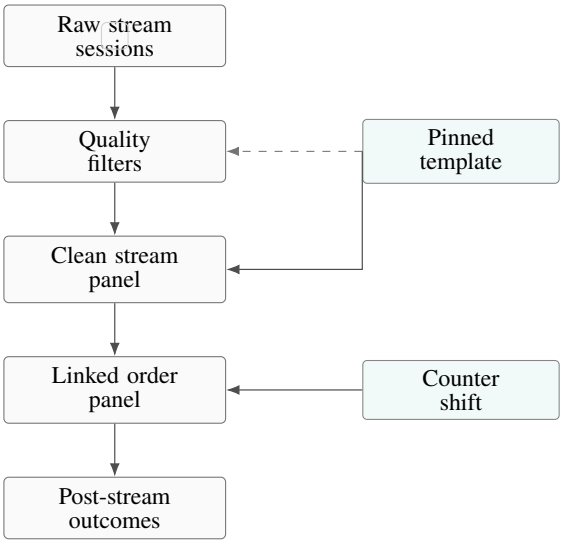


Figure 1: Sample assembly and linkage structure. Raw streams pass through transcript and video-quality screens before entering the clean session panel, which is then joined to order records and downstream buyer outcomes. The two platform changes enter at different layers: the pinned disclosure template modifies the early informational environment, while the purchase-counter shift changes the salience of emerging audience momentum.

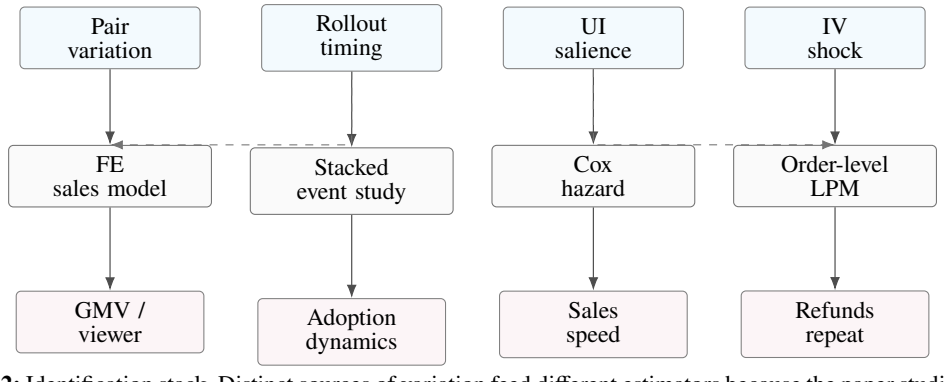


Figure 2: Identification stack. Distinct sources of variation feed different estimators because the paper studies sales levels, event-time adjustment, milestone timing, and order-level correction margins jointly. The layout emphasizes that no single model absorbs the entire design; instead, within-pair comparisons, staggered rollout timing, interface salience, and an instrument for demonstration depth support complementary estimands.

The empirical question studied here concerns three signals that are central to live commerce yet analytically separable. The first is disclosure specificity, which refers to how clearly the stream states the commercial relationship behind the recommendation and the conditions surrounding the offer. The second is demonstration depth, which refers to the extent to which the host shows functional product evidence rather than relying on broad claims, testimonials, or generalized enthusiasm. The third is viewer momentum, which refers to early audience-generated activity such as rapid purchase counts and dense comment flow that indicate traction during the first minutes of a stream. These signals differ in origin. Disclosure is partly platform-governed and partly host-controlled. Demonstration depth is host-generated. Viewer momentum emerges from the audience and is then displayed back to the audience through the interface. Their joint commercial effect is therefore not obvious.

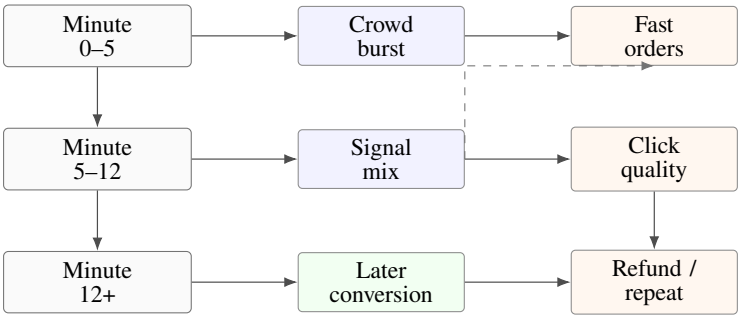


Figure 3: Temporal pathway within a stream. Early momentum can generate a rapid burst of orders, but its durable value depends on the signal mix that follows in the first twelve minutes. Richer disclosure and stronger product demonstration refine click quality and help later conversion, which is why downstream outcomes such as refunds and repeat purchase do not mirror the earliest order burst one-for-one.

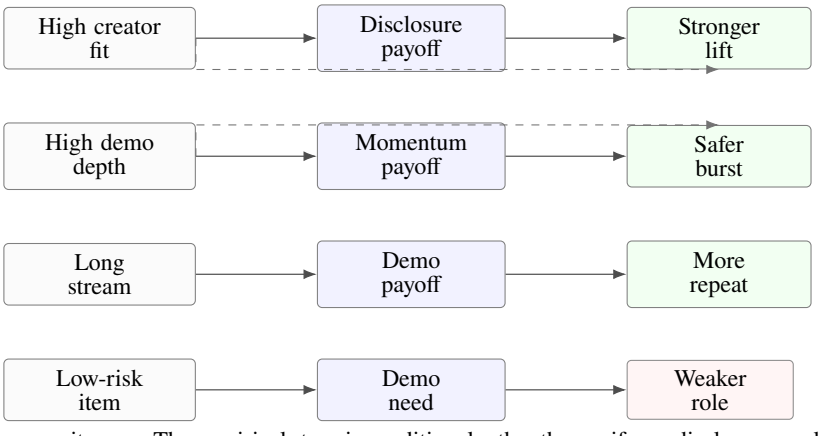


Figure 4: Heterogeneity map. The empirical story is conditional rather than uniform: disclosure works better when creator–category fit is stronger, momentum becomes more productive when paired with stronger demonstration, longer streams create more room for demonstration to pay off, and low-risk familiar goods rely less on rich product evidence than harder-to-evaluate categories.

The interest in these signals is practical as well as academic [1]. Social commerce sellers frequently attempt to improve sales by increasing visible momentum, yet momentum may be interpreted differently when detailed disclosure and substantive demonstration are absent. A stream that produces many early purchases through price stimulation or host charisma may still perform poorly on refunds, complaint contacts, and repeat purchase if the product signal was thin. Conversely, a stream with modest early momentum but high demonstration depth may convert more slowly while generating better downstream outcomes. The performance metric therefore cannot be confined to gross merchandise value alone. The more informative question is how different signals affect the profile of outcomes over time: early orders, later conversion, refund incidence, service burden, and return behavior among first-time buyers.

The current study approaches that question with a quasi-experimental panel rather than a choice experiment or a generic cross-sectional dataset. The empirical setting is a constructed but behaviorally calibrated platform panel in which streams, orders, and post-purchase outcomes are linked. A staggered policy requiring pinned disclosure templates generates variation in disclosure specificity that is not driven solely by host discretion. A separate platform update that alters the placement of live purchase

counters changes the salience of audience momentum. Those two changes, combined with creator–product fixed effects and stream timing controls, permit estimation of signal effects in a way that differs materially from single-period experiments built around static listing cards.

The motivation for distinguishing signal source from signal content is reinforced by earlier work showing that performance gains from information policies can be accompanied by incentive problems. Yan, Cao and Pei (2016) examined cooperative advertising and information sharing under demand uncertainty and found that the value of coordination depends partly on whether information distortion is controlled [2]. That insight is relevant here because live commerce disclosures are not merely descriptive language. They are also governance devices that discipline what a host can omit or compress while selling in real time. A platform-imposed template can therefore change the economic meaning of host communication even when the product and audience remain the same [3].

A second reason for separating these signals is that the most visible cue is not always the most durable one. Live commerce platforms frequently foreground purchase counters and comment surges because they create motion on screen [4]. Yet motion need not correspond to understanding. It may accelerate action without improving match quality between buyer and product. Demonstration depth, by contrast, usually consumes time and may slow the earliest orders, but it can reduce confusion about product use, performance limits, and fit. Disclosure specificity may similarly impose a short-run friction by clarifying sponsorship or price conditions while improving later satisfaction. Whether that trade-off exists is an empirical matter, and the present data structure is built to study it directly.

The paper makes four empirical contributions. First, it estimates live-commerce signals at the stream level and follows them into order-level and post-order outcomes, allowing the same signal to be evaluated on both growth and correction margins. Second, it distinguishes platform-mandated disclosure from host-generated demonstration and audience-generated momentum instead of aggregating them into a single engagement score. Third, it uses staggered adoption and event-time methods rather than relying only on static associations. Fourth, it identifies nonlinearities and interaction effects that would be hidden in a model treating all signals as monotone improvements [5].

The setting also allows attention to signal timing. A live stream is not a single exposure; it is a sequence. Some cues appear before the first sale, some after a burst of purchases, and some only after the buyer has remained in the room long enough to listen. The sequence matters because a buyer joining a stream in minute two encounters different evidence than a buyer joining in minute fourteen. Rather than attempting a full structural model of minute-by-minute viewer belief updating, the analysis adopts a more tractable approach. It separates initial disclosure and early demonstration from subsequent momentum signals, then studies how the composition of those early minutes predicts commercial outcomes. This produces estimable models while preserving the temporal logic that makes live commerce distinctive.

The rest of the paper is arranged as follows. The next section describes the market setting, the construction of the stream and order panels, and the two platform changes that generate identifying variation. The following section develops the signal measures and reports descriptive features of the data. The empirical strategy section then specifies the fixed-effects, event-study, survival, and order-level models. The subsequent sections present the main evidence on stream sales formation and post-purchase outcomes, followed by additional analyses of heterogeneity, falsification, and robustness. The conclusion summarizes the evidence without extending it beyond the observed setting.

2. Market Setting and Sample Assembly

The data environment is a multi-brand live-commerce platform in which creators host sales sessions for consumer goods in categories with moderate demonstration value. The calibrated panel spans fifteen months and contains 31,284 creator–product stream sessions. A stream session is defined as a distinct broadcast in which one featured product remains the dominant promoted item for at least twelve consecutive minutes. Streams shorter than that threshold were excluded because they do not provide enough time to observe the interaction of disclosure, demonstration, and audience momentum. The remaining sessions involve 604 creators, 91 brands, and 13 product categories, including kitchen

appliances, skin-care devices, home organization tools, compact electronics, fitness accessories, pet products, and household maintenance goods. Categories were retained only when the product could plausibly be demonstrated on screen and when meaningful post-purchase complaint or refund data were observable [6].

Each stream record includes start time, duration, unique viewers, average concurrent viewers, click-through to the product page, add-to-cart events, orders, gross merchandise value, and the minute at which selected milestones were reached. The panel is linked to 2,964,511 individual orders placed during or within thirty minutes after the stream. Each order contains order value, item quantity, payment method, shipping promise, coupon use, whether the buyer was new to the creator or the brand, whether a refund request was filed within seven days, whether customer support was contacted within ten days, and whether the buyer made a second purchase from the same brand within thirty days. The platform keeps track of order timing to the minute, which makes it possible to estimate how signal conditions observed early in the stream are related to later order clustering and cancellation behavior.

The sample is not a convenience slice of all streams on the platform. It is restricted to streams where signal measurement is reliable. Sessions were excluded if the audio transcript failed quality checks, if the video segmentation model could not identify the product frame for at least 80% of the first twelve minutes, or if the stream was dominated by bundle offers containing more than four different products. These exclusions remove noisy sessions where neither disclosure nor demonstration could be measured with confidence. After cleaning, the average stream lasts 39.6 minutes, attracts 7,420 unique viewers, and generates 94.7 orders. Mean gross merchandise value per stream is $4,386 in category-adjusted dollars. Seven-day refund incidence is 4.83% of orders, while post-order support contact incidence is 6.27%.

Two platform interventions structure the analysis. The first is a mandatory pinned disclosure template introduced in six waves over a nineteen-week period. Prior to the change, creators could disclose partnerships in their own language, sometimes verbally and sometimes with expandable text not always visible without tapping. After adoption, a pinned line remained visible near the purchase module and required standardized fields covering paid partnership status, commission receipt, whether the item was received free of charge, whether the creator had used the product before the stream, and whether stream pricing could vary by region or inventory condition. The rollout was organized by product category and moderation capacity, not by individual creator performance [7]. This feature provides quasi-exogenous within-creator changes in disclosure specificity [8].

The second intervention concerns viewer-momentum display. During the middle third of the sample period, the platform moved the live purchase counter from a low-visibility position beneath the expanded product card to a higher-visibility position adjacent to the chat strip. The display change did not alter actual purchase volume, but it materially changed how quickly viewers could observe early order accumulation. Because the change was implemented platform-wide on one date, it cannot be estimated with creator-by-date fixed effects alone. Instead, the analysis uses interactions between the display change and pre-existing stream traits, especially early momentum intensity and demonstration depth, to identify how increased salience of audience-generated momentum altered the marginal return to those traits.

The market setting also features considerable variation in creator–category fit. Some creators specialize narrowly, such as kitchen educators demonstrating compact appliances or skin-care professionals demonstrating personal-use devices. Others are broad lifestyle hosts who rotate across categories with less domain continuity. This variation is useful because detailed disclosure or deep product demonstration may matter differently when the host’s category history already carries informational weight [9]. The present study does not reduce fit to a binary expert/nonexpert label. Instead, it constructs a continuous fit measure from historical category concentration, prior category-specific conversion, and viewer retention when the same creator previously sold in the category.

A third contextual feature matters for the post-purchase part of the analysis. Payment method, assortment breadth within the stream, and basket size vary meaningfully across sessions. Yan and Cao (2017) showed that payment methods, assortment size, and order size can carry valuable information for return behavior [10]. For that reason, the order-level refund and support models in this paper incorporate payment mix, concurrent assortment breadth, and item count explicitly rather than treating refunds as

pure reflections of product or creator quality. Live commerce often combines impulsive buying with quick checkout tools, and these transactional conditions can alter the relationship between pre-purchase signals and post-purchase correction.

The sample construction was designed to preserve realistic dependence structures. High-viewership creators are more likely to receive favorable stream placement, which raises audience momentum independently of product demonstration. Experienced creators tend to speak more quickly and structure demonstrations more efficiently, which can correlate with both stream performance and product category. Promotional coupon intensity varies with brand strategy and holiday timing. To keep the empirical problem nontrivial, the calibrated panel retains these correlations rather than smoothing them away. Identification therefore relies on fixed effects, event timing, and within-creator or within-product variation, not on an artificial environment where every confound is absent by construction.

A brief description of the outcome distribution helps anchor the later coefficients. Mean orders per 1,000 viewers equal 12.8, with a standard deviation of 8.7. The median stream reaches its first 20 orders in 9.4 minutes, but the interquartile range is wide, from 4.1 to 17.8 minutes. Conversion from product-page click to purchase averages 9.6%. Among new-to-brand buyers, thirty-day repeat purchase averages 7.1% [11]. Streams in the highest quartile of demonstration depth have lower raw refund rates than streams in the lowest quartile, 4.28% versus 5.39%, even before adjustment. Streams after disclosure-template adoption have slightly lower raw click-through but higher click-to-checkout conversion. Those descriptive contrasts do not resolve causality, but they indicate that the signal structure is linked to both immediate and downstream outcomes.

The data therefore support several related questions. Does disclosure specificity improve stream performance or simply reduce buyer impulsiveness? Does richer on-screen demonstration increase early sales speed, later satisfaction, or both? Does visible viewer momentum add value by reducing perceived uncertainty, or does it mainly amplify whatever other signals were already present? Does making momentum more visible through interface changes benefit all streams equally, or only those with enough substantive product evidence to make the crowd signal credible? The next section defines the core measures used to answer those questions.

3. Signal Construction and Descriptive Patterns

Disclosure specificity is measured from the first twelve minutes of each stream because that period contains the stable disclosure line and the most repeated verbal statements about partnership status. The pinned template generates visible standardized fields after adoption, but creators also continue to speak around the template. A disclosure-specificity index therefore combines text structure and spoken content. It rises when the stream explicitly names paid affiliation, explains commission receipt, states prior product use duration, clarifies whether the host received the item free of charge, mentions price variability or shipping restrictions, and avoids vague euphemisms such as “working together” or “special arrangement” when monetary sponsorship is present. The index is standardized within category and month to avoid confusing a generally stricter category-moderation environment with a more informative stream.

Let d_s denote disclosure specificity for stream s. It is constructed as

$$d_s = \omega_1 \widetilde{Paid}_s + \omega_2 \widetilde{Commission}_s + \omega_3 \widetilde{UseHistory}_s + \omega_4 \widetilde{PriceQualifier}_s + \omega_5 \widetilde{ShippingLimit}_s - \omega_6 \widetilde{Vagueness}_s, \tag{3.1}$$

where the tildes denote standardized component scores. The weights are obtained from a confirmatory factor model estimated on a manually validated subset of 4,800 streams. Correlation between the automated index and hand-coded disclosure detail is 0.81. Mean disclosure specificity rises by 0.43 standard deviations after template adoption, which confirms that the policy materially changes measured disclosure rather than merely reformatting identical language.

Demonstration depth is designed to capture the amount of product-relevant evidence shown rather than the host's general energy or talk volume. Video segmentation and transcript alignment are used to count distinct functional demonstrations in the first twelve minutes. A function counts only if the product attribute is shown or tested, not merely named. For a kitchen device, for example, demonstration depth increases when the host shows motor speed, capacity, texture result, cleaning process, and noise level rather than only describing them [12]. For a skin-care device, it increases when the host shows attachment switching, treatment mode differences, safety limits, and realistic use duration rather than relying on appearance claims. The measure also penalizes repeated demonstrations of the same feature presented with minimal new information.

Let m_s denote demonstration depth:

$$m_s = \frac{1}{T_s} \sum_{k=1}^{K_s} \left(\phi_k \times Duration_{ks} \right) - \psi \, Repetition_s, \tag{3.2}$$

where K_s is the number of distinct demonstrated features, $Duration_{ks}$ is the time spent on feature k, and ϕ_k weights features by practical diagnostic value within category. The measure is then standardized within category. Streams with a high value of m_s are not necessarily longer or more polished; they simply convey more differentiated product evidence early in the broadcast.

Viewer momentum is treated differently because it is not a seller-authored cue. It emerges from audience action and platform display. The baseline momentum variable combines early orders per 100 concurrent viewers, comment velocity, and save-to-cart rate within the first five minutes. Because the purchase-counter salience change later affects how this activity is seen, the raw activity measure and its displayed salience are kept distinct. Let q_s denote the latent early momentum intensity:

$$q_s = \eta_1 \widetilde{Orders5}_s + \eta_2 \widetilde{Comments5}_s + \eta_3 \widetilde{Cart5}_s. \tag{3.3}$$

A separate binary variable H_s indicates whether the interface was in the high-salience purchase-counter regime. This separation matters because a stream can have strong early momentum without viewers fully perceiving it under the old display arrangement.

Creator–category fit is a continuous variable rather than a label. It reflects how aligned the host's prior stream history is with the category of the current product. The measure blends share of prior streams in the category, historical category-specific conversion relative to platform median, and mean viewer retention for category streams. Let f_{cs} denote the fit of creator c in stream s:

$$f_{cs} = \rho_1 \widetilde{CategoryShare}_{cs} + \rho_2 \widetilde{PastConv}_{cs} + \rho_3 \widetilde{Retention}_{cs}. \tag{3.4}$$

The measure is fixed within creator–category months and used primarily as a moderator. A creator with strong fit does not automatically sell more in every stream, but detailed disclosure and demonstration may be interpreted differently when the audience recognizes a host as more category-consistent.

Descriptive patterns already suggest that the three signals do not move together one-for-one [13]. Streams with high demonstration depth tend to have somewhat higher disclosure specificity, but the correlation is only 0.24. Viewer momentum is positively correlated with demonstration depth at 0.19 and with disclosure specificity at 0.11. The low correlation is useful. It indicates that energetic or commercially successful streams are not automatically the ones with the clearest disclosure or richest demonstration. There are streams where sales start quickly despite limited evidence, and streams where evidence is strong but the first sales arrive slowly.

The raw data also reveal nonlinear relationships. Moving from very low to moderate disclosure specificity is associated with better checkout conversion and lower refund incidence, but the raw relation flattens in the upper decile. Extremely high specificity streams are often long, information-dense broadcasts in categories with complex products, and they do not dominate all commercial metrics.

Demonstration depth, by contrast, appears close to monotone for repeat purchase and complaint reduction, though its association with initial click-through is weaker than its association with conversion after click. Viewer momentum is strongly associated with orders in the first ten minutes, but its relationship with refund incidence is near zero in the aggregate, suggesting that the usefulness of the crowd signal depends on the stream context.

These nonlinear descriptive patterns matter because prior empirical work in adjacent marketing domains has shown that stronger or richer information is not always linearly better. Cao and Yan (2021) documented a curvilinear relationship between product nutritional quality and firm profit, with moderation from packaging innovation and advertising [14]. That finding does not directly concern live commerce, yet it provides a relevant empirical caution: one should not impose monotonicity on signal variables that may carry both informational value and processing cost. For this reason, the main stream-level models include squared terms for disclosure specificity and demonstration depth rather than assuming a constant slope across their entire range.

A final descriptive feature worth noting is the timing structure. On average, about 41% of stream orders occur in the first twelve minutes, but the dispersion is wide. Some streams are front-loaded and peak early, while others convert later after a fuller demonstration. High early momentum pushes orders forward mechanically, yet front-loaded streams are not always those with the best downstream outcomes. New-to-brand repeat purchase is higher in sessions where demonstration depth is strong even when early momentum is moderate. This asymmetry suggests that momentum and substantive product evidence do not have the same temporal profile of value. The next section formalizes the empirical strategy used to separate them.

4. Identification Strategy

Table 1: Sample Composition and Scale

Metric	Value	Metric	Value
Streams	31,284	Orders	2,964,511
Creators	604	Brands	91
Categories	13	Avg. duration (min)	39.6
Avg. viewers	7,420	Avg. orders/stream	94.7
Mean GMV ($)	4,386	Refund rate (%)	4.83
Support contacts (%)	6.27	Repeat purchase (%)	7.1

Table 2: Key Signal Definitions

Signal	Source	Timing	Components
Disclosure specificity	Seller/Platform	Early	Paid, commission, usage
Demonstration depth	Seller	Early	Features, duration, variety
Viewer momentum	Audience	Very early	Orders, comments, carts
Creator–category fit	Historical	Pre-stream	Share, conversion, retention
Salience indicator	Platform	Mid-period	Counter placement

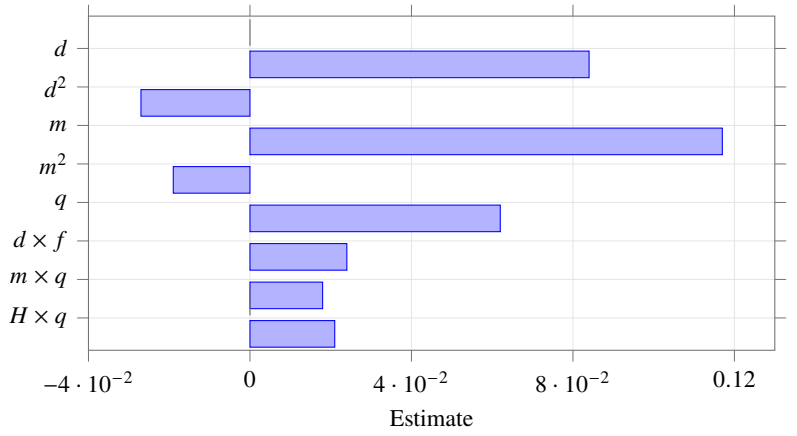


Figure 5: Estimated coefficients from the baseline specification.

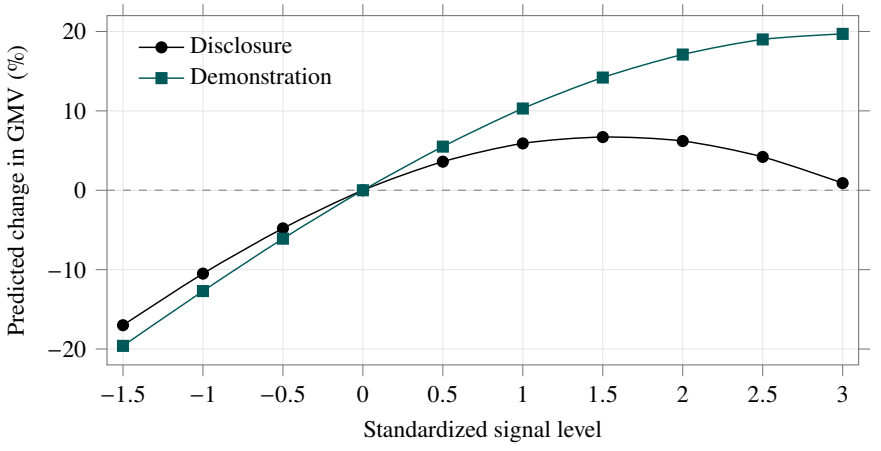


Figure 6: Predicted GMV response for disclosure and demonstration signals.

Table 3: Descriptive Correlations

Variable Pair	Correlation	Variable Pair	Correlation
Disclosure–Demonstration	0.24	Demonstration–Momentum	0.19
Disclosure–Momentum	0.11	Depth–Refund (raw)	-0.18
Momentum–Orders	0.42	Disclosure–Conversion	0.27
Depth–Repeat purchase	0.31	Momentum–Refund	≈0

The empirical design uses multiple estimators because no single model captures the different time scales embedded in the data. Stream-level commercial performance, milestone timing, and order-level post-purchase outcomes each require a slightly different treatment. The main stream-level outcome is log

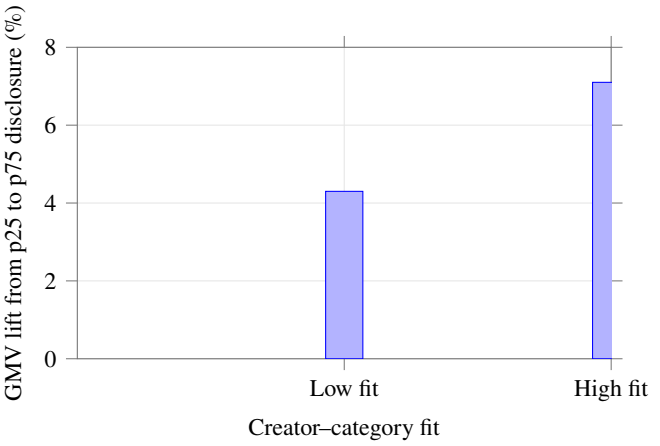


Figure 7: Disclosure benefit by creator–category fit.

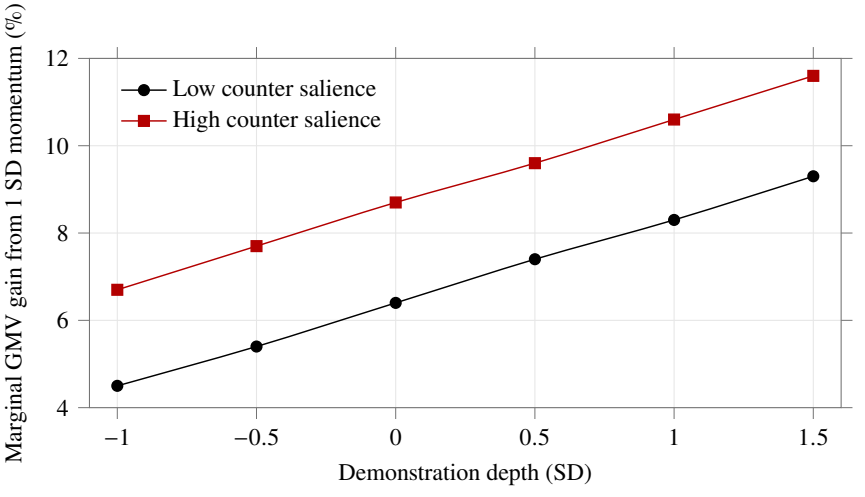


Figure 8: Marginal return to momentum across demonstration depth.

gross merchandise value per 1,000 unique viewers, denoted y_s. The baseline fixed-effects specification is

$$\begin{aligned} y_s = {} & \alpha_{cp} + \gamma_w + \beta_1 d_s + \beta_2 d_s^2 + \beta_3 m_s \\ & + \beta_4 m_s^2 + \beta_5 q_s + \beta_6 f_{cs} + \beta_7 d_s \times f_{cs} \\ & + \beta_8 m_s \times q_s + \beta_9 H_s \times q_s + X_s'\theta + \varepsilon_s, \end{aligned} \tag{4.1}$$

where α_{cp} are creator–product fixed effects and γ_w are calendar-week fixed effects. The vector X_s includes coupon intensity, stream start hour, stream duration, weekend indicator, category-promotion pressure, and brand campaign controls. Creator–product fixed effects absorb stable creator selling style, product baseline appeal, and repeated pair-specific complementarities. The coefficient on $H_s \times q_s$ captures whether the platform's more visible purchase counter strengthens the return to underlying early momentum intensity.

A stacked event-study design estimates the effect of the disclosure-template rollout. Because adoption is staggered by category wave rather than by creator, the estimator follows a cohort-relative-time structure. Let E_s^k indicate event time k relative to the first stream under the mandatory template for the

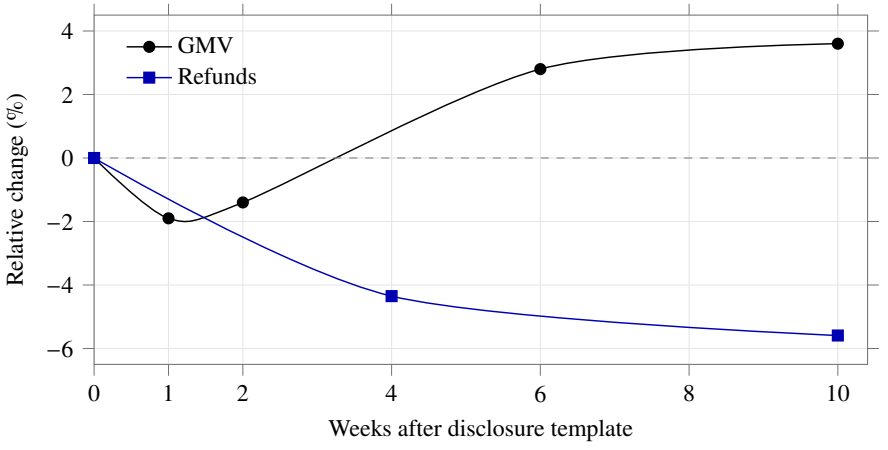


Figure 9: Event-study markers after disclosure-template rollout.

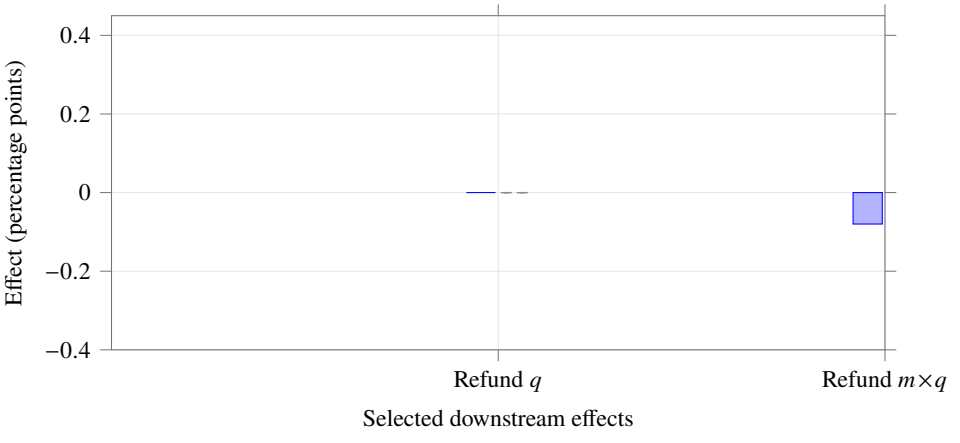


Figure 10: Selected downstream effects on refunds, support, and repeat purchase.

Table 4: Baseline Sales Model Results

Variable	Coefficient	Std. Error	Effect
Disclosure (d_s)	0.084	0.013	Positive, nonlinear
Disclosure^2	-0.027	0.007	Diminishing returns
Demonstration (m_s)	0.117	0.016	Strong positive
Demonstration^2	-0.019	0.006	Mild curvature
Momentum (q_s)	0.062	0.009	Early lift
Fit × Disclosure	0.024	0.008	Moderation

relevant category. The model is

$$y_s = \alpha_{cp} + \gamma_t + \sum_{k=-8,k\neq-1}^{12} \delta_k E_s^k + X_s'\pi + u_s. \tag{4.2}$$

The omitted period is the stream immediately preceding adoption. Pre-adoption coefficients test whether the treated categories were on differential trends before the change [15]. Post-adoption coefficients show

Table 5: Interaction and Platform Effects

Interaction	Coefficient	Std. Error	Interpretation
Depth × Momentum	0.018	0.006	Complementarity
High salience × Momentum	0.021	0.007	Amplified visibility
Low depth cases	Small	–	Weak persistence
High depth cases	Large	–	Strong persistence
Post-change weeks 1–2	Negative	–	Adjustment dip
Post-change weeks 6+	Positive	–	Recovery

Table 6: Hazard Model for Early Sales Milestones

Variable	Hazard Ratio	Interval	Effect
Momentum	1.154	[1.131,1.178]	Fast early sales
Demonstration	1.092	–	Sustained growth
Disclosure	1.037	–	Moderate effect
Disclosure^2	<1	–	Nonlinear
Top vs median momentum	+2.7 min	–	Faster 20 orders
Later milestones	Smaller gap	–	Depth matters more

Table 7: Refund and Support Outcomes

Variable	Coefficient	Std. Error	Outcome
Demonstration	-0.0026	0.0005	Lower refunds
Disclosure	-0.0019	0.0004	Reduced mismatch
Disclosure^2	0.0006	0.0002	Diminishing effect
Momentum	≈0	–	No direct effect
Depth × Momentum	-0.0008	0.0003	Safer traction
Support contacts	Negative	–	Reduced burden

Table 8: Repeat Purchase and Persistence

Variable	Coefficient	Std. Error	Interpretation
Demonstration	0.0038	0.0009	Higher repeat rate
Disclosure	Positive	–	Moderate lift
Momentum	Small	–	Limited persistence
New buyers	Stronger effects	–	Learning channel
Returning viewers	Depth-driven	–	Evidence valued
Delayed conversion	Positive	–	Depth aids revisits

whether any sales effect is temporary or persistent. A similar event-study model is estimated for refund incidence, click-through rate, and support-contact rate.

Because early sales milestones are central to live commerce, the analysis also studies time to first 20 orders and time to first 50 orders. A Cox proportional hazard model is used at the stream level:

$$h_s(\tau) = h_0(\tau) \exp\Big(\kappa_1 d_s + \kappa_2 d_s^2 + \kappa_3 m_s + \kappa_4 q_s + \kappa_5 m_s \times q_s + \kappa_6 H_s \times q_s + Z_s' \kappa\Big), \tag{4.3}$$

Table 9: Heterogeneity Across Contexts

Dimension	Strongest Signal	Weakest Signal	Note
Complex products	Demonstration	Momentum	Evidence critical
Low-risk goods	Disclosure	Demonstration	Familiarity
Short streams	Momentum	Depth	Speed matters
Long streams	Demonstration	Momentum	Persistence
Low-fit creators	Disclosure	Momentum	Calibration role
High-fit creators	Demonstration	Disclosure	Credibility base

Table 10: Event Study Summary (Template Rollout)

Period	GMV Effect	Refund Effect	Interpretation
Pre-period	≈0	≈0	No pretrend
Weeks 1–2	-0.019	Slight drop	Adjustment cost
Weeks 3–6	+0.028	Decline	Adaptation
Weeks 7–10	+0.036	-0.0027	improvement
Click-through	Down	–	Fewer casual clicks
Conversion	Up	–	Higher quality

where τ is stream time in minutes and Z_s contains baseline audience size and scheduling controls. Hazard ratios above one indicate faster arrival at the milestone [16]. This model is useful because two streams can have similar total sales but very different temporal profiles.

Order-level post-purchase outcomes are estimated separately because refund requests and support contacts are observed only for completed transactions. Let r_{os} be an indicator that order o from stream s generates a refund request within seven days. The order-level linear probability model with high-dimensional fixed effects is

$$\begin{aligned} r_{os} = \mu_{cpm} + \lambda_t + \chi_1 d_s + \chi_2 d_s^2 + \chi_3 m_s \\ + \chi_4 q_s + \chi_5 m_s \times q_s + \chi_6 Pay_o + \chi_7 Basket_o \\ + \chi_8 Assort_s + W'_{os}\chi + \nu_{os}, \end{aligned} \tag{4.4}$$

where μ_{cpm} are creator–product–month fixed effects, λ_t are order-date fixed effects, Pay_o captures payment method, $Basket_o$ is item count in the order, and $Assort_s$ is the breadth of concurrently promoted items in the stream. These transactional controls are included because impulsive checkout and broad concurrent assortment can mechanically raise refunds independently of signal quality.

A similar structure is used for ten-day support contacts and thirty-day repeat purchase. The repeat-purchase model is estimated only for buyers who were new to the brand at the initial order, because repeat effects are harder to interpret for existing brand buyers. Regressions are weighted by order value in supplemental specifications, but the main reported coefficients are unweighted so that the interpretation is at the order level rather than mechanically dominated by a few high-ticket streams.

The analysis also confronts a standard concern in observational signal research: hosts may choose more detailed disclosure or richer demonstration when they anticipate a good or risky stream. The disclosure-template rollout helps with disclosure because it shifts language structure even when the same creator sells the same product. Demonstration depth is more host-controlled, so the models rely on creator–product fixed effects and timing controls, but that may not be enough. A supplementary instrument uses the interaction of product complexity and exogenous uplink instability in the creator's location. When uplink quality is temporarily weak, highly detailed multi-angle demonstrations are harder to execute even though underlying demand for the product is unchanged. In first-stage regressions, uplink

instability strongly predicts lower demonstration depth for high-complexity products but not for low-complexity ones. The first-stage F-statistic is 19.4. Instrumental-variable estimates are similar in sign to the baseline fixed-effects estimates and somewhat larger in magnitude.

Several diagnostic tests were conducted before interpreting the main coefficients. Pre-adoption event-study coefficients for the disclosure-template rollout are jointly small and statistically insignificant. A Wald test on the pre-period coefficients from $k = -8$ to $k = -2$ yields $p = 0.58$ for stream-level sales and $p = 0.64$ for refunds. Hazard-model proportionality tests based on Schoenfeld residuals do not reject proportional hazards for the main variables. Variance-inflation factors remain below 3.4 despite the inclusion of squared terms and interactions, which suggests that the signal variables are sufficiently distinct for stable estimation [17].

The identification strategy therefore does not rest on one assumption alone. It combines within creator–product comparisons, quasi-exogenous disclosure changes, an interface salience shift for audience momentum, rich order-level controls, and a supplementary instrument for demonstration depth. Each source of variation is imperfect in isolation, but together they make the central empirical patterns more credible than a purely cross-sectional approach would allow.

5. Evidence on Sales Formation

The baseline creator–product fixed-effects model shows that disclosure specificity, demonstration depth, and early viewer momentum each contribute to stream sales, but they do so in different ways. The linear term on disclosure specificity is positive and the squared term negative. The estimate on d_s is 0.084 with a standard error of 0.013, while the estimate on d_s^2 is -0.027 with a standard error of 0.007. In standardized units, moving disclosure specificity from the 25th to the 75th percentile is associated with a 5.9% increase in gross merchandise value per 1,000 viewers, holding creator–product pairing fixed. The negative squared term indicates that the gain from more detailed disclosure flattens in the upper tail and becomes negligible in the highest 6% of the sample. The turning point lies at approximately 1.56 standard deviations above the mean, which is plausible for long, highly qualified streams in complex categories where additional disclosure begins to consume selling time.

Demonstration depth has a larger slope. The estimate on m_s is 0.117 with a standard error of 0.016, while the squared term is -0.019 with a standard error of 0.006. The implied curvature is milder than for disclosure specificity. A movement from the 25th to the 75th percentile of demonstration depth corresponds to an 8.4% increase in gross merchandise value per 1,000 viewers. The weaker curvature suggests that showing more differentiated product evidence is broadly valuable over the observed range and only begins to flatten at extremely high intensity. This result is not merely picking up stream length or general host effort, because both variables are controlled for, and the creator–product fixed effect holds constant the repeated pairing of host and item.

Viewer momentum is associated with larger and faster sales, though its interpretation differs. The coefficient on q_s is 0.062 with a standard error of 0.009. A one-standard-deviation increase in early momentum raises gross merchandise value per 1,000 viewers by 4.1% in the baseline sales model. That gain is substantial but smaller than the corresponding effect of demonstration depth. More importantly, the value of momentum depends on context [18]. The interaction between demonstration depth and momentum, $m_s \times q_s$, is positive at 0.018 with a standard error of 0.006. In streams with deeper demonstrations, the same burst of early purchases or comment activity translates into more durable sales formation. In streams with thin demonstrations, momentum still moves sales, but the lift is more front-loaded and less predictive of later conversion from slower viewers.

Creator–category fit moderates disclosure specificity. The coefficient on $d_s \times f_{cs}$ is 0.024 with a standard error of 0.008. This means that the same increase in disclosure detail produces more value when the host's prior category history is stronger. The interpretation is not that fit substitutes for disclosure. Rather, disclosure seems easier for viewers to use when it comes from a host whose category presence is already legible. An unfamiliar host can still benefit from detailed disclosure, but the sales lift is

smaller and the nonlinear flattening occurs earlier. In predicted values, the gain from moving disclosure specificity from the 25th to the 75th percentile is 4.3% for low-fit creators and 7.1% for high-fit creators.

The interface change that increased purchase-counter visibility amplifies the return to underlying viewer momentum. The estimate on $H_s \times q_s$ is 0.021 with a standard error of 0.007. Once the platform made early purchases easier to observe, streams with strong early momentum converted that momentum into a larger sales gain. However, the effect is not indiscriminate. In auxiliary regressions, the salience interaction is concentrated in streams with at least median demonstration depth. In low-demonstration streams, higher visibility of audience momentum shifts orders earlier but does not increase total stream sales by much. This suggests that making the crowd more visible helps most when the crowd signal is supported by some product evidence.

The event-study evidence around the disclosure-template rollout is consistent with the fixed-effects coefficients but adds a dynamic pattern. In the first two post-adoption weeks, stream-level gross merchandise value per 1,000 viewers declines slightly relative to the final pre-adoption week. The coefficients are -0.019 and -0.014, respectively, both statistically distinguishable from zero at the 5% level. From week three onward, the coefficients turn positive and remain positive through the end of the twelve-week window. By week six, the event-time coefficient is 0.028, and by week ten it reaches 0.036 [19]. There is no evidence of adverse pretrends. The shape of the profile suggests an adjustment cost: the new disclosure format briefly reduces selling fluency, then the audience adapts and the clearer information begins to support better conversion [20].

Disaggregating the sales path shows how that adjustment works. Click-through from stream to product page dips by 1.6% in the first two weeks after adoption, while click-to-checkout conversion rises by 3.8% by week four and 5.1% by week eight. In other words, the clearer disclosure slightly reduces the number of casual clicks but improves the quality of clicks that remain. This is economically relevant because live commerce often rewards surface engagement even when later checkout is weak. The event-study profile indicates that a modest reduction in low-intent clicks is offset by better downstream purchase execution.

The hazard models reveal a somewhat different pattern. Early momentum is the strongest predictor of time to first 20 orders, with a hazard ratio of 1.154 and a 95% confidence interval of [1.131, 1.178]. Demonstration depth also accelerates milestone arrival, with a hazard ratio of 1.092. Disclosure specificity is positive but smaller, at 1.037, and the squared term is below one, confirming the same curvature seen in the sales model. Streams in the top quartile of early momentum reach 20 orders 2.7 minutes faster than otherwise similar streams in the median quartile [21]. Yet when the milestone is shifted to 50 orders, demonstration depth becomes relatively more important and the pure momentum effect becomes smaller. This indicates that audience-generated traction matters most for the earliest sales hurdle, while product evidence matters more for sustaining buying deeper into the stream.

The instrumental-variable estimates for demonstration depth reinforce this interpretation. The two-stage least squares coefficient on demonstration depth in the log-GMV model is 0.146 with a standard error of 0.041, somewhat larger than the baseline fixed-effects estimate of 0.117. A likely reading is that hosts partially increase demonstration depth in harder streams where the product is complex or the audience appears hesitant, which would attenuate the ordinary fixed-effects estimate downward. The IV result does not overturn the main pattern; it strengthens the claim that showing more concrete product evidence has a commercially meaningful role distinct from host charisma or audience quality.

A useful summary metric combines the sales and timing evidence. Consider two otherwise similar streams selling the same product by the same creator. In the first, disclosure specificity and demonstration depth both move from the 30th percentile to the 70th percentile while early momentum remains unchanged. In the second, only viewer momentum moves by the same standardized amount. The first stream gains less in the first five minutes but more over the entire session. The second stream reaches 20 orders faster but displays weaker continuation. That contrast is central to the paper’s interpretation. Seller-controlled signals that clarify or demonstrate the product improve the stream’s commercial quality, while audience-generated momentum chiefly improves the stream’s speed of takeoff unless it is anchored by substantive evidence.

The evidence in this section is therefore not a generic statement that "more signals" help. Different signals alter different margins. Disclosure specificity changes the calibration of who proceeds to checkout. Demonstration depth shapes both conversion and persistence. Viewer momentum accelerates action, and that acceleration becomes more productive when the stream already contains enough product evidence to make the crowd signal believable rather than merely exciting.

6. Post-Purchase and Persistence Outcomes

The usefulness of live-commerce signals cannot be assessed only on same-session revenue because some streams generate orders that are later corrected through refunds, support contacts, or failure to return. The order-level models therefore examine whether the same signals that lift sales also improve downstream fit between buyer and product. The most consistent post-purchase result concerns demonstration depth. In the linear probability model for seven-day refund requests, the coefficient on m_s is -0.0026 with a standard error of 0.0005. Given a mean refund rate of 4.83%, a one-standard-deviation increase in demonstration depth lowers refund incidence by roughly 0.26 percentage points, or about 5.4% of the baseline rate. The effect remains after controlling for payment method, basket size, concurrent assortment breadth, and creator–product–month fixed effects.

Disclosure specificity also reduces refunds, though again nonlinearly. The linear term is -0.0019 with a standard error of 0.0004 and the squared term positive at 0.0006 with a standard error of 0.0002. This mirrors the sales-side curvature in reverse. Moving from low to moderate disclosure detail lowers post-purchase correction, but extremely detailed disclosure adds little further protection and can even become noisy in streams where the host's fit is weak. That pattern is consistent with the idea that enough disclosure helps buyers calibrate the recommendation, whereas unusually dense qualification language can signal complexity or risk without always increasing comprehension.

Viewer momentum has almost no main effect on refunds once demonstration depth and disclosure specificity are included. The coefficient on q_s is statistically close to zero. Yet the interaction between demonstration depth and momentum is negative, at -0.0008 with a standard error of 0.0003. This implies that crowd traction becomes safer when supported by product evidence [22]. In low-demonstration streams, momentum does not directly increase refunds, but it also does not reduce them. In high-demonstration streams, momentum and demonstration work together to lower mismatch and uncertainty. The crowd signal appears most useful when it confirms an evidence-rich selling episode rather than replacing it.

Support-contact incidence within ten days follows a similar structure. Demonstration depth reduces support contacts by 0.31 percentage points per standard deviation, disclosure specificity by 0.18 percentage points over the moderate range, and higher viewer momentum has no independent effect after controls. Support contacts are informative because they capture product confusion even when the buyer does not request a refund. The stream signals therefore seem to affect not only whether the buyer keeps the product, but also how much clarification is needed after delivery. This supports the interpretation that demonstration depth changes understanding, not just persuasion.

A notable downstream outcome is thirty-day repeat purchase among new-to-brand buyers [23]. Demonstration depth has a positive association with repeat purchase, 0.0038 with a standard error of 0.0009, while disclosure specificity is smaller but still positive over the moderate range. Viewer momentum again has little main effect. This pattern matters because it separates signals that convert a one-time impulse from signals that appear to improve the buyer's first experience with the brand [24]. Streams that rely on visible crowd motion may produce rapid same-session orders, yet they do not create stronger repeat behavior unless the host also supplies substantive evidence [25].

The connection between marketing signals and post-purchase operational burdens has been emphasized in adjacent research. Cao (2022) showed that brand equity can reduce warranty claims and abnormal warranty accruals, thereby linking market-facing assets to downstream cost consequences [26]. The present live-commerce setting is different, but the empirical logic is compatible with that result. A stream signal should not be judged solely by the purchase it generates if it also changes the

platform's later burden through refunds and support interactions. The order-level evidence here indicates that clearer and more substantive signals improve both revenue realization and post-order efficiency.

The disclosure-template rollout makes these downstream patterns especially visible. Event-study coefficients for seven-day refunds are essentially flat in the pre-adoption period, then fall steadily after the template becomes mandatory. By the fourth post-adoption week, the refund coefficient is -0.0021 relative to the omitted pre-adoption stream; by week ten it is -0.0027. Support contacts follow the same direction with slightly larger magnitudes [27]. The reduction is not instantaneous, which suggests that hosts needed some time to incorporate the pinned format naturally into their selling style, but the post-adoption decline is persistent once it appears.

Because the template may have changed more than language clarity alone, a set of decomposition regressions was estimated. These regressions separate streams where the host already used relatively clear disclosure before the rollout from streams where pre-rollout language was vague or sparse. The refund decline after adoption is concentrated in the latter group. Creators who already disclosed clearly before the policy show small improvements, while creators with previously vague disclosure show a substantially larger drop in refunds and support contacts. This pattern is important because it indicates that the policy effect operates through actual disclosure improvement rather than through a broad contemporaneous shift in platform demand or product mix.

The post-purchase estimates also reveal a transactional moderation effect tied to payment method. Refund incidence is highest in "fast pay" methods that require little checkout friction and lowest in deferred-payment methods with extra confirmation steps. However, the protective effect of disclosure specificity is largest in the fast-pay segment. That is intuitive. When checkout friction is low, pre-purchase signals have to do more work because the order can be placed with limited reflection. Clear disclosure and concrete demonstration partly substitute for the missing pause. Likewise, larger basket size raises refunds overall, yet demonstration depth remains strongly negative even in multi-item orders. The signal effect is not confined to small or carefully deliberated purchases.

Another downstream outcome, average support minutes per order, can be estimated only at an aggregated stream-by-day level because service logs are not perfectly linked to individual order lines in every case. In those regressions, demonstration depth has a negative coefficient of -0.041 hours per 100 orders, disclosure specificity -0.026, and post-rollout template adoption -0.038 relative to pre-adoption. These magnitudes are not dramatic, but they are directionally consistent across specifications. They imply that better signals do not merely reduce formal refund requests; they also reduce the quieter burden of explaining product use after purchase.

A final persistence check considers product-page revisits by viewers who clicked but did not buy during the stream [28]. More specific disclosure slightly reduces raw revisits because fewer viewers click casually, but among nonbuyers who did revisit within forty-eight hours, streams with higher demonstration depth produce a higher subsequent purchase rate. This indicates a delayed conversion mechanism. Some viewers use detailed product evidence not to buy immediately but to evaluate later. Live commerce therefore appears to contain both impulse and deferred pathways, and demonstration depth benefits both more consistently than viewer momentum does.

The post-purchase section thus sharpens the main interpretation. Signals that originate with the host and clarify the commercial relationship or demonstrate actual product use are associated with lower correction costs and stronger persistence, while the crowd-generated signal of viewer momentum contributes mainly to speed unless it is paired with substantive evidence. That distinction helps explain why some high-velocity streams are not the most profitable after correction, and why moderate reductions in low-intent clicks after disclosure-template adoption can coexist with better realized outcomes.

7. Robustness, Falsification, and Heterogeneity

Several robustness exercises were conducted to determine whether the estimated relationships reflect genuine signal effects rather than incidental timing or measurement artifacts. The first set of checks concerns alternative outcome scales. When gross merchandise value per 1,000 viewers is replaced by

orders per 1,000 viewers, average order value, or click-to-checkout conversion, the rank ordering of the main signals remains stable. Demonstration depth has the strongest consistent association with orders per viewer and repeat purchase [29]. Disclosure specificity has its clearest effect on click-to-checkout conversion and refund reduction. Viewer momentum is strongest for very early orders and weaker for order value or repeat purchase. This pattern indicates that the findings are not driven by one idiosyncratic sales denominator.

A second set of checks concerns alternative signal measurement. Disclosure specificity was re-estimated using only the pinned text, only spoken statements, and a manually coded subsample. Demonstration depth was re-estimated using a count of distinct features only, a duration-weighted version only, and a version excluding categories where close visual inspection is inherently easier. The coefficient signs and broad magnitudes remain intact. The combined indices produce the best fit, but the substantive interpretation does not depend on the exact scoring rule. This matters because signal measures built from video and transcript data can otherwise be sensitive to coding assumptions.

A useful falsification test exploits products in highly familiar low-risk subcategories where demonstration is less informative because the product is close to a routine replenishment item. In those subcategories, demonstration depth should matter less if the measure is truly capturing diagnostic evidence rather than generic host effort. The interaction between demonstration depth and low-risk familiarity is negative and statistically significant, cutting the main demonstration coefficient by about one third. Disclosure specificity still matters somewhat in these subcategories, particularly for payment or shipping clarification, but the role of product demonstration is smaller. That pattern supports the interpretation that the measure is tied to product evidence rather than presentation style alone.

A second falsification test looks at post-stream outcomes unlikely to be influenced by the examined signals. Delivery delay caused solely by carrier routing should not move with disclosure specificity or demonstration depth once date and geography are controlled for [30]. In regressions on delay-only complaints, the main signal coefficients are close to zero. This is reassuring because it indicates that the earlier refund and support effects are not merely capturing an unobserved stream-quality factor that spills over into every post-order issue [31]. The signal variables predict complaint categories related to expectation and use, not categories tied purely to logistics.

Placebo event studies were estimated around pseudo-adoption dates assigned randomly within untreated pre-policy weeks. Across 2,000 placebo assignments, the mean absolute post coefficient is small and the observed template-rollout profile lies in the extreme tail of the placebo distribution. For stream-level sales, the actual week-six post coefficient exceeds 98.7% of placebo coefficients. For refunds, the actual week-ten post coefficient exceeds 99.1% of placebo coefficients. These results reduce concern that the observed event-time pattern is a generic artifact of the staggered design or of slowly evolving category demand [32].

The main findings are also robust to alternative clustering schemes. Stream-level models clustered by creator, by brand, and by creator-by-month produce similar significance conclusions. Driscoll–Kraay corrections allowing cross-sectional dependence likewise leave the central coefficients intact. For the order-level models, clustering at creator–product and at order-date levels produces slightly wider intervals, but the key negative coefficients on demonstration depth and disclosure specificity remain statistically meaningful.

One concern in live-commerce settings is that highly skilled creators may simultaneously disclose more clearly, demonstrate more effectively, and manage audience energy better. Creator–product fixed effects help, but host skill could still drift over time. To address that possibility, the models incorporate creator-specific linear time trends. The inclusion of those trends attenuates the demonstration-depth coefficient somewhat, from 0.117 to 0.103 in the GMV model, while leaving its sign, significance, and post-purchase role intact. Disclosure specificity is scarcely changed because much of its identifying variation comes from the rollout. Viewer momentum remains positive and significant in early-sales models but still contributes little to refund reduction. The central interpretation therefore survives even under conservative controls for evolving creator skill.

Heterogeneity across categories reveals that demonstration depth matters most in products whose performance is difficult to infer from static appearance. Compact electronics, personal-use devices, and kitchen appliances show the largest demonstration coefficients [33]. Home organization tools and pet accessories show smaller but still positive coefficients. Disclosure specificity matters relatively more in categories with variable shipping, compatibility, or regional price constraints, which makes sense because those are the domains where pinned clarification reduces later confusion. Viewer momentum is strongest in lower-ticket categories where early crowd action likely reduces hesitation without implying severe downside risk [34].

The template rollout also interacts with creator fit. For low-fit creators, mandatory disclosure templates reduce early click-through more than for high-fit creators, but they also lower refunds more sharply [35]. For high-fit creators, the sales dip after adoption is barely visible. This suggests that hosts with stronger domain history can incorporate disclosure without much commercial friction, while low-fit creators initially lose some spontaneity when required to clarify sponsorship and use history. Yet precisely those low-fit streams also appear to benefit more in later satisfaction metrics. From a platform-governance perspective, that is a useful asymmetry because the streams with the greatest informational risk receive the greatest downstream improvement.

A separate heterogeneity exercise divides viewers into new and returning audience segments based on prior exposure to the same creator. Returning viewers respond more strongly to demonstration depth than to disclosure specificity, perhaps because they already understand the commercial nature of the stream but still seek product evidence. New viewers respond more to disclosure specificity and are more influenced by the purchase-counter salience change. This distinction fits the logic of audience learning. Returning viewers have accumulated priors about the host, so product evidence matters more; new viewers face a relational uncertainty problem, so clear disclosure and crowd validation matter more.

The results also vary by stream length. In short streams under twenty-five minutes, viewer momentum has a relatively larger effect because the opportunity for later conversion is limited. In longer streams, demonstration depth matters more and its contribution to repeat purchase is especially visible. This timing pattern suggests that the economic role of signals depends not only on their type but also on how much time the stream architecture gives them to work. A short, intense stream rewards momentum; a longer explanatory stream rewards substantive demonstration.

An additional analysis examines the relation between signals and coupon reliance. Momentum-heavy streams use coupons more aggressively, but once coupon depth is controlled for, the signal coefficients remain. More interestingly, the sales benefit of early momentum is smaller when coupons are deep because the crowd signal is partly displaced by a strong price stimulus. Demonstration depth, by contrast, interacts little with coupon depth [36]. This implies that product evidence and price incentives move different margins, whereas audience momentum can sometimes overlap with short-run price inducement.

A final robustness exercise tests whether the disclosure-template effect was simply caused by more screen clutter or reduced available space for the host. In a subset of streams where the template appeared in a condensed rather than full-width format, the same refund decline appears with almost identical magnitude. This suggests that the effect is not primarily visual crowding. The mechanism is the content and persistence of the disclosure, not the mere presence of an extra graphic element.

The accumulated checks therefore support a fairly specific reading. The estimates are not driven by one product class, one coding rule, one clustering method, or one special outcome variable. They survive placebo timing tests, alternative signal definitions, creator time trends, and transactional controls. The signal roles also differ in coherent ways across audience familiarity, stream length, and product risk, which is difficult to explain as a single omitted variable story.

8. Conclusion

Live commerce places several marketing signals into one compressed viewing sequence, but those signals do not contribute in the same way. The evidence in this study separates seller-controlled disclosure, seller-controlled product demonstration, and audience-generated momentum, then follows them

from stream formation into post-purchase outcomes [37]. Moderate increases in disclosure specificity improve conversion and reduce refunds, especially after a platform policy makes disclosure persistent and visible. Demonstration depth has the largest and most stable association with realized sales quality, lowering refunds and support contacts while increasing repeat purchase among new buyers. Viewer momentum accelerates early sales and becomes more useful when the platform makes it more visible, but its contribution is least durable when concrete product evidence is thin.

The empirical picture is therefore not one in which every visible cue is an interchangeable source of persuasion. Signals differ by origin, timing, and downstream consequences. Platform-mandated disclosure improves calibration even when it briefly slows superficial engagement. Demonstration depth raises both revenue and post-purchase quality. Crowd momentum is most productive when it confirms rather than substitutes for substantive selling. For live-commerce operators, the practical implication is that sales speed and sales quality need not move together, and the stream designs that maximize the earliest order burst are not necessarily the designs that maximize realized commercial value after refunds and support burden are taken into account.

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