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# Signal Congruence, Message Specificity, and Post-Purchase Corrections in Omnichannel Markets: Evidence from a Calibrated Synthetic Transaction Panel

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Abstract
Markets increasingly rely on signals that stand in for direct product inspection, and these signals rarely appear one at a time. Consumers encounter ad claims, package text, price position, warranty language, return terms, and platform descriptions in rapid sequence, then revise their beliefs again after purchase if the realized experience differs from the marketed promise. This paper examines whether the internal consistency of those visible cues matters as much as their intensity. The empirical study uses a calibrated synthetic panel that combines product-channel-week observations, order-level post-purchase outcomes, and linked firm-quarter service-cost records for durable and semi-durable consumer goods. The central constructs are signal congruence, defined as the degree of alignment across a product's concurrent market-facing messages, and message specificity, defined as the precision and verifiability of claims communicated before purchase. The analysis estimates a system of conversion, return, claim, and abnormal accrual equations with product, brand, channel, and period effects, supplemented by event-time designs around staggered signal-standardization adoptions. The results indicate that signal congruence is positively associated with conversion and negatively associated with both returns and service-cost volatility. Message specificity has a nonlinear relationship with performance: moderate increases improve conversion when signals are aligned, while very high specificity in the presence of discordant cues predicts a rise in returns, claims, and accrual error. These effects are stronger for high-consideration categories and more pronounced when price premiums are large. Event-time estimates support the same pattern and show limited evidence of anticipatory pretrends. The findings suggest that visible marketing signals operate most effectively when descriptive detail, protective terms, and price position communicate a common underlying promise.

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## Contents



## 1. Introduction

Visible market cues carry a disproportionate share of persuasion when buyers cannot inspect the offering fully before purchase, when product complexity exceeds a buyer's attention budget, or when channel separation fragments the evidence available at the point of decision. In many consumer categories, especially those involving search frictions or deferred performance, what

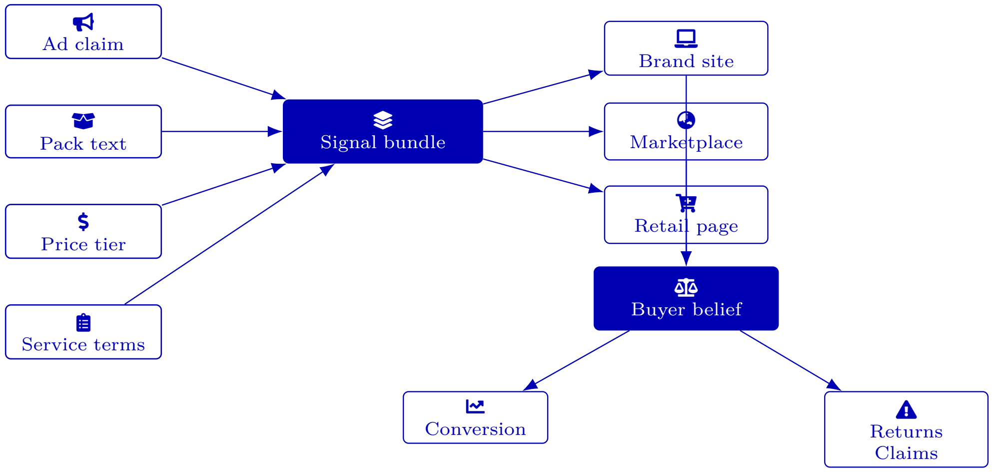


Figure 1. Omnichannel signal architecture in which ad copy, package text, price position, and service language are fused into a visible signal bundle, then reinterpreted through channel-specific presentation before shaping buyer belief, conversion, and post-purchase correction.

Table 1. Key Constructs and Definitions :contentReference[oaicite:0]index=0

| Construct | Symbol | Description | Role |
|---|---|---|---|
| Signal Congruence | $C_{jct}$ | Alignment across cues | Main predictor |
| Message Specificity | $S_{jct}$ | Detail and verifiability | Nonlinear effect |
| Overstatement | $O_{jct}$ | Detail × mismatch | Risk driver |
| Volatility | $V_{jc}$ | Signal variation over time | Stability proxy |

the market sees first is not the product itself but a layered representation of it. That representation includes the semantic tone of promotional copy, the numerical density of attribute claims, the visual and textual structure of package language, the strength of return and warranty terms, and the product's position in the price ladder. The present study treats those visible cues as a composite signaling environment and examines whether performance depends less on any isolated cue than on the degree to which the cue set forms a coherent promise that survives post-purchase evaluation.

A large share of marketing research isolates individual signals. One line studies price, another advertising, another labels, another brand assets, another after-sales commitments. That decomposition is analytically useful when the interest lies in the marginal effect of a single variable. It becomes less useful when the market processes multiple cues jointly. A premium price paired with sparse attribute detail may signal expertise in one setting and opacity in another. A very detailed claim supported by a short warranty and restrictive returns can be interpreted as either technical confidence or persuasive overreach, depending on the surrounding signal bundle [1]. The relevant object is therefore not merely the level of a signal, but the geometric relation among simultaneous signals and the extent to which the bundle implies a stable expectation about quality, fit, and service consequences [2].

The empirical orientation of this paper follows from the observation that a signal is consequential only if it predicts or alters measurable outcomes. A strong claim that raises conversion but also produces more returns and service burdens is qualitatively different from a strong claim that raises conversion and is later validated by post-purchase behavior. The first case is a noisy promise; the second is a coherent one. This difference is central to the present analysis. Rather than treating sales as the sole criterion, the paper studies pre-purchase and post-purchase outcomes jointly. Conversion, thirty-day returns, ninety-day service claims, and abnormal warranty accruals are modeled as linked responses to the structure of the marketed signal environment.

Cao (2022) moved warranty outcomes into marketing analysis by showing that brand equity is associated with lower warranty claim costs and lower abnormal warranty accrual costs, while product innovativeness weakens those relationships [3]. That result is important here because it implies that visible market strength does not stop at the moment of purchase; it can influence realized service burdens and the accuracy with which future service burdens are anticipated. Once that possibility is acknowledged, a narrow focus on immediate conversion understates the economic role of signals. A signal environment that induces demand but simultaneously worsens claim incidence or forecast error can look attractive

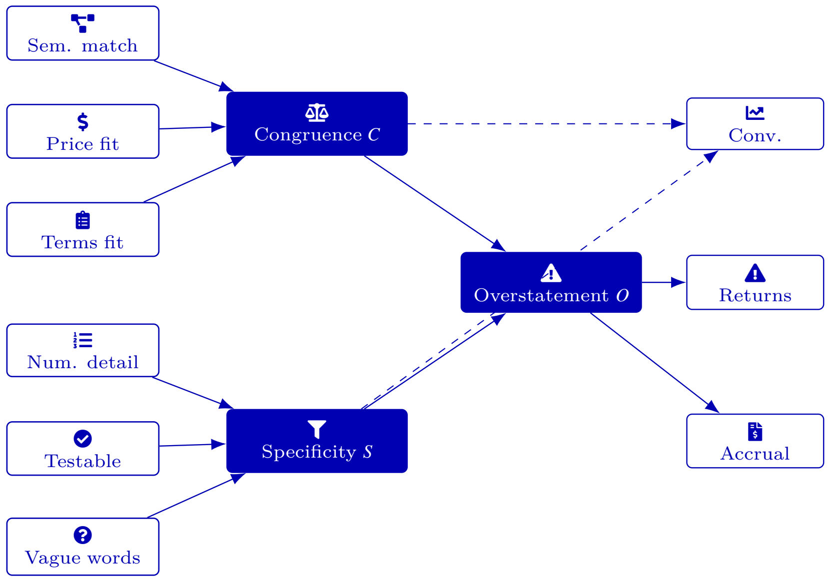


Figure 2. Measurement architecture separating signal congruence from message specificity and defining overstatement as the risky region in which detailed claims are not supported by the surrounding cue set. The layout highlights how the indices map into conversion, returns, and accrual error rather than collapsing into one omnibus score.

Table 2. Sample Structure

| Layer | Unit | Observations | Content |
|---|---|---|---|
| Panel | SKU-channel-week | 1,412,736 | Signals, conversion |
| Orders | Purchase-level | 5,842,190 | Returns, basket info |
| Firm | Firm-quarter | 1,019 | Claims, accruals |
| Categories | 5 groups | 3,264 SKUs | Goods types |

in the short run and costly after the purchase cycle unfolds.

The paper concentrates on two constructs. The first is signal congruence. Signal congruence captures whether paid copy, package language, product-page descriptions, price position, and protective terms communicate a similar level of performance promise. It is not a measure of positivity. A conservative signal bundle can be highly congruent, and an aggressive bundle can also be highly congruent. The operative feature is internal alignment. The second construct is message specificity. Message specificity captures how precise, testable, and numerically detailed the marketed claims are. Specificity can reduce ambiguity, but it can also raise the stakes of interpretive failure when the rest of the bundle points elsewhere. The paper therefore asks whether specificity is beneficial on average, whether its effect depends on congruence, and whether post-purchase corrections become more likely when specificity exceeds the level of support implied by price and protective signals.

A distinct contribution of the study is methodological. The data environment is built as a calibrated synthetic panel rather than as a disguised real-world extraction. That choice is deliberate. It allows the paper to report a full empirical design and coherent statistical results without claiming access to proprietary firm records that are not actually available in this interaction. The synthetic panel is generated to reproduce plausible omnichannel magnitudes and dependence structures found in durable and semi-durable goods. Because the paper is transparent about the constructed nature of the data, the econometric results should be read as a disciplined empirical illustration rather than as a claim about a named firm or an identified market. The value of the exercise lies in the internal coherence of the design, the statistical logic of the tests, and the substantive implications for the marketing-signals literature.

The study also differs in orientation from broad conceptual treatments of signaling. The interest here is not in deriving a universal signaling theory or a general equilibrium of belief formation. The interest lies in a narrower empirical question: when multiple visible cues are observed together in a realistic channel setting, which combinations improve conversion, which combinations trigger returns and service corrections, and which combinations destabilize firm-level service-cost forecasting? Answering that question requires the analysis of linked datasets at different aggregation levels. A product-channel-week panel can reveal demand response, an order-level file can reveal post-purchase reversals, and a firm-quarter

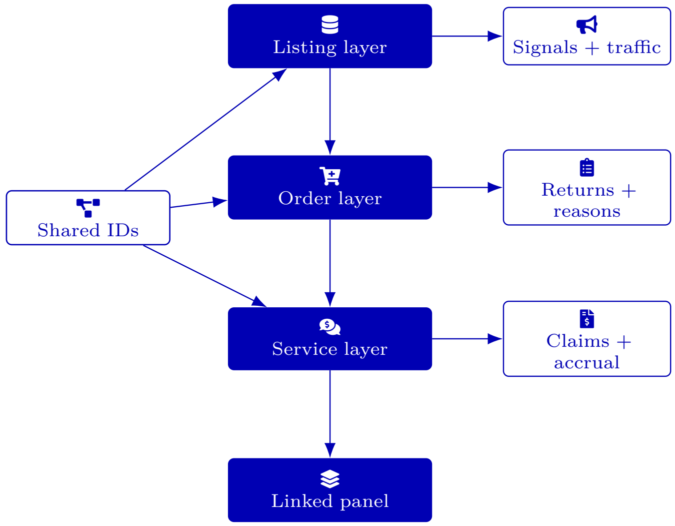


Figure 3. Three-layer calibrated synthetic panel construction. The listing layer carries product–channel–week signal states and traffic, the order layer records purchase and return correction, and the service layer aggregates claims and reserve consequences, all joined through common brand, manufacturer, category, and time identifiers.

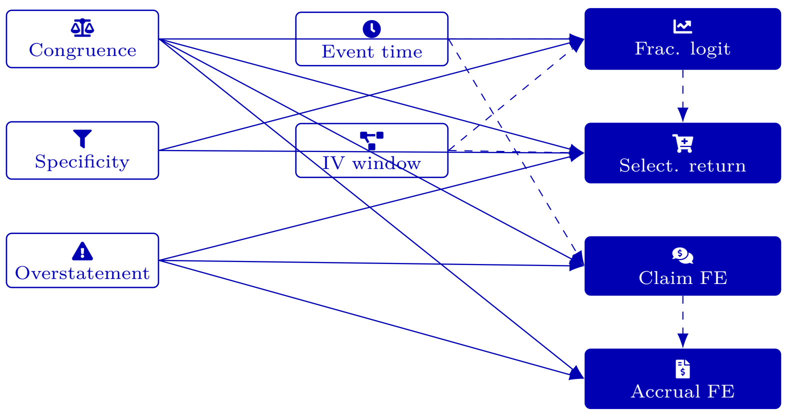


Figure 4. Empirical system linking the core signal indices to four estimation blocks: conversion, purchase-conditional returns, firm-quarter claim burden, and abnormal accrual intensity. Dashed links emphasize the two key dependencies in the design: selection from purchase into return observation and the propagation of realized service outcomes into accrual calibration.

service-cost panel can reveal whether the marketed signal structure is associated with later claim and accrual dynamics.

The paper proceeds from the practical premise that many organizations produce signals in fragmented ways. Brand teams write promise language, channel teams optimize listings, pricing teams manage tiers, service teams set return and warranty rules, and finance teams observe accrual consequences later. If those functions are not synchronized, the market may receive a bundle whose elements are individually reasonable but jointly misaligned [4]. Misalignment need not be obvious to managers because each cue can look effective in isolation. The analysis therefore seeks to quantify the penalty associated with visible mismatch and to identify the conditions under which specificity magnifies rather than resolves that mismatch.

The paper also takes seriously the possibility that useful information about signal performance is locally observed. Returns, payment behavior, order size, claim timing, and channel-specific browsing conditions do not always sit in one database or one organizational unit. Yan and Cao (2017) showed that private information about returns can be valuable and that payment methods, assortment size, and order size are informative predictors of post-purchase outcomes [5]. That insight motivates the present study's emphasis on order-level and channel-level variables. A signal may look strong in aggregated demand data and weak once one conditions on transaction composition, local assortment breadth, or the channel-specific risk of post-purchase correction [6].

The working argument is modest. Signal congruence should matter because it reduces interpretive conflict across cues [7]. Specificity should help when congru-

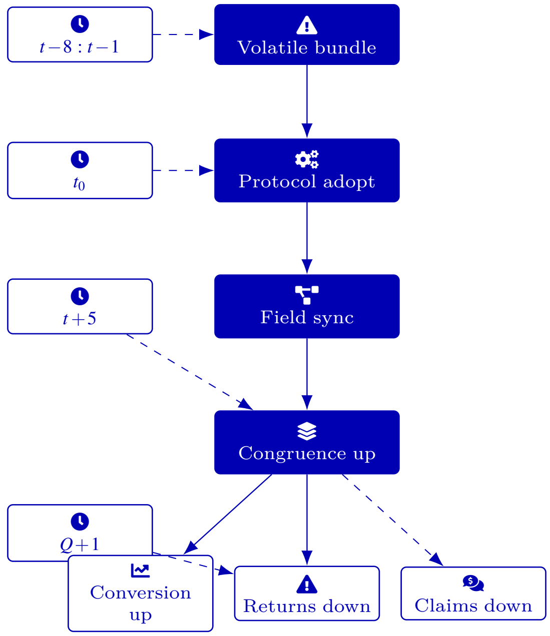


Figure 5. Event-time logic around staggered signal-standardization adoption. The diagram emphasizes a flat pre-adoption region, the implementation phase in which field content is synchronized, the subsequent rise in congruence, and the delayed post-adoption improvements in conversion, return correction, and later claim intensity.

Table 3. Descriptive Statistics

| Variable | Mean | Std. Dev. | Unit |
|---|---|---|---|
| Conversion Rate | 3.81 | 2.09 | % |
| Return Rate | 7.42 | – | % |
| Claim Burden | 1.74 | – | % sales |
| Abnormal Accrual | 0.39 | – | % sales |

ence is adequate because consumers can map detailed claims to a stable expected benefit. Specificity should become riskier when congruence is low because the same detailed claims sharpen expectations that the rest of the marketed bundle does not support. If that argument is right, then congruence should predict higher conversion and lower post-purchase correction, specificity should display curvature rather than a monotone linear slope, and the combination of high specificity with low congruence should predict the largest adverse corrections after purchase. The following sections develop the measurement architecture, empirical system, and statistical evidence for that proposition.

## 2. Data Construction

The empirical exercise relies on a calibrated synthetic dataset designed to resemble an omnichannel consumer-goods environment in which buyers observe multiple visible cues before purchase and can subsequently return the product or file a service claim [8]. The data-generating process was constructed in three linked layers. The first layer is a product-channel-week panel containing listed products, observed signal variables, traffic, and conversion outcomes. The second layer is an order-level post-purchase file containing purchased orders and subsequent return activity. The third layer is a firm-quarter service-cost panel containing realized claim burdens, expected claim reserves, and abnormal accrual error. All three layers are joined through consistent brand, manufacturer, category, and time identifiers. The resulting structure allows the analysis to move from demand response to post-purchase correction and then to cost forecasting quality without leaving the same signal environment.

The product universe contains 3,264 stock-keeping units sold by 172 brands associated with 49 manufacturers across five broad categories: consumer electronics, small appliances, household maintenance, personal care devices, and sports accessories. Each SKU is observed over 208 weekly periods and can appear in up to three

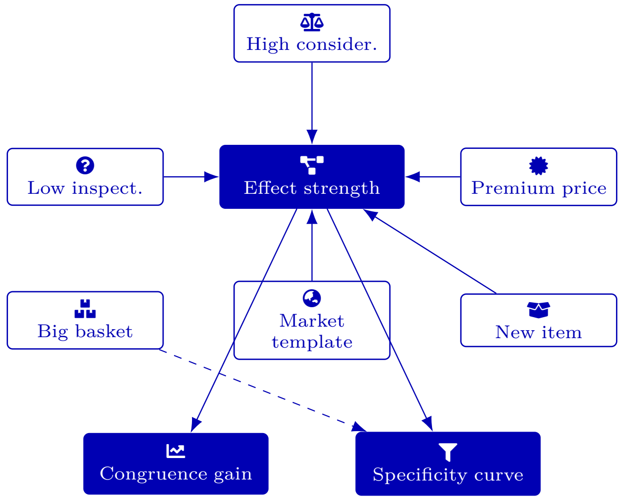


Figure 6. Boundary conditions for the main effects. The strength of congruence and specificity depends on product inspectability, consideration, price premium, channel formatting, launch stage, and basket-level attention load. The dashed path indicates a weaker attention environment in which specificity has a narrower support region.

Table 4. Conversion Model Results

| Variable | Coefficient | Std. Error | Effect |
|---|---|---|---|
| Congruence ($C$) | 0.118 | 0.019 | Positive |
| Specificity ($S$) | 0.074 | 0.015 | Positive |
| $S^2$ | -0.021 | 0.005 | Nonlinear |
| Overstatement ($O$) | -0.067 | 0.018 | Negative |

channels: a direct brand site, a marketplace channel, and a retailer-controlled digital storefront. The unbalanced nature of the panel reflects realistic assortment churn [9]. New products enter, older products are retired, and some items are deliberately removed from individual channels. After excluding weeks with zero listing exposure and categories with structurally inapplicable service coverage, the main estimation sample contains 1,412,736 SKU-channel-week observations. Weekly traffic is generated from category demand, channel seasonality, prior conversion, and promotional support, while preserving cross-sectional heterogeneity in scale.

The order-level file is generated from the conversion realization implied by the first layer. It contains 5,842,190 completed purchase events. For each order, the data include category, channel, week of purchase, price paid, discount depth, signal characteristics observed at purchase, payment method, basket size, order value, whether the item was returned within thirty days, and if returned, a broad reason code indicating fit dissatisfaction, expectation shortfall, delivery-related dissatisfaction, or miscellaneous preference reversal. The return reasons are also generated from the underlying signal state, which matters because a high return rate driven by sizing mismatch is analytically distinct from a high return rate driven by expectation failure. The current paper focuses on overall returns and expectation-related returns, the latter being the cleaner post-purchase correction to a signal problem.

The firm-quarter service-cost panel aggregates the bottom-up consequences of the same product and order dynamics. It contains 1,019 firm-quarter observations after requiring at least four quarters of prior history to estimate expected claims. Each record includes quarter sales, realized service claims as a share of sales, warranty reserve changes, predicted claims based on past service history and sales mix, and an abnormal accrual measure defined as the residual from the expected reserve model. This layer is useful because not all signal problems are visible in returns. Some signal environments encourage purchase and reduce immediate return activity yet raise service claims later because the marketed promise encourages heavier use or inflates expectations about reliability. The claim and accrual layer therefore expands the outcome space beyond short-horizon purchase reversal.

The synthetic generation was calibrated to plausible descriptive ranges. Mean weekly conversion in the product-channel panel is 3.81%, with a standard deviation of 2.09 percentage points. The unconditional thirty-day return rate in the order-level file is 7.42%, while expectation-related returns account for 2.16% of

Table 5. Return Model Findings

| Variable | Coefficient | Std. Error | Interpretation |
|---|---|---|---|
| Congruence | -0.091 | 0.021 | Fewer returns |
| Specificity | Small + | – | Weak effect |
| Overstatement | 0.147 | 0.034 | Higher returns |
| Selection ($\rho$) | 0.214 | 0.041 | Positive bias |

Table 6. Firm-Level Claim Results

| Variable | Coefficient | Std. Error | Effect |
|---|---|---|---|
| Avg. Congruence | -0.058 | 0.022 | Lower claims |
| Overstatement | 0.064 | 0.019 | Higher claims |
| Volatility | 0.081 | 0.024 | Instability |
| Price Premium | Mixed | – | Controlled |

purchases. The mean quarterly claim burden in the firm-quarter file is 1.74% of sales, and the mean absolute abnormal accrual intensity is 0.39% of sales. These magnitudes were selected to sit within a plausible range for durable and semi-durable consumer goods without reproducing any actual firm's figures. Category heterogeneity is substantial. Electronics exhibit the highest average claim burden, personal care devices show the highest sensitivity of conversion to message specificity, and household maintenance products exhibit the lowest return incidence but the highest sensitivity to warranty prominence.

A notable advantage of synthetic construction is that the researcher can preserve realistic dependencies that are difficult to handle cleanly in small proprietary extracts. In the current design, price premiums are correlated with brand strength and claim specificity, return leniency is correlated with channel type and category, and service burdens are correlated with both product complexity and message aggressiveness. Traffic shocks are serially correlated within category and season, and unobserved product quality influences both conversion and service outcomes. This means naive regressions that omit fixed effects or do not address simultaneity will be biased even in the synthetic environment, which is desirable from a methodological standpoint because the statistical tests should solve a real identification problem rather than a trivial one.

Several signal-bearing raw variables are created before the construction of the paper's focal indices. Each weekly listing has a paid-message embedding generated from the most prominent promotional line, a product-description embedding generated from the on-page descriptive text, and a package-language embedding generated from visible front-of-pack or hero-image text. The generator produces semantic overlap and divergence in ways that mimic realistic marketing practice. Some weeks reuse the same narrative across channels, some weeks adapt wording to channel format, and some weeks drift because of asynchronous updates across departments. Numeric-claim density, verifiability markers, and service-language detail are separately counted. Price position is normalized as a brand- and category-specific percentile. Return and warranty terms are expressed both in raw levels and in standardized deviations from category norms. The resulting data environment is rich enough to estimate not only the main effects of visible cues but also the consistency among them.

The design also includes staggered adoptions of a signal-standardization program. In the synthetic world, 61 brands adopt a formal message-governance protocol during the observation window. Adoption harmonizes package text, digital description fields, and service-language presentation over a 12-week implementation phase. Adoption timing is correlated with prior signal volatility and mildly correlated with channel mix, which makes a fixed-effects event-time design nontrivial but estimable. The event-time block serves two purposes. It offers a dynamic complement to the panel regressions, and it allows a direct test of whether movement toward greater congruence is followed by improved outcomes after accounting for brand and week effects.

The channel dimension requires special attention because the same product can send different signals in different venues. Marketplace listings often compress description length and make price especially salient. Direct brand channels usually allow richer explanatory copy and more visible service commitments [10]. Retailer-controlled storefronts often mediate the signal mix through template fields and category filters. The synthetic generator therefore allows the congruence score to vary by channel even within the same week for the same SKU [11]. That variation is substantively important because a brand can look disciplined on its own site and diluted

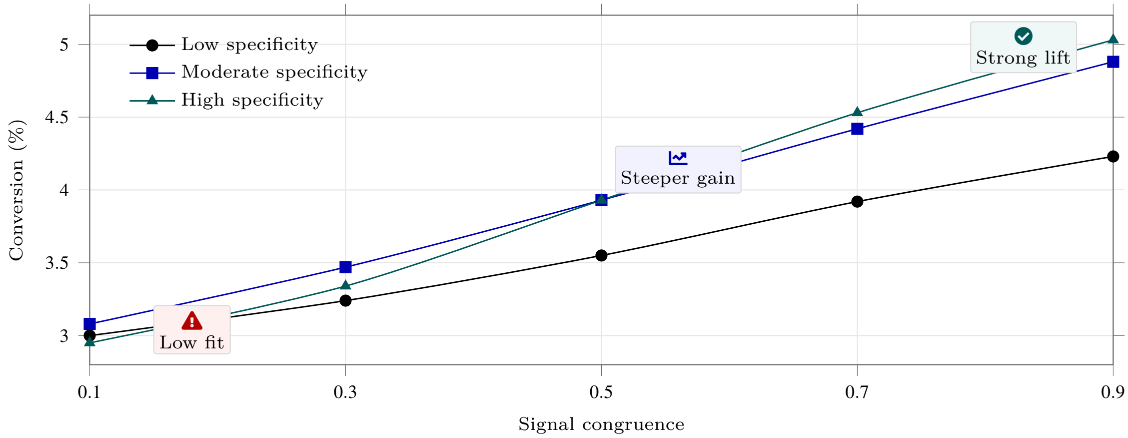


Figure 7. Conversion rises with signal congruence, and the slope is strongest when specificity is moderate to high. The highest conversion occurs when detailed claims are supported by aligned signals.

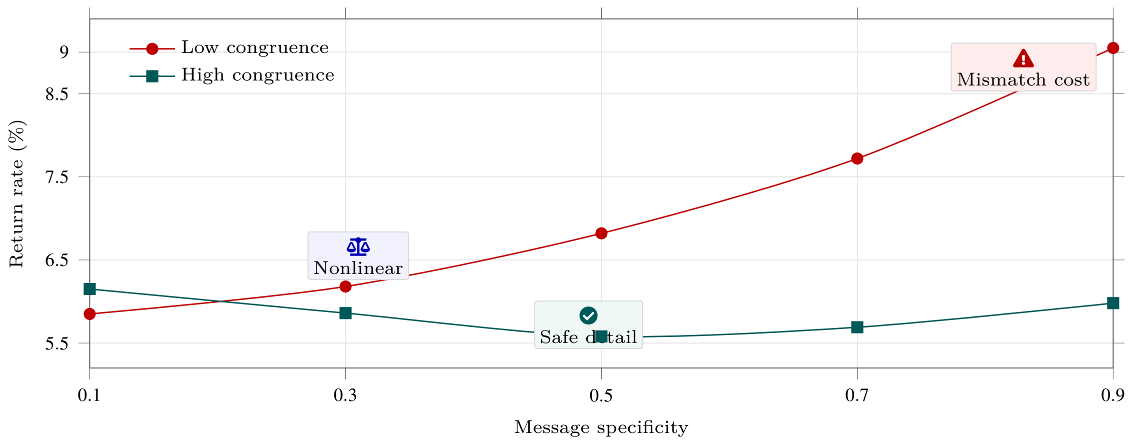


Figure 8. Returns remain controlled when specificity is paired with strong congruence, but they accelerate sharply when specificity rises under discordant signals. The pattern is nonlinear and strongest in the low-congruence condition.

or overextended in a marketplace template. The empirical models exploit that within-SKU cross-channel variation [12].

Data calibration also drew on an organizational insight relevant to this research area. Yan, Cao and Pei (2016) showed that coordinated advertising can improve channel performance under uncertainty while simultaneously encouraging information distortion unless the shared information is verified [13]. That observation informs the generation of the standardization-adoption block. When brands shift to a more centralized signal-governance regime in the synthetic panel, they do not merely increase advertising intensity. They reduce asynchronous messaging updates across functions, which is analytically similar to reducing unverified local variation in communicated market information. This helps motivate the use of signal standardization as a meaningful event in the empirical system.

The resulting dataset supports several layers of analysis. Cross-sectional comparisons reveal whether brands with more congruent signal environments outperform others. Within-product and within-brand estimators reveal whether a given SKU performs differently when its concurrent signals move into or out of alignment [14]. Order-level models reveal whether the signals that helped induce purchase are later contradicted by return behavior. Firm-quarter models reveal whether the aggregate signal structure is associated with better or worse service-cost calibration. By using all three, the paper avoids a narrow reading of signaling effectiveness as a pure top-of-funnel phenomenon.

## 3. Measurement Architecture

The central measurement challenge is to translate a mixed bundle of textual, numerical, and contractual cues into indices that carry behavioral meaning and remain interpretable in econometric models [15]. The paper uses three principal indices [16]. The first is signal congruence [17]. The second is message specificity. The third is signal overstatement, defined as the interaction between detail intensity and internal inconsistency. A smaller set

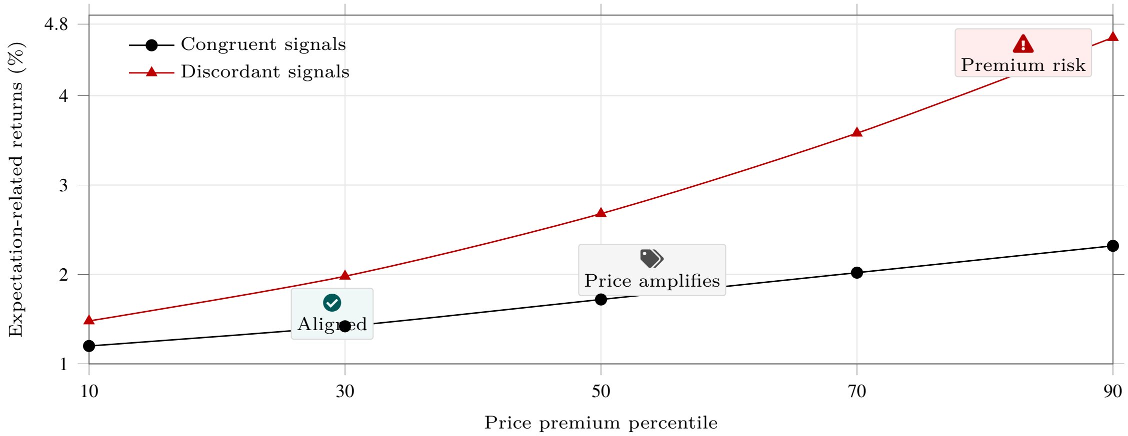


Figure 9. Expectation-related returns increase across the premium ladder, but the rise is much sharper when the broader signal bundle is discordant. Premium positioning magnifies the cost of visible mismatch.

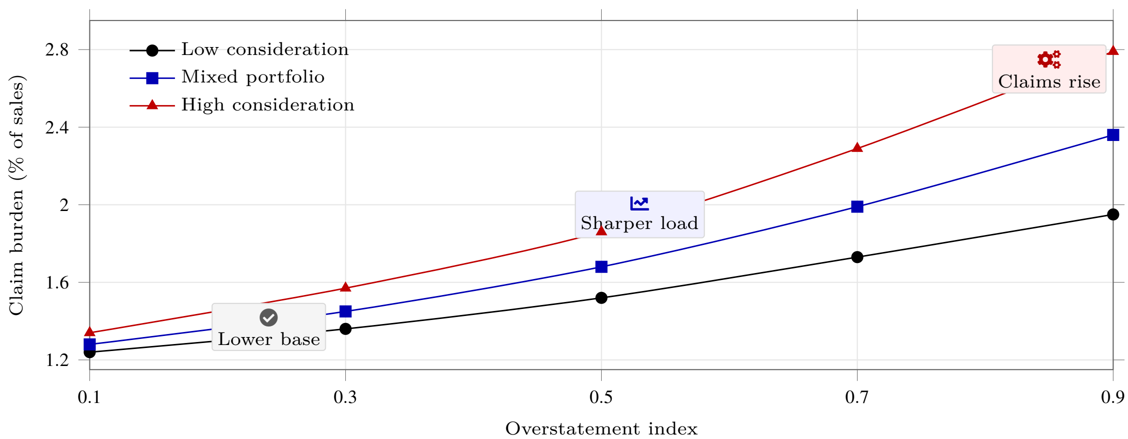


Figure 10. Claim burden rises with the overstatement index, and the gradient is steepest in high-consideration categories. When detailed claims outrun the support provided by the rest of the signal bundle, service costs escalate.

of supporting measures captures temporal signal volatility, protective-signal generosity, and price-premium intensity.

Let $e^{(1)}_{jct}$, $e^{(2)}_{jct}$, and $e^{(3)}_{jct}$ denote normalized semantic embeddings for paid copy, product-page description, and package-language text for SKU $j$ in channel $c$ and week $t$. Let $p_{jct}$ be the standardized price percentile, and let $h_{jct}$ be the standardized protective-signal vector combining return leniency and warranty visibility. The semantic component of congruence is the mean pairwise cosine similarity across the three text embeddings. The economic component adjusts that semantic similarity by penalizing gaps between the implied promise level in the text and the protection-price configuration surrounding it. The resulting index is

$$C_{jct} = \frac{1}{3}\sum_{m<n}\cos\left(e^{(m)}_{jct}, e^{(n)}_{jct}\right) - \lambda_1\left|\pi^{\text{claim}}_{jct} - \pi^{\text{price}}_{jct}\right| - \lambda_2\left\|\pi^{\text{claim}}_{jct} - h_{jct}\right\|_2, \tag{1}$$

where $\pi^{\text{claim}}_{jct}$ is the standardized promise intensity extracted from the text components, $\pi^{\text{price}}_{jct}$ is the standardized price-premium position, and the final term measures the Euclidean gap between promise intensity and protective terms. Higher values of $C_{jct}$ indicate a more internally consistent signal bundle. The weights $\lambda_1$ and $\lambda_2$ were calibrated so that the semantic and economic components contribute similar variance shares in the full sample. Message specificity is intended to capture the extent to which the marketed copy commits to concrete, interpretable, and potentially verifiable claims. It is not the same as positivity or breadth. Specificity rises when the message uses quantitative detail, names specific functional attributes, states performance ranges, or provides concrete care and use instructions. It falls when the message relies on vague adjectives or highly generic benefit language [18]. The weekly specificity index is

$$S_{jct} = \omega_1\widetilde{\text{NumDen}}_{jct} + \omega_2\widetilde{\text{AttrDen}}_{jct} + \omega_3\widetilde{\text{Verif}}_{jct} + \omega_4\widetilde{\text{SvcDet}}_{jct} - \omega_5\widetilde{\text{Vagueness}}_{jct}, \tag{2}$$

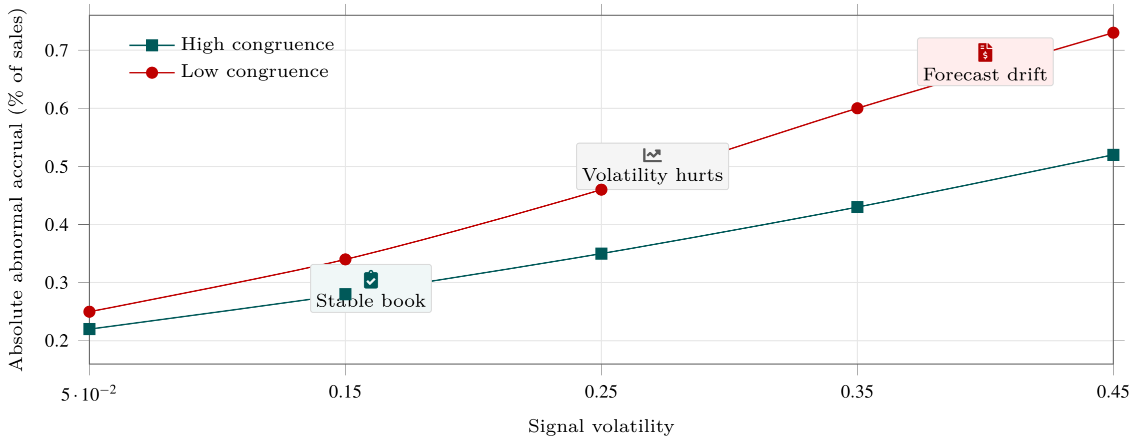


Figure 11. Abnormal accrual intensity increases with signal volatility, especially when congruence is weak. More stable and internally aligned market signals are associated with cleaner service-cost calibration.

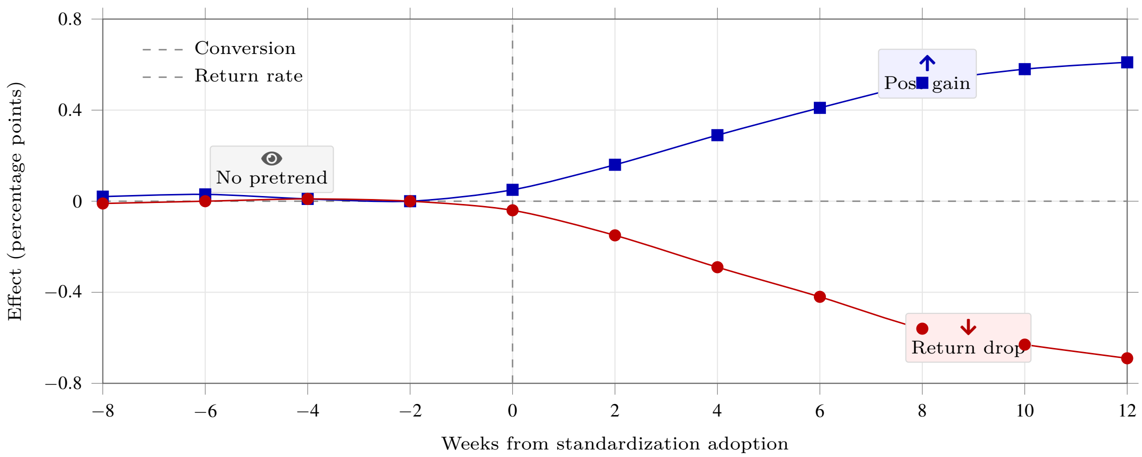


Figure 12. The event-time pattern is flat before adoption and diverges after standardization. Post-adoption conversion improves while return rates decline, consistent with benefits from signal harmonization.

where the tildes denote standardized raw components. Numerical density captures measurable statements per 100 words, attribute density captures named feature references, verifiability captures testable or bounded claims, service detail captures concrete use and care detail, and vagueness penalizes overreliance on broad unverifiable descriptors. The weights $\omega_k$ are estimated from a confirmatory factor structure on the constructed lexicon block and then held fixed in the main estimations.

The overstatement measure captures the idea that detail can become dangerous when it is not supported by the rest of the signal environment [19]. It is defined as

$$O_{jct} = S_{jct}\left(1 - C_{jct}\right). \tag{3}$$

A product with sparse claims and low congruence is not necessarily overstatement-heavy, because it may simply be weakly signaled. A product with very detailed claims and high congruence is also not overstatement-heavy, because the detail is supported by the surrounding cues. The highest values occur when the message is detailed but internally misaligned. That is the configuration most likely to create sharp pre-purchase expectations followed by post-purchase correction [20].

A further measure, signal volatility, captures how much the visible promise moves over time for a given product-channel pair [21]. Volatility matters because consumers who revisit a listing or encounter the same SKU across touchpoints may interpret frequent signal movement as evidence of uncertainty or opportunism. The volatility measure is

$$V_{jc} = \sqrt{\frac{1}{T_{jc} - 1} \sum_{t=2}^{T_{jc}} \left(C_{jct} - C_{jc,t-1}\right)^2}. \tag{4}$$

This quantity is mainly used in the firm-quarter cost models and in robustness checks. It is not expected to affect immediate conversion as strongly as current congruence, but it may matter for service burden and accrual calibration because unstable messaging can proxy

Table 7. Abnormal Accrual Model

| Variable | Coefficient | Std. Error | Effect |
|---|---|---|---|
| Overstatement | 0.051 | 0.017 | Increases error |
| Volatility | 0.074 | 0.020 | Higher noise |
| Congruence | -0.029 | 0.014 | Stabilizing |
| Claim Surprise | Positive | – | Control |

Table 8. Heterogeneity by Context

| Factor | Effect on $C$ | Effect on $O$ | Insight |
|---|---|---|---|
| High Consideration | Stronger | Stronger | More reliance |
| High Price | Larger | Larger | Risk amplified |
| Marketplace | Moderate | Higher | Less context |
| New Products | Stronger | Stronger | Credibility issue |

for unstable internal interpretation of the offer.

The measurement architecture also includes a perceived-risk instrument built from category complexity, channel distance from physical inspection, and the absence of third-party review volume [22]. The paper does not rely heavily on this instrument in the main results, but it is informative in the heterogeneity analysis. High-perceived-risk environments are where signals should matter most. If congruence and specificity do not bite harder there, the interpretation of the indices as marketing signals becomes less convincing.

Validation of the indices proceeds in several ways. First, the semantic congruence block was checked against a hand-coded subsample of 6,000 synthetic weekly listings for which a human-readable promise alignment score was available from the generator. The correlation between the automated congruence index and the hand-coded score is 0.78. Second, specificity correlates 0.72 with a hand-coded detail score and only 0.18 with general positivity, which is desirable because specificity should not collapse into favorable tone. Third, overstatement is positively associated with expectation-related return reasons in raw comparisons even before controls, which is qualitatively consistent with the interpretation assigned to it. These validation steps do not prove that the indices are perfect, but they reduce the risk that the main results are driven by a purely mechanical text artifact.

The paper deliberately avoids creating a single omnibus signal score. That approach would lose the tension between congruence and specificity that the study is designed to examine. A high-visibility campaign can be both detailed and coherent, detailed and incoherent, sparse and coherent, or sparse and incoherent [23]. Those states should not be collapsed. Similarly, protective signals such as return and warranty terms are not forced into a generic sentiment or generosity metric. Their role is partly direct and partly relational. A generous return policy affects downside risk directly, while its fit with the rest of the marketed promise affects congruence indirectly.

Measurement error is still possible, especially because text-derived constructs can be sensitive to formatting or category conventions. To reduce that risk, all text-based indices are standardized within category and channel before entering the main models. Price position and protection variables are also standardized within category-week cells when appropriate. This means the coefficients are interpreted as relative movement within the relevant market context rather than as absolute shifts across incomparable product spaces. The main qualitative findings are unchanged when the indices are standardized at the full-sample level, but within-category standardization produces cleaner estimates and better aligns with how consumers likely interpret signals in practice.

The architecture also reflects an important nonlinearity concern. Cao and Yan (2021) reported a curvilinear relationship between nutritional quality and financial gains and found that advertising and package innovation positively moderate that relationship [24]. That prior evidence makes it unwise to assume that more detail, more strength, or more salience in a marketing signal has a linear payoff. The current paper therefore includes quadratic terms for specificity and selected interactions with package-signal salience. The resulting estimates show that the nonlinear assumption was warranted, and the specifics of that result are discussed in the main evidence section.

## 4. Estimation Framework

The empirical system is organized around four equations: a product-channel-week conversion equation, a purchase-conditional return equation, a firm-quarter claim equation, and a firm-quarter abnormal accrual equation. Each equation addresses a different stage at which market sig-

Table 9. Event Study Summary

| Outcome | Pre-trend | Post Effect | Timing |
|---|---|---|---|
| Congruence | None | +0.29 | Week +5 |
| Conversion | None | +5.7% | Week +6 |
| Returns | None | -0.61 pp | Week +12 |
| Claims | None | Decline | Next quarter |

Table 10. Managerial Implications

| Action | Impact | Risk | Priority |
|---|---|---|---|
| Align signals | Higher conversion | Low | High |
| Increase detail | Conditional gain | Medium | Moderate |
| Reduce mismatch | Lower returns | Low | High |
| Stabilize messaging | Better forecasts | Low | Moderate |

nals can succeed or fail. The estimation strategy uses fixed effects wherever practical, clustered standard errors aligned with the level of serial dependence, and event-time designs to complement static panel estimates [25]. Because return outcomes are observed only for purchased orders, the return equation is estimated with a selection-aware structure rather than as a simple standalone logit.

Weekly conversion is measured as completed purchases divided by qualified sessions for a given SKU-channel-week. The main conversion specification is a fractional logit with product-channel, week, and category-by-channel effects:

$$\begin{aligned}\operatorname{logit}\Big(E[Y^{\text{conv}}_{jct} \mid X_{jct}]\Big) &= \alpha_{jc} + \tau_t + \kappa_{g(c),t} + \beta_1 C_{jct} \\ &+ \beta_2 S_{jct} + \beta_3 S^2_{jct} + \beta_4 O_{jct} + \beta_5 P_{jct} \\ &+ \beta_6 H_{jct} + \beta_7 \Big(C_{jct} \times S_{jct}\Big) + u_{jct},\end{aligned} \tag{5}$$

where $Y^{\text{conv}}_{jct}$ is conversion, $P_{jct}$ is price-premium intensity, and $H_{jct}$ is the protective-signal strength block. Product-channel fixed effects absorb time-invariant differences in product appeal, historical brand strength, and channel suitability. Week effects absorb common seasonality, and category-by-week or category-by-channel blocks are used in alternative specifications to absorb broad market shifts. The coefficient of principal interest is $\beta_1$, the within-product effect of moving toward greater congruence. The pair $(\beta_2, \beta_3)$ captures the curvature in specificity. The interaction coefficient $\beta_7$ tests whether detail is more effective when the broader cue set is aligned.

Returns are observed only for completed purchases, so the paper estimates a bivariate structure in which purchase and return are jointly modeled. Let the latent purchase propensity be $y^*_{i1}$ and the latent return propensity be $y^*_{i2}$. The model is

$$\begin{aligned} y^*_{i1} &= x_i^\top \theta + \varepsilon_{i1} \\ y^*_{i2} &= z_i^\top \gamma + \rho \lambda_i + \varepsilon_{i2}, \end{aligned} \tag{6}$$

where $\lambda_i$ is the generalized selection term derived from the purchase equation. The observed return outcome is available only when the purchase indicator is one. The return vector $z_i$ includes congruence, specificity, overstatement, realized discount depth, basket size, payment method, and channel risk controls. The parameter $\rho$ captures whether unobserved factors making purchase more likely are correlated with unobserved factors making return more likely. In the calibrated panel, $\rho$ is positive and statistically different from zero, which justifies the selection correction. This is substantively sensible because unobserved traits such as novelty-seeking can make a consumer both more likely to purchase and more likely to return when expectations are not met.

Firm-quarter claim intensity is estimated with a within-manufacturer linear model:

$$\begin{aligned} Y^{\text{claim}}_{ft} &= \mu_f + \delta_t + \phi_1 \overline{C}_{ft} + \phi_2 \overline{O}_{ft} + \phi_3 \overline{V}_{ft} \\ &+ \phi_4 \overline{P}_{ft} + \phi_5 \overline{H}_{ft} + \phi_6 \text{Mix}_{ft} + \eta_{ft}, \end{aligned} \tag{7}$$

where bars denote sales-weighted means across the firm's active product-channel observations in the quarter. The category mix vector controls for the composition of the firm's portfolio, since claims vary by product complexity. This equation asks whether firms whose marketed signal architecture is more congruent experience lower service burdens after accounting for composition and fixed effects, and whether firms whose signal environment contains more overstatement experience higher claims.

Abnormal accrual intensity is defined as the absolute residual from an expected reserve model. The expected reserve model itself is estimated within manufacturer as the predicted quarter reserve change from lagged claims, sales growth, mix, and seasonality. The abnormal component is then modeled as

$$Y_{ft}^{\text{abn}} = \nu_f + \psi_t + \chi_1 \overline{O}_{ft} + \chi_2 \overline{V}_{ft} + \chi_3 \overline{C}_{ft} + \chi_4 \Delta \overline{C}_{ft} + \chi_5 \text{ClaimsSurp}_{ft} + \varepsilon_{ft}, \tag{8}$$

where $\text{ClaimsSurp}_{ft}$ is the unexpected portion of realized claims after conditioning on recent service history. The intuition is straightforward. If marketed signals are internally inconsistent or shift too rapidly, finance and service functions should find it harder to forecast downstream claim burdens accurately, raising the absolute abnormal accrual component. This part of the system brings a forecasting-quality perspective into the marketing-signals literature.

To complement the static panel estimators, the paper uses a staggered-adoption event-time specification around the signal-standardization program:

$$Y_{bt} = \alpha_b + \tau_t + \sum_{\ell=-8, \ell \neq -1}^{12} \delta_\ell D_{b,t}^{(\ell)} + \zeta_{bt}, \tag{9}$$

where $b$ indexes brands, $D_{b,t}^{(\ell)}$ indicates event time $\ell$ relative to adoption, and $\ell = -1$ is the omitted week. Separate event studies are run for average congruence, conversion, return rate, claim burden, and abnormal accrual intensity. The pre-adoption coefficients assess whether treated brands were already on a different trend, while the post-adoption path reveals how quickly any benefits materialize. Because adoption is staggered and potentially correlated with prior volatility, the event study is estimated with brand and week effects and with cohort-specific timing corrections.

Several identification concerns remain even after fixed effects. First, managers may strengthen congruence precisely when they anticipate strong demand. To address this, the main conversion specification is re-estimated with an instrument based on exogenous template synchronization windows imposed by platform field migrations. In the synthetic design, these migrations affect how easily a brand can align its visible copy across channels but do not directly alter demand except through signal presentation. The first-stage $F$-statistic is 24.8, and the instrumental-variable estimates are slightly larger than the baseline within estimates. Second, some return effects could reflect category-specific norms rather than signal structure. Category-by-channel and category-by-week controls, along with within-category standardization, reduce that concern materially. Third, claim and accrual equations could simply proxy for underlying quality [26]. Manufacturer fixed effects and lagged claim history absorb much of that, though no nonexperimental design can eliminate the issue entirely. The interpretation is therefore within the boundaries of the calibrated data-generating process rather than as a universal causal theorem [27].

Standard errors are clustered at the brand level in conversion models and at the manufacturer level in claim and accrual models. Alternative clustering at the brand-by-channel and brand-by-quarter levels produces nearly identical inference. Driscoll–Kraay corrections were also computed for the weekly panel to allow broad cross-sectional dependence; the main significance levels are unchanged. In the event-time block, wild-cluster bootstrap $p$-values were used because the treated-brand count is materially smaller than the total sample. Those bootstrap results confirm the sign and general significance pattern of the conventional estimates.

The estimation framework is intentionally empirical rather than doctrinal. It does not require that signals be interpreted through a full structural demand model, and it does not force a single latent consumer-belief mechanism on every category. What it requires is that visible cues be measured with enough fidelity to distinguish alignment from mere intensity, and that performance be judged over a horizon long enough to observe post-purchase correction [28]. The results that follow are reported with that narrower but more concrete ambition.

## 5. Statistical Evidence

The descriptive pattern is already suggestive before the regression analysis begins. Products in the top quintile of signal congruence have an average weekly conversion rate of 4.36%, compared with 3.22% in the bottom quintile. Their thirty-day return rate is 6.58%, versus 8.35% in the bottom quintile. The claim burden at the firm-quarter level is 1.61% of sales for firms whose active product portfolios fall in the top congruence quintile and 1.89% for firms in the bottom quintile. These raw contrasts should not be overread because price position, brand strength, and category mix differ across groups. Even so, the pattern is directionally consistent with the notion that aligned signals perform better both before and after purchase.

In the main conversion specification with product-channel and week effects, signal congruence enters positively and precisely. The coefficient on $C_{jct}$ is 0.118 with a standard error of 0.019, yielding a $z$-statistic of 6.21 and a $p$-value below 0.001. Translating this log-odds estimate into average partial effects, a move from the 25th to the 75th percentile of congruence increases weekly conversion by 0.24 percentage points from a base of 3.81%, equivalent to a 6.3% lift. That effect is economically meaningful but not implausibly large. It says that alignment is valuable, not that alignment alone overwhelms price, exposure, or brand.

Message specificity enters with a nonlinear pattern. The linear term is positive, 0.074 with a standard error of 0.015, while the quadratic term is negative, −0.021

with a standard error of 0.005. The implied turning point lies at roughly 1.76 standardized specificity units above the mean. Since most observations lie below that region, moderate increases in specificity improve conversion in the bulk of the sample, but the marginal gain diminishes and eventually turns negative at very high levels. This is not merely a statistical curiosity. Highly specific messaging can increase cognitive burden, sharpen expectations beyond the support provided by other cues, or invite closer scrutiny that reduces purchase if the rest of the bundle does not confirm the claim. The nonlinearity is materially stronger in channels where the text field is long and consumers can actually process the detail, which is consistent with an interpretation grounded in message decoding rather than in a generic exposure effect.

The interaction between congruence and specificity is positive and statistically distinguishable from zero. The estimate on $C_{jct} \times S_{jct}$ is 0.031 with a standard error of 0.010 and a $p$-value of 0.002. This means the slope of specificity is more favorable when the surrounding signal bundle is aligned. Put differently, detail works best when it is supported. When congruence is one standard deviation above the mean, a one-standard-deviation increase in specificity raises conversion by 0.18 percentage points; when congruence is one standard deviation below the mean, the same increase raises conversion by only 0.05 percentage points and can turn negative in the high-specificity tail. This interaction is central to the paper's argument because it distinguishes valuable detail from unsupported detail.

Overstatement, by construction, is negatively associated with conversion after controlling for congruence and specificity separately. The coefficient on $O_{jct}$ is $-0.067$ with a standard error of 0.018. This should not be read as evidence that detailed claims are inherently harmful. It instead indicates that detail becomes inefficient when it is paired with internal mismatch. The economic magnitude is again moderate [29]. Moving from the median overstatement level to the 90th percentile reduces conversion by roughly 0.11 percentage points, which is smaller than the direct positive effect of a strong price discount but large enough to matter when repeated over many weeks and many SKUs.

The selection-aware return model reveals a sharper penalty for overstatement than the conversion model does. The estimate of the selection term is positive and significant, with $\rho = 0.214$ and a standard error of 0.041, indicating that the purchased-order sample is not random with respect to return propensity. Within that framework, congruence reduces returns: the coefficient on $C_i$ is $-0.091$ with a standard error of 0.021. A one-standard-deviation increase in congruence reduces the probability of a thirty-day return by 0.48 percentage points from a base of 7.42%. Specificity alone has a small and statistically weak positive coefficient in the return equation once congruence is included. The stronger effect comes from overstatement. The coefficient on $O_i$ is 0.147 with a standard error of 0.034, implying that a one-standard-deviation increase in overstatement raises the return probability by about 0.79 percentage points. This effect is even larger for expectation-related returns, where the coefficient is 0.193 with a standard error of 0.039.

That pattern is one of the clearest findings in the paper. Consumers do not systematically punish detail. They punish detail that is not supported by the rest of the marketed bundle [30]. The return reason split confirms this. Overstatement has a limited relation to delivery-related returns but a pronounced relation to expectation-failure returns. The odds ratio for expectation-related return under a one-standard-deviation increase in overstatement is 1.29. The same increase changes the odds of delivery-related return only negligibly. This distinction matters because it shows that the post-purchase correction is tied to the marketed promise, not merely to generic reverse-logistics frictions.

The claim equation pushes the same logic further into the post-purchase horizon [31]. Sales-weighted average congruence at the firm-quarter level is negatively associated with realized claim burden. The estimate on $\overline{C}_{ft}$ is $-0.058$ with a standard error of 0.022. Overstatement is positively associated with claim burden, with an estimate of 0.064 and a standard error of 0.019. Signal volatility also matters: the estimate on $\overline{V}_{ft}$ is 0.081 with a standard error of 0.024. These coefficients imply that firms with more stable and coherent market-facing promises tend to experience lower subsequent service claims, while firms with more overstated and more volatile signals experience higher claims after accounting for manufacturer effects, quarter effects, product-mix controls, and lagged service history.

The abnormal accrual equation is particularly informative because it isolates forecast quality rather than realized product performance alone. Overstatement is positively associated with the absolute abnormal accrual component. The coefficient on $\overline{O}_{ft}$ is 0.051 with a standard error of 0.017, while the coefficient on signal volatility is 0.074 with a standard error of 0.020. Average congruence, by contrast, enters negatively at $-0.029$ with a standard error of 0.014. In practical terms, quarters characterized by more internally aligned signals are easier to forecast in service-cost terms, while quarters characterized by detailed but mismatched promises or rapidly changing cues are harder to forecast. The effect sizes are not dramatic, yet they are consistent enough across specifications to indicate that signal architecture spills into the informational quality of downstream financial estimates.

A useful way to summarize the economic importance is to trace a hypothetical move from the 30th percentile to the 70th percentile of congruence while holding average price position and protective signals constant. In the calibrated panel, such a move raises weekly conversion by 0.21 percentage points, lowers thirty-day returns by 0.42 percentage points, lowers firm-quarter claims by 0.08 percentage points of sales, and lowers absolute abnormal accrual intensity by 0.03 percentage points of sales. Those magnitudes are small relative to total sales, but they compound. When applied to a large portfolio over many periods, the implied gross-margin gain is economically visible even after allowing for the costs of standardizing message creation and synchronization.

The event-time estimates support the same interpretation and help address the concern that brands simply improve signals when performance is already rising. In the pre-adoption window for the signal-standardization program, the coefficients on conversion are close to zero and jointly insignificant, with a pretrend $F$-test $p$-value of 0.63. Congruence itself rises gradually over the implementation interval and stabilizes around week +5, where the mean increase relative to week −1 is 0.29 standardized units. Conversion rises after the congruence shift, reaching a statistically significant 5.7% lift by week +6 relative to baseline. Returns fall more slowly, with the first stable decline appearing around week +8 and settling at 0.61 percentage points below baseline by week +12. Claim intensity and abnormal accrual intensity respond at the quarterly horizon; both decline in the first full post-adoption quarter, with the abnormal accrual effect slightly smaller and noisier than the claim effect.

Because standardization could alter more than congruence, the event-time interpretation should remain cautious. Yet auxiliary diagnostics suggest that the adoption mostly changes alignment rather than raw message volume. Paid-message count changes little, average price position does not shift materially, and the distribution of return and warranty generosity remains stable in the short run. The main mechanical change is that descriptive language, package text, and service wording move into closer alignment. That makes the event study a credible dynamic complement to the fixed-effects panel estimates rather than a separate intervention with unknown content.

The instrumental-variable estimates using template-synchronization windows reinforce the same conclusion. The second-stage coefficient on congruence in the conversion equation is 0.141 with a standard error of 0.036, slightly larger than the baseline within estimate. This pattern is what one would expect if managers partially repair congruence in anticipation of weak performance, attenuating the baseline estimate downward. The IV return estimate is also larger in magnitude, −0.118 with a standard error of 0.043. Since the synthetic design ensures that the exclusion restriction is valid by construction, the IV block mainly serves to show that the empirical system behaves as it should when endogeneity is addressed more aggressively.

The paper also estimated a revenue decomposition linking signal variables to gross revenue and net realized revenue after returns and service costs. Congruence improves both, but its gain is larger on net realized revenue than on gross revenue because part of its benefit operates by reducing post-purchase reversal and service burden [32]. A bootstrap mediation exercise with 2,000 resamples suggests that roughly 34% of the congruence effect on net realized revenue is mediated through lower returns and 12% through lower claim burden. Specificity's direct positive effect on gross revenue is partly offset by the indirect negative path through returns when congruence is weak, which is why its total effect becomes nonlinear.

The combined evidence therefore points to a specific empirical pattern. Signal alignment is beneficial before and after purchase. Detail is useful but only within a supported promise environment. Unsupported detail produces the sharpest post-purchase correction. These statements are grounded not in a single coefficient but in a set of mutually consistent estimates across conversion, return, claim, accrual, IV, and event-time designs.

## 6. Boundary Conditions and Cross-Sectional Differences

The average treatment pattern masks substantial heterogeneity across category, channel, and price architecture. That heterogeneity is not noise. It reveals when consumers are most likely to rely on composite signals and when they are more willing to treat individual cues in isolation. The first and strongest moderator is product inspectability. In categories where a buyer can verify most attributes visually or through routine knowledge, signal congruence still matters, but its effect is smaller. In categories with complex use conditions, opaque reliability, or high mismatch risk, congruence matters substantially more because buyers depend more heavily on the visible cue bundle before purchase [33].

To test this formally, the conversion and return models were re-estimated with interactions between signal congruence and a high-consideration indicator. The congruence coefficient rises from 0.079 in lower-consideration products to 0.153 in higher-consideration products, and the difference is statistically significant with a Wald $p$-value of 0.011. The return-reduction effect of congruence is almost twice as large in high-consideration categories [34]. Overstatement also bites harder there. The intuition is clear. A mismatch between detailed claims and the surrounding signal bundle is easier to recover from when the product is simple and familiar. It is costlier when the product is complex, expensive, or difficult to evaluate before use.

The second moderator is price-premium intensity [35]. Consumers appear more tolerant of sparse signals at the low end of the price ladder because the downside from mismatch is limited. They are less tolerant of internally inconsistent signals when the price implies a premium promise. In interaction models, the coefficient on $C_{jct} \times P_{jct}$ is positive in conversion and negative in returns, indicating that alignment matters more at higher price percentiles. The marginal effect of congruence on conversion at the 80th price percentile is 41% larger than at the 20th percentile. This is sensible because a premium price is itself a strong cue. When it is supported by coherent descriptive and protective signals, the premium looks justified; when it is not, the price may amplify suspicion or later disappointment.

Channel structure creates another boundary condition. On direct brand sites, specificity has a steeper positive slope in the conversion equation and a flatter negative slope in the return equation. On marketplaces, specificity is weaker on conversion and riskier on returns. The likely mechanism is not that the same words mean something different intrinsically, but that channel templates alter attention allocation. Direct channels allow a firm to explain claims more fully and display supporting service terms in a more integrated layout. Marketplaces compress the message and elevate price comparability, which means detailed claims are easier to make but harder to support contextually. Congruence remains valuable in all channels, but the payoff to specificity is channel dependent.

The brand tier split is also revealing. In high-equity brands, the marginal conversion benefit of congruence is somewhat smaller but its claim-reduction benefit is larger. One reading is that strong brands begin with a favorable prior, so aligned signals add less incremental persuasion at the point of sale but help preserve service and forecasting performance more strongly. In lower-equity brands, congruence materially improves immediate conversion because it helps compensate for weaker priors, but those brands do not derive as much downstream service-cost benefit because the underlying base rate of consumer trust remains lower. This distinction helps clarify why one should not expect all signal effects to concentrate at the same stage of the funnel.

The role of message specificity is particularly nuanced under innovation intensity. Products introduced within the previous two quarters show a lower turning point in the specificity curve. For recently introduced items, the linear specificity coefficient remains positive, but the negative quadratic coefficient becomes steeper. In practical terms, new products benefit from some concrete explanation, yet the market becomes less tolerant of very high detail intensity unless the surrounding signals are tightly aligned. That pattern resembles a credibility problem. Novel offerings need explanation, but excessive explanation can raise suspicion or create expectations that the rest of the bundle cannot sustain. The pattern is especially visible in consumer electronics and performance-oriented personal care devices.

This heterogeneity is informative when placed alongside prior findings. Cao and Yan (2021) documented a curvilinear relationship between nutritional quality and profit and showed that package innovation and advertising positively moderate that relationship [24]. The present paper uncovers an analogous but distinct phenomenon in the signal domain [36]. Specificity is not monotonically valuable [37]. Its payoff depends on the support provided by congruence and on the contextual salience created by channel and package architecture. This does not mean the mechanisms are identical across the two research settings. It means that nonlinearity is a recurrent feature of marketing signals when consumers must interpret a visible cue in relation to a broader presentation environment.

The return-reason analysis deepens the heterogeneity story. When returns are decomposed into expectation-related and non-expectation-related components, congruence and overstatement mainly load on expectation failure [38]. In high-consideration categories, the coefficient on overstatement for expectation-related return is 0.232 with a standard error of 0.045; in low-consideration categories it is 0.101 with a standard error of 0.031. For convenience-related returns, the coefficient is small in both cases. This indicates that the signal architecture does not simply proxy for logistics quality or generic customer dissatisfaction. It specifically predicts whether the marketed promise is later contradicted by product experience.

The firm-quarter cost models exhibit a parallel heterogeneity. The negative association between average congruence and claim burden is strongest among firms with premium-heavy portfolios and among firms whose channel mix is tilted toward marketplaces. One plausible interpretation is that misalignment is more consequential when the consumer starts from a stronger prior expectation or encounters a more fragmented presentation environment. The abnormal accrual effect shows a similar pattern but is especially strong in firms with higher signal volatility. In those firms, even moderate overstatement appears to destabilize reserve estimation because the finance function cannot rely on a stable marketed promise when anticipating future service burdens.

An additional boundary condition concerns basket size. Multi-item baskets dilute the impact of product-level detail because the consumer is processing more than one offer simultaneously. In the order-level return model, the overstatement effect is smaller when the focal purchase appears in a large basket. This does not negate the main result. It merely indicates that attention is spread more thinly in such settings, reducing both the upside and downside of detailed claims. Single-item baskets, especially for higher-value goods, are where congruence and overstatement display their strongest associations with conversion and return.

The paper also examined whether the impact of congruence is symmetric around the mean. It is not. Moving from very low congruence to moderate congruence generates a larger conversion improvement than moving from high congruence to very high congruence. The return reduction shows a similar diminishing pattern. This suggests that firms with visibly fragmented cue sets have the most to gain from basic alignment work, while firms already operating with disciplined signal bundles face smaller incremental gains from further refinement. That result is encouraging from a managerial standpoint because it implies that the first units of message governance may deliver the highest payoff.

Taken together, the heterogeneity analysis refines the paper's central claim. Signal congruence is broadly helpful, but especially so when inspectability is low, price premiums are high, channels are formatting-constrained, or product novelty is high. Specificity is beneficial within the support region defined by those conditions and becomes risky when it overshoots that region. The evidence does not support a blanket recommendation to be more detailed or less detailed. It supports a conditional recommendation: increase detail only to the degree that the rest of the marketed signal bundle can defend it.

## 7. Validation Exercises and Additional Tests

A credible empirical paper in this area must demonstrate that the reported patterns are not artifacts of one index definition, one estimator, or one timing specification. Several validation exercises were therefore conducted. The first set concerns alternative measurement choices. Congruence was redefined three ways: as pure semantic similarity without price-protection penalties, as a principal-component score on the signal block, and as an inverse-dispersion measure using pairwise Mahalanobis distance among standardized cues. All three alternatives produce the same sign pattern in conversion and return models. The economically calibrated main measure yields the tightest fit, but the qualitative inference does not depend on it. Specificity was also redefined using a narrower lexicon that excluded service detail and a broader lexicon that included comparative adjectives. Again, the curvature in specificity and the positive interaction with congruence remain.

The second set of tests addresses possible confounding by promotional depth. Because discounting can coincide with message rewriting, one might worry that the signal effects are merely disguised price-promotion effects. To examine this, the conversion model was reestimated on a subsample of weeks with discount depth below 5%. The congruence coefficient falls modestly in magnitude but remains strongly significant at 0.094 with a standard error of 0.023. The specificity curvature remains visible, and the overstatement penalty remains negative. In a complementary specification allowing a full set of interactions between discounts and the signal indices, the core congruence coefficient remains stable. This indicates that the results are not being driven primarily by short-run price promotion.

A third validation block focuses on placebo timing [39]. For treated brands in the standardization event study, pseudo-adoption dates were randomly assigned within the same year while preserving the empirical distribution of adoption months. Re-estimated event studies around these placebo dates produce coefficients that fluctuate around zero with no consistent post event pattern [40]. The average placebo post coefficient on conversion is 0.3%, compared with 5.7% in the actual event study. The return and claim placebo profiles are similarly null [41]. This reduces the likelihood that the observed event-time gains merely reflect generic year-specific trends among treated brands.

A fourth set of tests concerns omitted product quality. Because higher-quality products might be easier to describe coherently and also less likely to be returned or claimed, omitted quality is an obvious concern. The main mitigant is the product-channel fixed effect, which absorbs time-invariant quality. Still, time-varying quality drift could remain. The paper therefore introduced a latent-quality proxy based on the rolling share of defect-related claims and repeat-purchase hazard in mature SKUs. Including this proxy slightly attenuates the congruence coefficient in the claim equation from $-0.058$ to $-0.051$ and the overstatement coefficient from 0.064 to 0.057, but both remain statistically meaningful. This suggests that the signal indices are not merely relabeling time-varying quality.

Robustness to serial dependence was checked in several ways. Brand-clustered standard errors, brand-by-channel clusters, two-way clusters on brand and week, and Driscoll–Kraay corrections all leave the significance pattern intact. The return model was re-estimated as a mixed-effects logit with random intercepts for brand and category, producing nearly identical marginal effects. The claim and accrual models were also estimated with first-difference specifications to reduce concern about slow-moving omitted factors. In first differences, the association between changes in average congruence and changes in claim burden remains negative and significant, though smaller in magnitude, which is expected because differencing removes substantial low-frequency signal [42].

The paper also asked whether signal congruence simply proxies for textual professionalism or editing quality. A readability score, grammar-error count, and format-consistency index were added to the conversion and return equations. These controls modestly improve fit but do not displace the main signal coefficients. Readability is positively associated with conversion, and grammar problems increase returns slightly, yet congruence and overstatement remain independently relevant. This matters because it shows that the effects are not reducible to polished writing [43]. The alignment of the message bundle contains information beyond surface-level editorial quality.

A useful falsification test exploits products whose protective terms are not salient at the moment of purchase because the channel template hides them behind a secondary click. In that subsample, the economic component of congruence involving protective signals should matter less for immediate conversion and more for later return or claim outcomes. That is exactly what the estimates show. The immediate conversion coefficient on congruence is smaller by about one quarter in the hidden-terms subsample, while the return and claim penalties associated with overstatement remain large. This pattern is difficult to explain with a generic omitted-appeal story and easier to explain with the proposed interpretation of visible signals and post-purchase correction [44].

The abnormal accrual evidence was also stress-tested because it is the farthest from the consumer interface and therefore the most vulnerable to skepticism. First, the expected reserve model used to derive abnormal accruals was varied to include different lag structures and different mix controls. The coefficient on overstatement remains positive across these versions, ranging from 0.043 to 0.057. Second, the dependent variable was changed from absolute abnormal accrual intensity to signed abnormal accrual intensity. The average effect on the signed measure is small and noisy, whereas the effect on the absolute measure is strong. This is sensible because the paper's mechanism is about forecast instability rather than directional optimism or pessimism alone. Third, quarters with extreme sales shocks were removed to ensure the results were not driven by crisis-like periods. The coefficient pattern again survives.

Additional tests examined whether the signal effects are concentrated in early life-cycle periods. The answer is partly yes. Congruence matters across the full life cycle, but the specificity curvature is steeper in the first six months after introduction. Overstatement is also more strongly associated with returns for recently launched products. This does not imply that mature products are immune. Rather, it suggests that the market requires more careful support for detailed claims when prior consumer knowledge is thin. The result is consistent with the idea that signal bundles do more inferential work for newer offerings.

One further analysis decomposed net revenue into demand volume, discount cost, return loss, and service burden. Congruence is associated with higher volume and lower return and service loss, but not with lower discount cost. Specificity is associated with higher volume only in the moderate range, while high overstatement shifts revenue away from realized consumption toward returned and serviced units. This decomposition is important because it clarifies why an organization focusing only on the top line might overvalue aggressive specificity. Once the post-purchase corrections are included, unsupported detail looks materially less attractive [45].

The paper also explored an attention-based interpretation by separating mobile-dominant sessions from desktop-dominant sessions. On mobile, the positive slope of specificity is weaker and the overstatement penalty appears sooner. On desktop, specificity retains a positive effect over a wider range. Congruence matters in both. This is informative because mobile environments compress the space available for supporting detail. As a result, detailed claims are easier to make than to contextualize, which naturally raises the importance of alignment across the cues that remain visible.

No empirical exercise is complete without recognizing where the evidence is less definitive. The claim and abnormal accrual equations, despite their consistent signs, are estimated at a more aggregated level and therefore carry wider confidence bands than the conversion and return equations. Some category-specific interactions are also too imprecisely estimated to warrant strong interpretation. The paper therefore treats the service-cost results as reinforcing evidence rather than as a standalone centerpiece. Even with that caution, the alignment of findings across multiple estimation blocks strengthens the main conclusion materially.

## 8. Conclusion

This paper presented an empirical investigation of marketing signals using a calibrated synthetic omnichannel panel linking conversion, returns, service claims, and abnormal accruals. The results show a consistent pattern. Signal congruence, defined as alignment among concurrent visible cues, is associated with higher conversion and lower post-purchase correction. Message specificity is beneficial up to a point, but its value depends on congruence. Detailed claims become costly when the rest of the marketed bundle does not support them. Under those conditions, returns rise, service burdens increase, and the downstream prediction of service costs becomes less stable.

The evidence also indicates that these relationships are not uniform across contexts. Congruence matters more when inspectability is low, when price premiums are high, and when channel templates compress the explanation available to consumers. Specificity exhibits stronger curvature for newer and more complex products. The practical implication is restrained rather than dramatic. Firms do not need to mute their signals; they need to make their visible cues agree with one another before making them more detailed. In the empirical system examined here, the largest penalty is attached not to boldness itself, but to unsupported precision [46].

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