Generative AI Content Governance and Market Outcomes: Evidence from Food Delivery Platforms

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Abstract

Platforms are seeing a surge in AI-generated content but lack clear policies to govern it. Some have moved to restrict or ban such content, yet the impact on merchant sales, platform competition, and broader economic outcomes remains unclear. We study this in India's food delivery market. After India's two largest food delivery platforms, Zomato and Swiggy, rolled out AI tools for generating dish images in late 2023, Zomato imposed a platform-wide ban in August 2024, citing authenticity concerns, while Swiggy continued to allow them. Using a unique panel of consumer purchases across both platforms from March 2024 to February 2025, we implement a difference-in-differences design with Zomato restaurants as the treated group and Swiggy restaurants as the control group. We find that following the ban, Zomato restaurants experience significant increases in order volume and revenue relative to restaurants on Swiggy. Consumers also become more willing to try previously unvisited restaurants on Zomato and reallocate demand toward the platform. Consistent with the role of authenticity and trust, the relative demand advantage of Zomato is largest when compared to Swiggy restaurants whose images appear more AI-like. Overall, our findings suggest that restricting AI-generated dish images may increase consumer trust and strengthen platform demand by improving perceived authenticity. These results highlight the importance of carefully governing generative AI content in digital marketplaces where visual authenticity is critical to consumer decision-making.

Keywords Generative AI, food delivery, platform governance, multi-modal analysis

1 Introduction

The rapid proliferation of generative artificial intelligence (Generative AI) has fundamentally transformed the creation and distribution of digital content. Images, text, music, and videos can now be generated at a low marginal cost and disseminated at a massive scale across online platforms. As a result, the volume of AI-generated content on the internet has grown exponentially in recent years, reshaping how information is produced and consumed in digital marketplaces (Demirci et al., 2025; Shan and Qiu, 2025). While generative AI creates substantial opportunities for businesses to improve productivity, personalization, and user engagement, it simultaneously raises important concerns regarding misinformation, authenticity, and consumer protection (Campante et al., 2025).

These concerns have triggered an ongoing global debate regarding how AI-generated content should be governed. Policymakers across countries and states are experimenting with different regulatory approaches. For example, the European Union's AI Act introduces disclosure requirements for synthetic content, and the California AI Transparency Act (AB 853) mandates that large generative AI providers implement hard-to-remove disclosures on AI-generated content (European Union, 2024; California State Legislature, 2025). Other jurisdictions, such as Japan, have also proposed legislation targeting false or misleading AI-generated content (BABL AI, 2025). At the same time, technology platforms themselves have started implementing their own governance mechanisms. Major platforms such as Meta and Apple Music now require labels indicating whether images or audio are AI-generated to maintain user trust and transparency,[1] while other platforms choose to ban AI-generated content entirely.[2]

Despite these growing regulatory and platform-level interventions, the economic implications of governing AI-generated content remain largely unknown. On the one hand, generative AI may enhance visual appeal and improve marketing effectiveness by producing high-quality content at low cost. On the other hand, AI-generated content may reduce perceived authenticity and erode consumer trust if users believe that such content misrepresents reality. Understanding how consumers respond to AI-generated content, therefore, becomes a critical question for both platform operators and policymakers.

These issues are particularly salient in digital marketplaces where consumers rely heavily on visual information as a signal to evaluate product quality under conditions of information asymmetry (Spence, 2002). The online food delivery industry provides a prominent example. Platforms such as Uber Eats, Swiggy, and Zomato have transformed how consumers discover and purchase food, and images play a central role in influencing consumers' purchase decisions (Li and Xie, 2020; Zhang and Luo, 2023). For many consumers, dish images serve as the primary signal of food quality prior to purchase.

[1] See `https://www.nytimes.com/2024/02/06/technology/meta-ai-standards-labels.html` and `https://www.billboard.com/pro/apple-music-introduces-ai-song-tagging/` (accessed March 2026).

[2] See, e.g., Economic Times (August 2024) and Wall Street Journal (April 2026) (accessed April 2026).

Recently, food delivery platforms and restaurants have increasingly adopted generative AI tools to create or enhance dish images. These technologies allow merchants to generate visually appealing menu images even when professional photography is unavailable, significantly lowering the cost of producing high-quality visuals. While image manipulation in restaurant menus is not new, and restaurants have long used professional photography or editing tools to enhance presentation, the rapid diffusion of generative AI represents a qualitatively distinct shift. Compared with traditional photo editing, generative AI enables images to be created without the dish being prepared or photographed, allowing large numbers of restaurants to rapidly generate stylized and visually attractive menu images.

Nevertheless, this rapid diffusion of AI-generated images has also sparked controversy. If AI-generated menu images differ substantially from the actual food delivered, consumers may perceive such images as misleading. In online communities, users have increasingly criticized food delivery platforms for allowing images that appear artificially generated and do not accurately represent the delivered food.[3] Such concerns raise important questions about whether AI-generated images improve consumer experience by enhancing visual appeal, or instead undermine trust by weakening the link between visual representation and actual product quality.

Against this backdrop, food delivery platforms have begun experimenting with different governance approaches toward AI-generated images. In India, the two largest food delivery platforms, Zomato and Swiggy, adopted divergent policies. While both platforms initially introduced generative AI tools that allow restaurants to generate dish images in late 2023, Zomato later implemented a platform-wide ban on generative AI menu images on August 18, 2024, citing concerns that such images could mislead consumers and erode trust. In contrast, Swiggy continued allowing restaurants to use AI-generated images. This divergence creates a unique opportunity to study how consumers respond to the regulation of AI-generated content in real-world digital marketplaces.

This paper therefore asks: *How does restricting AI-generated content affect consumer behavior and platform competition in digital marketplaces? What are the potential mechanisms and economic implications?*

We conduct our empirical analysis using comprehensive datasets from India's two largest food delivery platforms, Zomato and Swiggy, which are comparable along key economic dimensions. Each generated approximately 2 billion USD in revenue in 2025.[4] In late 2023, following the global boom of generative AI technologies, both platforms introduced generative AI–based image generation and enhancement tools that allowed restaurant owners to generate dish images based on dish names and select from a variety of

[3] See https://www.reddit.com/r/mildlyinfuriating/comments/1euhwvl/ai_pics_on_swiggy_are_misleading/ and https://tinyurl.com/bdhfxhs6 (accessed November 2025).

[4] See https://www.swiggy.com/corporate/wp-content/uploads/2025/10/Q2-FY2026-Shareholder-letter.pdf and https://b.zmtcdn.com/investor-relations/Eternal_Shareholders_Letter_Q3FY26_Results.pdf (accessed March 2026).

background options.[5] While Swiggy continued permitting restaurants to use AI-generated images throughout 2024 and 2025, Zomato imposed a platform-wide ban on August 18, 2024, citing consumer complaints that AI-generated images were misleading and risked eroding trust. Restaurants that violated the policy faced de-listing from the platform.[6]

Using a unique and large-scale panel of aggregated restaurant-level transactions from March 2024 to February 2025, we implement a difference-in-differences design that compares sales outcomes on Zomato to those on Swiggy before and after Zomato's generative AI image ban. We find that restaurants on Zomato experience a 10.4% increase in order volume and 9.3% increase in revenue relative to Swiggy restaurants following the policy change, which is statistically and economically significant. Decomposing orders by source, we show that the increase is driven primarily by customers new to the restaurants, with additional gains from returning customers. This suggests that new customers may have greater trust, and returning consumers may also reduce disappointment from expectation mismatch. At the user level, consumers reallocate demand toward Zomato and exhibit higher rates of platform switching from Swiggy to Zomato. These patterns are consistent with the interpretation that removing AI-generated dish images improves perceived authenticity and reduces consumers' reluctance to explore restaurants on the platform.

To investigate the underlying mechanisms, we provide evidence at both the platform and restaurant levels. First, we document substantial media coverage and widespread social media discussion following Zomato's ban, suggesting that the policy likely increased consumer awareness of AI-generated dish images. Second, we combine multi-modal image-forensic analyses and classifier-based AI image detection to show that dish images on Swiggy exhibit substantially stronger signatures of generative AI manipulation. Perhaps surprisingly, while Swiggy dish images with a higher AI likelihood tend to be associated with a stronger alignment score with their dish text descriptions, they are perceived as less aesthetically appealing. At the restaurant level, these effects are strongest when comparing Zomato restaurants with Swiggy restaurants whose dish images appear more AI-like, and largely disappear when the Swiggy restaurants use the same dish images across both platforms, where AI-generated images are less likely to be present because of Zomato's ban. Moreover, restaurants with higher AI likelihood images receive lower consumer ratings. Overall, the evidence is consistent with the view that restricting AI-generated imagery may strengthen platform demand by improving perceived authenticity.

Our empirical analysis and findings shed light on platform governance of AI-generated content (Chen et al., 2025a). We find that while generative AI may reduce content-production costs and enhance the semantic alignment between dish images and text descriptions, its use in high-stakes consumption settings where consumers rely on images as pre-purchase quality cues, such as food delivery, may undermine consumer

[5] See `https://tinyurl.com/49mbspbu` and `https://tinyurl.com/2e2atrty` (accessed June 2025).
[6] See `https://tinyurl.com/4yr24ffs` (accessed June 2025).

trust and reduce demand. Governing AI-generated content at the platform level may help improve the brand image of the marketplace. From the merchants' perspective, avoiding salient AI-generated content may help improve sales performance by attracting both new and returning customers.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the policy background. Section 4 describes the dataset and presents model-free evidence. Section 5 analyzes the overall treatment effect at the restaurant level. Section 6 examines users' platform-switching behavior following the policy change. Section 7 analyzes dish images on the two platforms using several independent and validated multi-modal machine learning methods. Section 8 investigates the mechanisms underlying the main results. Section 9 presents a set of robustness checks, and Section 10 concludes.

2 Literature Review

Our paper connects to multiple areas of research at the intersection of signaling theory, platform governance, image analytics, and consumers' perception of AI-generated content.

First, our work contributes to the signaling theory literature (Chen et al., 2025b; Zhang et al., 2026). To reduce information asymmetry, sellers deploy signals to convey product quality in contexts ranging from IT investments (Salge et al., 2022) and health consultations (Chen et al., 2025b) to product advertising (Pan and Feng, 2025), visual arts (Huang et al., 2023), and refund insurance (Zheng et al., 2023). On food delivery platforms, dish photographs function as visual quality signals through which merchants advertise both product and establishment quality (Nian and Sundararajan, 2022; Zhang and Luo, 2023; Khern-am nuai et al., 2024). Classic signaling theory assumes signals are costly to fake (Spence, 2002). When signals are perceived as deceptive, however, consumers do not merely discount quality inferences — they attribute manipulative intent, which independently suppresses purchase intention regardless of underlying product quality (Riquelme et al., 2016; Steigenberger, 2025). Generative AI intensifies this dynamic by significantly reducing the cost of producing deceptive signals, systematically threatening the integrity of image-based quality signals in digital marketplaces. Yet it remains empirically unclear how consumers respond when such deception is revealed at scale. We address this gap by exploiting a platform ban on AI-generated images as an exogenous credibility shock, and examine how consumers revise purchasing behavior in response to revealed signal manipulation. Our work extends signaling theory from individual deception episodes to platform-level signal environment correction regarding generative AI content.

Our paper also connects to the literature on platform governance (Lee et al., 2015; Dewan et al., 2017; Li and Agarwal, 2017; Kuang et al., 2019; Li and Wang, 2025), especially on information credibility. Prior work shows that platforms face inherent tensions in governing the authenticity of seller-generated signals. Ananthakrishnan et al. (2020) show that displaying fraudulent reviews alongside authentic ones can paradoxically improve consumer trust by aiding consumer decision making. Bai et al. (2025) find that eliminating certification fees on a labor platform dilutes the signaling value of credentials, suggesting that governance choices that lower barriers to content creation can undermine the credibility of existing signals. Chen et al. (2025a) show analytically that labeling AI-generated content can boost consumer engagement by restoring trust when platforms enforce a strict rule by setting the detection threshold low. We complement these studies by providing causal field evidence that outright restricting AI-generated seller content improves platform demand by strengthening the authenticity of visual product signals.

A growing literature examines the importance of images on consumer purchase intentions. Images play a central role in consumers' purchase decisions (Zhang et al., 2022) and are often described as being "worth a thousand words" (Li and Xie, 2020). Prior research shows that images are more memorable than text and are more effective at capturing consumers' attention (Pieters and Wedel, 2004). For example, Li and Xie (2020) use propensity score matching and data collected from online social media to show that the presence of images increases consumer engagement. Zhang et al. (2022) show that various characteristics of images may affect consumers' booking decisions on rental platforms. However, most of this literature predates ChatGPT, when consumers had no concerns about image origin. Generative AI disrupts this by introducing image origin as a potentially consequential extrinsic attribute, which consumers may weigh independently of perceived image quality. Whether origin authenticity operates as a distinct evaluative dimension in consumers' image processing remains unexamined. We extend this line of research by conducting large-scale multi-modal analysis, such as image forensic tests and classifier-based AI signature detection models, and capturing consumers' reactions to images that are more likely to be AI-generated in digital marketplaces.

Lastly, this study enriches the broader empirical research on consumers' perceptions of AI-generated content (Lee et al., 2025; Shan and Qiu, 2025). Since the launch of ChatGPT in late 2022, generative AI has been transforming the business models of enterprises across industries. Recent experimental and empirical research has examined consumers' perception of AI-generated images in the industries of advertisements (Exner et al., 2025; Hartmann et al., 2025; Huang and Katona, 2025; Lee et al., 2025), hospitality service management (Krakowski et al., 2025), as well as AI-generated text summaries in digital deal platforms (Li et al., 2025). Horton Jr et al. (2023) find that consumers may value content created by AI less compared with human-made content, if they know the content is AI-generated. Closely related to our work, Belanche et al. (2025) leverage laboratory experiments and find that participants prefer hospitality services advertised with real images over AI-generated images, particularly for hedonic products such as food, compared with utilitarian products. In addition, Exner et al. (2025) investigate a quasi-experiment on an advertisement platform and show that AI-generated ads receive more clicks compared with human-generated images only if these AI-generated images do not "look like AI". Yet whether this latent aversion translates to behavioral change at market scale remains untested; existing evidence rests largely on experimental designs with stated preferences or click-through proxies. To our knowledge, this paper provides the first large-scale causal field evidence that restricting AI-generated product images in a real consumption marketplace affects actual consumer purchasing behavior and platform competition. While recent work studies how allowing labeled AI-generated content changes outcomes in creative-goods markets (Goldberg and Lam, 2025), our setting is distinct: food delivery images function as quality signals for offline products, making authenticity central to consumer trust and choice.

3 Institutional Setting and Policy Background

Zomato and Swiggy are the two dominant online food delivery platforms in India and compete head-to-head in most major cities. Both operate nationwide, follow similar marketplace business models, and connect consumers with a wide range of restaurants, including national chains and small independent establishments, through mobile apps and websites. Restaurants may either single-home or multi-home across the two platforms, and consumers frequently hold accounts on both, allowing them to compare menus, prices, and visual presentation before placing an order.

The two platforms are comparable along economically relevant dimensions, with similarly sized consumer bases,[7] restaurant populations,[8] and annual revenues.[9] Both monetize primarily through restaurant commissions and delivery fees, use similar menu layouts, and prominently display dish images as a core input into consumers' purchase decisions. From the restaurant side, establishments typically use the same kitchens, staff, and menus to fulfill orders regardless of platform, implying that cross-platform differences in sales outcomes are unlikely to be driven by differences in underlying food quality or production capacity (Competition Commission of India, 2020). Consistent with this institutional similarity, observable restaurant characteristics are closely aligned across platforms, with comparable distributions of chain affiliation, multi-homing status, and order volumes, as outlined in Section 4.

Both platforms began introducing generative AI–based dish image generation tools in late 2023, allowing restaurants to create or modify images based on dish names or stylistic templates.[10] The key institutional divergence arises on August 18, 2024, when Zomato imposed a platform-wide ban on AI-generated dish images, citing consumer complaints that such images were misleading and undermined trust. The ban

[7] See `https://www.lakewateradvisors.com/wp-content/uploads/2024/09/Lakewater_-Zomato.pdf` and `https://www.medianama.com/2024/12/223-swiggy-earnings-q2fy25-active-users-increase-to-17-million-yoy/` (accessed January 2026).

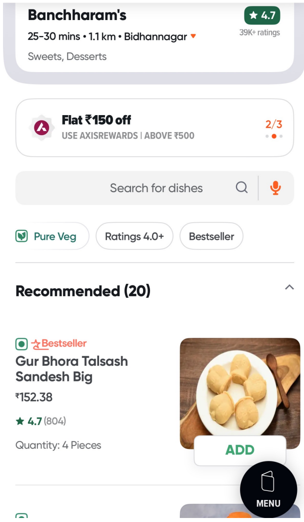
[8] See `https://www.feedough.com/zomato-statistics-facts-user-counts/` and `https://www.swiggy.com/corporate/wp-content/uploads/2024/10/Annual-Report-FY-2023-24-1.pdf` (accessed January 2026).

[9] See `https://tinyurl.com/63m7s2ns` and `https://www.eternal.com/investor-relations/results/`(accessed July 2025).

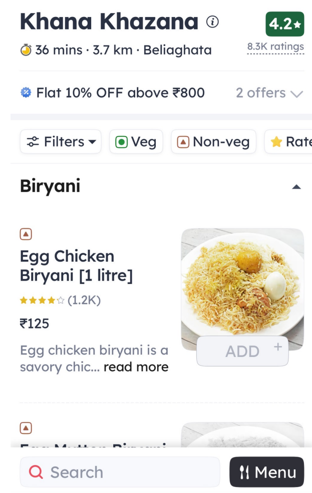
[10] See `https://tinyurl.com/49mbspbu` and `https://tinyurl.com/2e2atrty` (accessed June 2025).

Figure 1: Sample Restaurant Pages on Swiggy and Zomato

(a) Swiggy Sample Restaurant Homepage



(b) Zomato Sample Restaurant Homepage



applied uniformly across restaurants and was enforced through image audits and the threat of de-listing. To ensure image authenticity, Zomato actively employs in-house generative AI detection tools to identify and remove AI-generated dish images, both for new uploads and for images previously posted. Restaurants found in violation of the policy may be de-listed from the platform. In contrast, Swiggy continued to permit AI-generated dish images throughout the remainder of the sample period. For more details and news coverage regarding the generative AI image ban, see Online Appendix A.1. Figure 2 illustrates how a Swiggy restaurant uses generative AI to display dish images. In this example, the watermelon juice is rendered green rather than its natural red color, and two watermelon slices appear to unnaturally merge in the background.[11]

[11]See `https://www.swiggy.com/city/chennai/doveton-cafe-purasavakkam-purasaiwakkam-rest18341` (accessed October 2025). The same restaurant is also listed on Zomato, where no AI-generated images are used, as shown at `https://www.zomato.com/chennai/doveton-cafe-purasavakkam/order` (accessed October 2025).

Figure 2: One Swiggy Restaurant Using Generative AI Dish Images

While data limitations prevent us from directly observing historical dish images prior to the policy change, qualitative evidence suggests that AI-generated dish images became particularly salient on Swiggy after Zomato banned such images. Discussions on Reddit frequently criticize Swiggy for allowing restaurants to post AI-generated or heavily modified dish images and often describe these images as misleading or inauthentic. By contrast, we observe substantially fewer comparable discussions focused on Zomato following its policy ban. Although these online discussions are not comprehensive measures of AI usage, they suggest that AI-generated dish images became a salient consumer concern and were more prominently associated with Swiggy after the Zomato generative AI image ban. Table A2 in Online Appendix A.2 provides representative examples.

In addition, multi-homing restaurants listed on both platforms sometimes display different dish images across platforms, with images that appear more AI-generated on Swiggy while avoiding similar images for corresponding dishes on Zomato. Examples are shown in Online Appendix B. Based on a manual and model-assisted comparison, around 20% of multi-homing restaurants exhibit cross-platform image divergence. This pattern is consistent with restaurants adjusting image presentation in response to Zomato's enforcement of restrictions on generative AI dish images.

4 Dataset and Model-Free Evidence

4.1 Dataset

Our research combines two datasets from different sources. The first is a unique dataset of 13,755 consumers' food delivery purchase records on Zomato and Swiggy in India, obtained from Measurable AI, a leading market intelligence company specializing in tracking consumers' platform transactions. In Online Appendix C, we show that the sample is relatively representative of the food delivery consumers in India. The dataset covers the period from March 1, 2024, to February 28, 2025, which is six months before and after Zomato's generative AI dish image ban. It includes purchase records from the same set of consumers across both platforms, which contain rich information such as consumer ID, purchase timestamp, order value, restaurant name, number of dish items purchased, and restaurant address. A key feature of this dataset is its ability to observe individual consumers' behavior across platforms, enabling direct cross-platform comparisons. This feature is particularly valuable when implementing our cross-platform analyses. We restrict users to consumers with non-zero pre-policy orders to ensure that they are affected by the policy change, which leaves us with a final sample of 9,723 consumers. Because restaurants on Zomato are the entities directly treated by the policy change, we aggregate consumers' order volumes to obtain restaurant-level sales, measuring restaurant demand.

The second dataset consists of restaurant dish images and characteristics that we collected from Zomato and Swiggy websites in Kolkata, one of the largest cities in India. It contains detailed restaurant information as displayed on the website, including restaurant address, rating, number of reviews, cuisine, price category, dish price, dish name, dish description in English, and dish images. In total, we compile 35,083 Swiggy dish images and 51,045 Zomato dish images into a large-scale dataset for our multi-modal analysis. We merge the restaurant sales dataset (restricted to Kolkata) with the restaurant image and characteristics dataset using restaurant name and address when conducting the multi-modal image analysis and mechanism analysis. We also run a robustness check using seven additional cities of different locations and sizes, and obtained similar results to our main analysis.

We present summary statistics of restaurants in Table 1. Overall, restaurants on the two platforms are comparable, though Zomato hosts slightly more restaurants, while Swiggy restaurants have marginally higher pre-policy order volumes and lower average order values.[12]

Table 1: **Sample Descriptive Statistics**

Platform	Variable	Count	Mean	Std. Error	Median	Min	Max
Zomato	Chain (=1)	30,836	0.39	0.00	0.00	0.00	1.00
Zomato	Pre-Policy Order Volume	30,836	1.17	0.01	1.00	0.00	49.00
Zomato	Pre-Policy Order Value (Indian Rupees)	19,068	342.86	1.92	270.02	19.36	11,039.09
Zomato	Multi-homing	30,836	0.11	0.00	0.00	0.00	1.00
Swiggy	Chain (=1)	27,894	0.40	0.00	0.00	0.00	1.00
Swiggy	Pre-Policy Order Volume	27,894	1.32	0.01	1.00	0.00	92.00
Swiggy	Pre-Policy Order Value (Indian Rupees)	18,343	322.83	1.86	253.00	0.00	6,080.00
Swiggy	Multi-homing	27,894	0.12	0.00	0.00	0.00	1.00

[12]Pre-Policy Average Order Value is missing for restaurants with zero pre-policy orders.

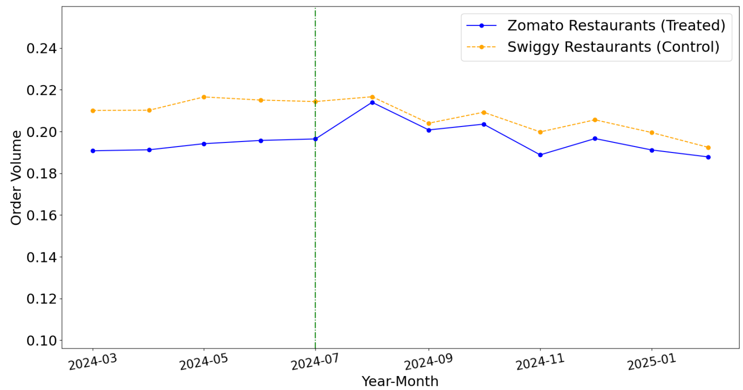
4.2 Descriptive Patterns and Model-Free Evidence

Figure 3 plots the average monthly order volume per restaurant on Zomato and Swiggy between March 2024 and February 2025, after adjusting for platform-specific monthly seasonality. July 2024, which is the month before the policy change, is marked by the green dotted vertical line. Using the additional sample from August 2023 to February 2025, we first compute average monthly orders per restaurant for each platform and estimate platform-by-month fixed effects. We then subtract the corresponding month effect from each observation and add back the overall platform mean, so that levels remain interpretable while removing recurring within-year patterns. The mathematical details are shown in Online Appendix D. This procedure is analogous to the seasonal adjustments applied to GDP and employment statistics by the Bureau of Labor Statistics and the IMF, where raw series are purged of estimated seasonal components before analysis (Jaditz, 1994; Lee, 2017), and to the use of month fixed effects in macro time-series regressions (e.g., Wilson (2019)). A figure without seasonality adjustment is shown in the Online Appendix D.1 and demonstrates a similar trend.

Before July 2024, the month before Zomato banned the use of generative-AI–created dish images, restaurants' order volumes on the two platforms evolved in a roughly parallel fashion. Following the ban, however, the trajectories begin to diverge: Zomato restaurants experience a relative increase in order volume compared with restaurants on Swiggy. Because the figure controls for common monthly seasonality, this divergence is unlikely to be driven by the typical post–summer-break slowdown in food delivery demand (U.S. Department of Agriculture, 2025). This descriptive evidence suggests that the ban may have contributed to improved restaurant performance on Zomato, a pattern we examine more formally in the difference-in-differences analysis that follows.[13]

[13] The average number of orders per restaurant may appear small in magnitude due to the sample size limitation and the naturally sparse purchase frequency of food delivery consumers. Our objective is to highlight the relative divergence around the policy change between the two platforms, thereby capturing the policy's effect while preserving the underlying purchase patterns of consumers.

Figure 3: Average monthly number of orders per restaurant on two platforms in India



Notes: The figure is seasonality-adjusted.

5 Restaurant-Level Regression Analysis

5.1 Restaurants' Order Volume and Revenue

We conduct a difference-in-differences analysis to examine the impact of the generative AI image ban on restaurants' order volume. The control group is restaurants on Swiggy, while the treatment group is restaurants on Zomato, which are banned from using generative AI dish images after August 2024. A similar identification strategy has been used in prior literature assessing policy changes' impact on merchant sales and platform competition, for example, Li and Zhu (2021). The regression model that we use is,

$$\mathrm{Y}_{rt} = \alpha + \beta_1 Treat_r \times PostPolicy_t + \delta_r + \gamma_t + \varepsilon_{rt} \tag{1}$$

where the dependent variable Y_{rt} includes restaurants' weekly number of orders and total revenue (in Indian Rupees). Additional analysis about consumer traffic is shown in Online Appendix E. $Treat_r$ indicates whether a restaurant is a Zomato restaurant or not, $PostPolicy_t$ indicates whether week t is after the policy change or not, δ_r is the platform-restaurant fixed effect to control restaurant time-invariant characteristics, and γ_t is the year-week fixed effect to control seasonality and time trend. Standard errors are clustered at the restaurant level (Abadie et al., 2023). Note that we treat multi-homing restaurants as different restaurants on each platform. This is because the same restaurant may use different images for the same dish, especially given that they may continue to use generative AI to generate their dish images on Swiggy. The estimation results are displayed in Table 2.

We find that after Zomato banned restaurants from using AI-generated images, restaurants on the

Table 2: **Impact of the Policy Change on Restaurants' Order Volume and Revenue**

	(1) Order Volume	(2) Revenue
Treat × PostPolicy	0.00544***	1.566***
	(0.000802)	(0.302)
Constant	0.0447***	15.41***
	(0.000230)	(0.0867)
Platform-Restaurant FE	Yes	Yes
YearWeek FE	Yes	Yes
Observations	3112690	3112690
R^2	0.086	0.078
Pre-policy Control Mean	0.0525	16.885

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

platform experienced a 10.4% increase in order volume and 9.3% increase in revenue compared to Swiggy restaurants' pre-policy mean.[14] It is also worth noting that this difference is an average and relative change between Zomato and Swiggy restaurants (Li and Zhu, 2021). This suggests that consumers likely value authenticity and consistency between dish images and the delivered food more than the visual appeal of the images themselves, and the generative AI ban may enhance Zomato's competitiveness. Because generative AI image usage is not directly observed in the platform data, we validate cross-platform differences in image generation and processing using digital forensic tests, classifier-based evidence, LLM-based image classification results, multi-modal alignment analysis using CLIP models, and perceived visual aesthetics in Section 7.

5.2 Heterogeneity by Customer Type: New versus Returning

To better understand which margins contribute to the overall increase in Zomato restaurants' order volume, we decompose total orders into those placed by new versus returning customers. The first margin is orders from new customers to restaurant r. Before the ban, when Zomato restaurants might commonly use generative AI for dish images, customers might have been reluctant to try unfamiliar restaurants because of the risk that the food would look different from the online images (Riquelme et al., 2016; Steigenberger, 2025). Following the platform-level ban on generative AI for dish images, Zomato consumers may have regained

[14]The pre-policy Swiggy restaurants' average order volume per week is 0.0525. Using the difference-in-differences (DiD) estimation coefficient 0.00544 divided by the control group's pre-policy mean yields the percentage change of the policy's impact on the treated group, which is 10.4%. Note that, because we only observe around 10,000 consumers, the absolute order volume values are naturally small. Our analyses, therefore, focus on the relative changes in merchants' sales outcomes among these representative food delivery consumers. Similarly, the pre-policy Swiggy restaurant weekly revenue is 16.885 Indian Rupees, and we can obtain the percentage change by calculating the ratio between the revenue DiD coefficient and the control group pre-policy baseline, which is 9.3%.

trust in the authenticity of images, making them more willing to explore new restaurants. The second margin is returning customers. In the past, a customer might have been drawn to a Zomato restaurant with appealing images. However, after receiving food that did not match the photos, they may not reorder from the restaurant (Oliver, 1980; Gefen, 2000). With the generative AI ban on dish images, there should be improved consistency between images and actual dishes on Zomato, and consumers may reorder from the same restaurant more frequently. Nevertheless, this remains an empirical question worth further investigation.

To examine this, we conduct a subgroup analysis categorizing restaurant orders by source, distinguishing between new and returning customers. We define a new customer as a first-time buyer at restaurant r; otherwise, they are classified as a returning customer at restaurant r. We then sum the orders from new and returning customers for restaurant r in week t, defining them as Order Volume New Customers$_{rt}$ and Order Volume Returning Customers$_{rt}$, respectively. These two measures serve as dependent variables in Equation 1, and we re-run the regression model for all restaurant entities. The estimation results are presented in Table 3.

Table 3: **Order Source Analysis**

	(1) Order Volume New Customers	(2) Order Volume Returning Customers
Treat × PostPolicy	0.00390***	0.00154**
	(0.000385)	(0.000651)
Constant	0.0243***	0.0204***
	(0.000111)	(0.000187)
Platform-Restaurant FE	Yes	Yes
YearWeek FE	Yes	Yes
Observations	3112690	3112690
R^2	0.013	0.134
Pre-policy Control Mean	0.034	0.019

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We find that the policy change has a significant positive impact on Zomato restaurants in attracting both new customers' and returning customers' orders, with a larger contribution from new customers.[15] This pattern is consistent with the interpretation that improved image authenticity may reduce consumers' reluctance to try unfamiliar restaurants, while also improving retention among prior customers. For new customers, they may place greater trust in unfamiliar restaurants after generative AI dish images are banned. Meanwhile, for returning customers, there may be reduced disappointment from the expectation mismatch

[15] 11.5% increase for new customers compared to 8.1% increase for returning customers. Pre-policy means for control group restaurants' Order Volume New Customers and Order Volume Returning Customers are 0.034 and 0.019, respectively.

between dish images and delivered food.

6 User-Level Analysis

6.1 User-Level Reallocation

Thus far, we have presented restaurant-level evidence on how the policy change affects merchant sales across platforms. We now turn to user-level behavior to examine whether these patterns are also reflected in consumers' order allocation and platform switching.

Unlike the restaurant-level setting, where restaurants on Zomato can be treated as exposed units in a difference-in-differences framework, users are not directly exposed to the policy change. Accordingly, the user-level analysis is descriptive rather than causal. Our goal is therefore not to identify a causal treatment effect on users, but to assess whether changes in users' post-policy ordering behavior are consistent with the restaurant-level findings and the mechanisms discussed above. A similar descriptive approach is used in Johnson et al. (2023) and Chung et al. (2024).

We begin by examining whether users reallocate their orders across Zomato and Swiggy after the policy change. Specifically, we estimate the following reduced-form specification:

$$Y_{it} = \beta \, PostPolicy_t + U_i + \varepsilon_{it}, \tag{2}$$

where Y_{it} denotes user i's monthly order volume difference between Zomato and Swiggy (the number of Zomato orders minus the number of Swiggy orders in month t for user i), and U_i represents user fixed effects that absorb time-invariant user characteristics and preferences. The coefficient β captures whether users shift their ordering activity toward Zomato following the policy change.

Table 4 reports the estimates. Consistent with the restaurant-level results, the coefficient on $PostPolicy_t$ is positive and statistically significant, indicating that users, on average, reallocate orders from Swiggy to Zomato after the policy change.

Table 4: **Impact of the Policy Change on Users' Consumption on Two Platforms**

	(1) Order Volume Zomato minus Order Volume Swiggy
PostPolicy	0.0648***
	(0.0197)
Constant	-0.0148
	(0.0115)
User FE	Yes
Observations	115848
R^2	0.623

Notes: Robust standard errors are clustered at the user level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

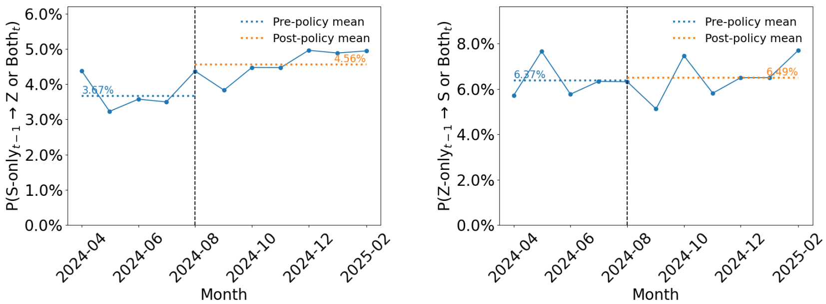
6.2 Platform Switching

To further examine whether this reallocation reflects users switching away from Swiggy, we next study month-to-month changes in platform usage status. In each month, we classify users into three mutually exclusive states: Swiggy-only, Zomato-only, and multi-homing. Users with no orders in a given month are excluded from that month's analysis. Based on these monthly states, we construct indicators for switching behavior. In particular, $Switch\ from\ Swiggy_{it}$ equals 1 if user i was Swiggy-only in month $t-1$ and becomes either Zomato-only or multi-homing in month t, and 0 otherwise. Similarly, $Switch\ from\ Zomato_{it}$ equals 1 if user i was Zomato-only in month $t-1$ and becomes either Swiggy-only or multi-homing in month t.[16]

Figure 4 presents the descriptive switching patterns. Conditional on being Swiggy-only in the previous month, the share of users who switch to Zomato or become multi-homing increases after the policy change, with the mean rising from 3.67% to 4.56%. By contrast, the corresponding share of users switching away from Zomato changes little, increasing only from 6.37% to 6.49%. Although these changes are modest in magnitude, their direction is consistent with a net reallocation of user activity toward Zomato.

[16]Naturally, users with no orders in a previous month are also excluded from that month's switching analysis. Hence, our analysis in this subsection is concentrated among frequent users who have at least two orders in two consecutive months.

Figure 4: Users' Platform Switching Patterns



We next quantify these patterns in a regression framework:

$$Y_{it} = \beta\, PostPolicy_t + X_i + \varepsilon_{it}, \tag{3}$$

where Y_{it} denotes the user-level switching outcome, and X_i includes user characteristics measured before the policy change: average order value, order volume, and the ratio of Zomato restaurants to the total number of Zomato and Swiggy restaurants in the user's city. Standard errors are clustered at the user level.

Table 5 shows that switching away from Swiggy increases significantly after the policy change, whereas switching away from Zomato does not change significantly. This asymmetry is consistent with the patterns shown in Figure 4: Zomato becomes relatively more attractive following the generative AI image ban.

Overall, while the estimated magnitudes are small and the explanatory power of the switching regressions is limited—reflecting the rarity of month-to-month platform switching at the individual level—the results align with both the descriptive evidence in Figure 4 and the restaurant-level findings. Post-policy growth in Zomato demand reflects not only increased activity among existing and returning customers, but also a modest reallocation of users away from Swiggy.

Table 5: **Impact of the Policy Change on Users' Platform Switching Behavior**

	(1) Switch from Swiggy	(2) Switch from Zomato
PostPolicy	0.00713***	0.000484
	(0.00276)	(0.00372)
Constant	-0.00000650	0.140***
	(0.00443)	(0.0119)
User Controls	Yes	Yes
Observations	19611	16562
R^2	0.012	0.013

Notes: Robust standard errors are clustered at the user level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Multi-Modal Analysis

A central empirical challenge to our analysis is that we do not directly observe whether a restaurant uses generative AI to create its dish images. To validate the plausibility and cross-platform relevance of this channel, we bring in multi-modal evidence from the images themselves. Specifically, we combine (i) digital forensic diagnostics that capture compression and high-frequency artifacts, (ii) three independent and validated classifier-based AI-image detection models together with an LLM prediction model in a zero-shot setting, and (iii) multi-modal alignment analysis using CLIP models and perceived image aesthetic scores. These analyses provide complementary measures of whether Swiggy images exhibit stronger signatures of AI-based generation than Zomato images, thereby supporting the interpretation of the policy shock in our subsequent mechanism analyses.

7.1 Forensic Tests

To assess whether Swiggy dish images are more likely to be generated or heavily enhanced relative to Zomato, we first apply a set of digital forensic diagnostics to a large sample of restaurant dish images from both platforms. We implement three complementary techniques: (i) Error Level Analysis (ELA), which detects inconsistencies in JPEG recompression artifacts; (ii) Noise and frequency-spectrum diagnostics, which capture sharpness and high-frequency texture amplification; and (iii) GAN residual (fingerprint) analysis, which summarizes statistical irregularities that can arise from synthetic generation pipelines.

We focus on three primary measures—ELA mean, image sharpness, and the standard deviation of residuals. These methods are widely used in digital image forensics and provide triangulated diagnostics of non-natural image processing (Dzanic et al., 2020; Neves et al., 2022; Geethanjali et al., 2024; Exner et al., 2025). We validate the discriminative power of these measures using a large set of 87,750 constructed human-made and AI-generated food images with ground-truth labels, as shown in Online Appendix F.

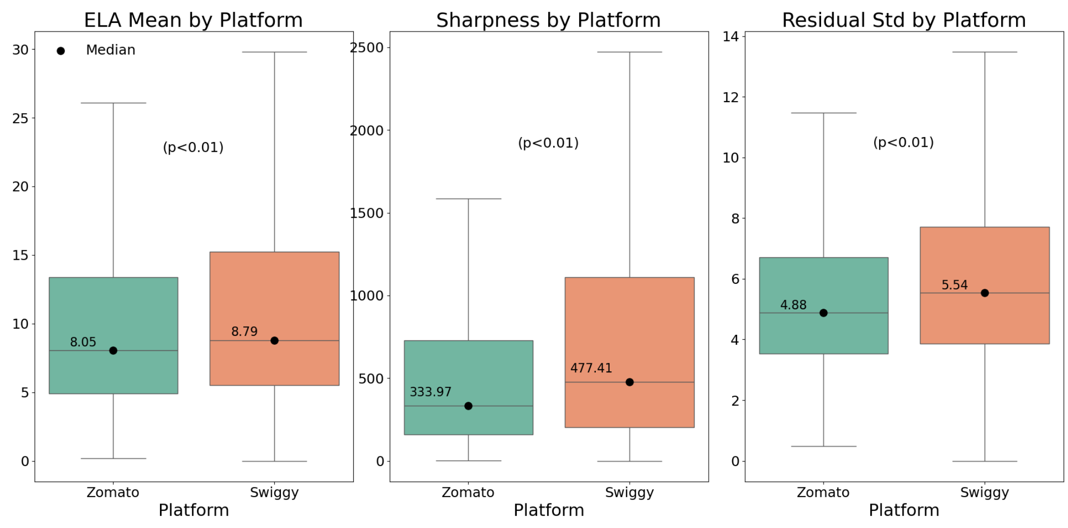
Figure 5 illustrates these forensic diagnostics for the representative Chicken Biryani dish images provided by a restaurant named Akram's.[17] The Swiggy image exhibits substantially higher sharpness (1,808 vs. 147), consistent with stronger edge enhancement and high-frequency amplification. It also shows a larger residual dispersion (SD = 9.20 vs. 2.28) and higher ELA intensity (mean = 41.6 vs. 30.1; 95th percentile = 150 vs. 90), patterns consistent with heavier post-processing and re-compression.

[17] Their URLs on the two platforms are `https://www.zomato.com/kolkata/akrams-kestopur/order` and `https://www.swiggy.com/city/kolkata/akrams-kestopur-lake-town-rest779306` (accessed September 2025).

Figure 5: Images of "Chicken Biryani" from *Akram's* (Left Swiggy, Right Zomato)

Extending this analysis to the complete sample of restaurant dish images (Swiggy: 35,083 images; Zomato: 51,045 images), we observe systematic and highly consistent differences across all three forensic dimensions. Figure 6 presents the distribution of these three measures using box plots for each platform, highlighting the consistent right-shift of Swiggy's distribution across all metrics. On average, compared with Zomato's dish images, Swiggy's dish images exhibit 17.2% higher error level analysis (ELA) values ($p < 0.01$), 47.9% higher sharpness ($p < 0.01$), and 12.3% higher JPEG residual standard deviations ($p < 0.01$).[18] These patterns indicate that Swiggy images are, on average, more heavily processed or digitally enhanced than their Zomato counterparts.

Figure 6: Distribution of Forensic Measures for Dish Images by Platform



[18]Percent differences are computed as the difference between the mean forensic test values of Swiggy and Zomato dish images, divided by the mean forensic test value for Zomato for each measure.

7.2 Generative AI Image Detection Analysis

To further assess whether dish images on Swiggy are more likely to be generated or modified by generative AI relative to Zomato, we apply three independent HuggingFace detection models to all dish images from restaurants on the two platforms.[19] All three detectors are supervised and Transformer-based image classification models, fine-tuned on labeled datasets containing both real (human-captured) images and AI-generated images. They leverage pretrained vision backbones and learn to identify statistical and structural patterns that tend to differ between natural images and images produced or modified by generative models (e.g., texture irregularities, noise patterns, unnatural edges or object boundaries, and artifacts induced by diffusion or generative pipelines). The detectors output a continuous probability score ranging from 0 to 1, reflecting the model's confidence that an image is AI-generated rather than human-produced, which we refer to as "AI likelihood".

Note that while the generative AI image detectors tend to be reliable, they are not completely accurate and may make errors, similar to human annotators (Exner et al., 2025). Our expectation is that the detectors will predict dish images on Swiggy to be significantly more likely to be AI-generated than those on Zomato, while acknowledging the possible existence of Type I and Type II errors for individual dish images. We tested the accuracy of the three detectors using a self-constructed large-scale food image sample with ground-truth labels as described in Online Appendix G. As shown in Figure G1 in Online Appendix G, while detectors may make mistakes, they tend to consistently show a significant difference in AI likelihood between human-taken images and AI-generated images overall.

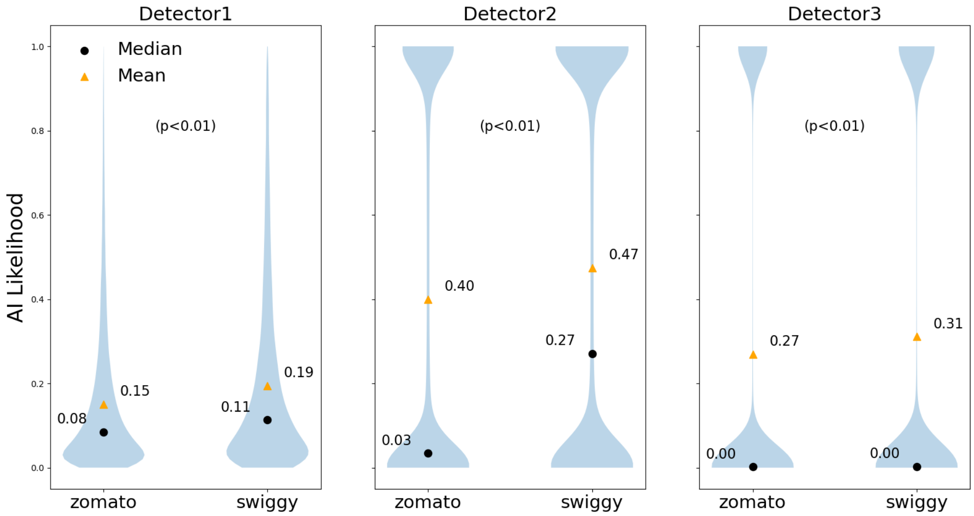
Figure 7 presents the distribution of AI likelihood scores for the full sample of 86,128 dish images across both platforms, shown separately for each of the three independent detectors. Across all detectors, dish images on Swiggy exhibit systematically higher AI likelihood distributions than those on Zomato, with the differences statistically significant at the 1% level in all cases ($p < 0.01$).

Although the detectors vary in their sensitivity and calibration, they consistently indicate higher AI likelihood levels for Swiggy images relative to Zomato. On average, AI likelihood scores on Swiggy are 28.6% higher than Zomato's mean according to Detector 1, 18.7% higher according to Detector 2, and 15.4% higher according to Detector 3.[20] Given that not all Swiggy restaurants necessarily use generative AI to create dish images, this difference provides consistent evidence that a substantial share of images on Swiggy are more likely to be AI-generated than those on Zomato after the policy change.

[19]The open-source models are available at "`umm-maybe/AI-image-detector`," "`Smogy/SMOGY-Ai-images-detector`," and "`Ateeqq/ai-vs-human-image-detector`"

[20]Percent differences are computed as the difference between the mean AI likelihood score of Swiggy dish images and that of Zomato dish images, divided by the mean AI likelihood score of Zomato dish images for each detector.

Figure 7: Distribution of AI Likelihood for Dish Images by Platform



We further complement the classifier-based evidence with an LLM-based labeling approach. Specifically, we use a vision-enabled large language model (LLM) in a zero-shot setting to classify whether a dish image is likely to be AI-generated and the reasons why it classifies the image as an AI-generated one, based on a random sample of 200 dish images from each platform. The implementation details are provided in Online Appendix H.

The LLM-based labeling yields qualitatively consistent results: dish images on Swiggy are more likely to be classified as AI-generated compared to those on Zomato. In addition, the model identifies several recurring visual features associated with higher AI likelihood, including overly uniform textures, unnatural symmetry, and shape distortions, as shown in Figure H2 in Online Appendix H. These explainable features align closely with the patterns detected in our forensic analysis and classifier-based measures.

7.3 Semantic Alignment and Visual Aesthetics of Swiggy Restaurants

We also examine how AI likelihood relates to two distinct visual signals captured by modern vision–language models: semantic alignment and perceived visual aesthetics. Specifically, we leverage image embeddings derived from CLIP (Radford et al., 2021) and an aesthetic score trained on large-scale internet image datasets (Schuhmann et al., 2022). These measures allow us to separate two dimensions of dish imagery that may influence consumer reactions: (i) the degree to which an image (image embeddings) matches the textual dish descriptions (text embeddings), measured using cosine similarity, which yields a CLIP image-text alignment score ranging from -1 to 1; and (ii) the perceived aesthetic quality of the image, captured using a large-scale pretrained aesthetic model released by LAION. The model is trained on human-annotated real-world photographs and outputs a continuous aesthetic score ranging from 1 to 10. Because the training data primarily consist of human-taken images, the score reflects web-native aesthetic preferences and is correlated with photographic realism, rather than explicitly measuring generative AI usage. For technical details, see Online Appendix I. The regression model that we employ is,

$$\text{Image AI Likelihood}_{im} = \beta_0 + \beta_1 \text{Aesthetic Score}_{im} + \beta_2 \text{Image-Text Alignment CLIP Score}_{im} + \delta_r R_r + \varepsilon_{im} \tag{4}$$

where Image AI Likelihood_{im} is the mean value of the AI likelihood predicted by the three classifiers of each dish image on Swiggy for an image im, Aesthetic Score_{im} is the aesthetic score predicted by the LAION model, and Image-Text Alignment CLIP Score_{im} is the cosine similarity score between the dish image and corresponding dish text descriptions. We include a platform-restaurant fixed effect to control for platform-restaurant heterogeneity and cluster the standard errors at the restaurant level. Note that different restaurant entities (e.g., chain locations) may share the same dish images while using different text descriptions. As a result, the number of observations is larger than the number of Swiggy images reported in Section 4.

Table 6 reports the results. We find that Swiggy dish images having a higher AI likelihood tend to be associated with a significantly higher average CLIP similarity score, suggesting that such images are more strongly aligned with the dishes' textual descriptions. At the same time, perhaps surprisingly, AI likelihood is negatively associated with the aesthetic score. This pattern indicates that AI-like images are not necessarily perceived as more visually appealing; instead, they may appear to be more "prototypical" or standardized relative to common online imagery.

Text-to-image systems are trained to maximize correspondence between textual prompts and visual features, prioritizing semantic alignment and recognizability over cultural or material authenticity (Radford et al., 2021). While such images may appear polished, they may also reduce perceived informational content by making dishes look overly generic or exaggerated relative to real-world expectations. In a food delivery context, where consumers rely on images as quality signals, overly standardized visuals may weaken trust and reduce the credibility of product representations.

Table 6: **Correlation between Image AI Likelihood and Characteristics**

	(1) Image AI Likelihood
Aesthetic Score	-0.0524***
	(0.00677)
Image-Text Alignment CLIP Score	0.0874**
	(0.0383)
Platform-Restaurant FE	Yes
Observations	52629
R^2	0.287

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8 Mechanism Analysis

In this section, we investigate the mechanisms underlying the post-policy demand effects. While the baseline results document a significant increase in order volume for Zomato restaurants following the ban on generative AI dish images, they do not by themselves explain why consumers respond to the policy. Broadly, two mechanisms may account for the observed shift in orders from Swiggy to Zomato.

First, the effect may operate at the platform level. Zomato's public ban on generative AI dish images may have increased consumers' awareness of AI-generated content on food delivery platforms. This heightened awareness could improve Zomato's brand image as a platform that actively safeguards authenticity.

Second, the effect may operate at the restaurant level. Consumers' responses to AI-generated images on Swiggy may be heterogeneous, with demand shifting primarily away from restaurants whose images appear more likely to be AI-generated, rather than reflecting a broad platform-wide boycott.

The first mechanism is not directly testable as we cannot assess consumers' perception of platform brand images. We instead provide some model-free evidence on the public discourse surrounding AI-generated dish images. In particular, we document heated Reddit discussions about AI-generated dish images on Swiggy and extensive media coverage by major outlets such as the *Economic Times*, which explicitly debated the authenticity and potential deceptiveness of AI-generated food images on food delivery platforms after Zomato's generative AI dish image ban. Together, this evidence suggests that the policy was broadly salient to consumers and plausibly increased awareness of AI-generated content at the platform level.

We then investigate how the policy change affects restaurants' sales outcomes based on Swiggy restaurants' tendency to use AI images by examining two complementary mechanisms. First, we study whether the treatment effects vary systematically with the likelihood of AI usage on Swiggy restaurants' dish images, which speaks to heterogeneity in exposure to the policy. Second, we exploit cross-platform variation among multi-homing restaurants to construct alternative, behaviorally grounded control groups that help isolate the role of image authenticity from other platform-specific factors.

8.1 Platform-Level Awareness and Brand Response

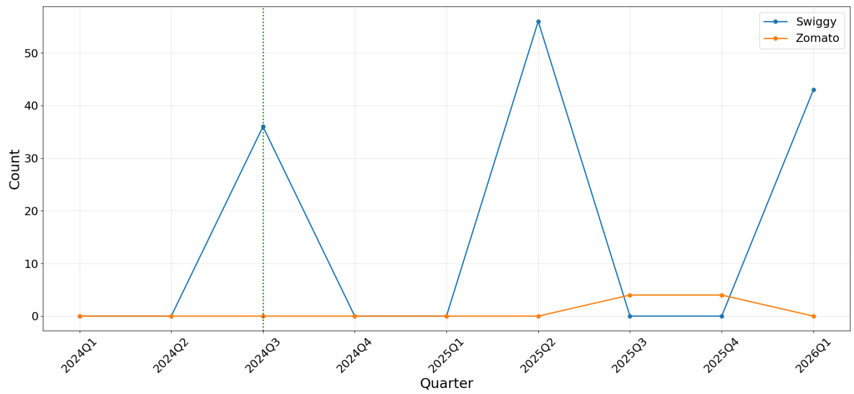
Zomato's ban on generative AI dish images attracted substantial public attention and media coverage. Major Indian news outlets, including *Economic Times*, *The Times of India*, *India TV News*, and *The Indian Express*, reported on the policy and highlighted concerns that AI-generated food images could misrepresent the actual dishes delivered to consumers. This coverage likely increased public awareness of AI-generated imagery on food delivery platforms and may have strengthened Zomato's brand image as a platform emphasizing authenticity and consumer trust. Table A1 in Online Appendix A.1 summarizes representative news coverage of the policy.

In parallel, user discussions on Reddit and other social media platforms revealed heated debates regarding the use of generative AI dish images on Swiggy, with many users questioning the credibility of food presentation and expressing distrust toward restaurants on the platform perceived to rely on synthetic imagery.

Figure 8 plots the quarterly number of Reddit posts and comments discussing AI-generated dish images on the two food delivery platforms.[21] The vertical dashed line marks the timing of Zomato's announcement banning generative AI dish images. As shown in the figure, online discussions regarding AI-generated food images on Swiggy increased noticeably following the policy announcement, while the discussion volume was relatively low for Zomato. This pattern suggests that the ban may substantially elevate public awareness of AI-generated imagery on food delivery platforms, especially Swiggy, and trigger broader consumer conversations about the authenticity of food presentation.

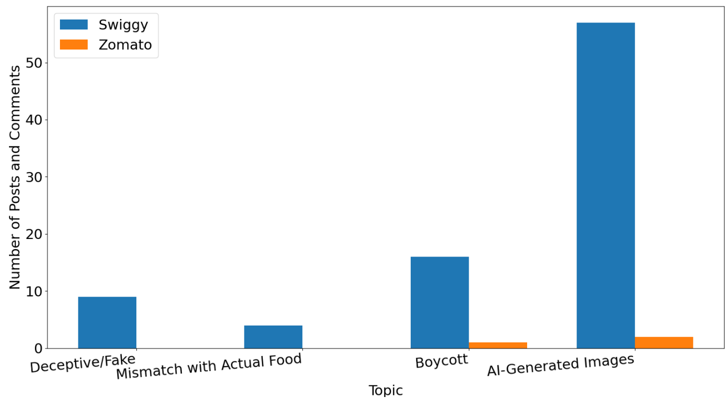
[21] We search across Reddit communities and retrieve posts containing keywords such as "Swiggy (Zomato) AI-generated dish images" and "Swiggy (Zomato) AI dish images," among related variations.

Figure 8: Quarterly Number of Reddit Posts and Comments Discussing AI-Generated Dish Images on Swiggy and Zomato



To further characterize the content of these discussions, we conduct keyword-based topic classification on the collected Reddit posts and comments. Specifically, we classify posts and comments into topics using a keyword-matching approach. We manually define four thematic categories based on a preliminary reading of the corpus: *Deceptive/Fake* (e.g., keywords: *fake*, *misleading*, *scam*, *trust*), *Mismatch with Actual Food* (e.g., *looks nothing like*, *actual food*, *what I got*), *Boycott* (e.g., *boycott*, *uninstall*, *never*), and *AI-Generated Images* (e.g., *AI*, *generated*, *synthetic*). Each post or comment is assigned to a category if its text contains any of the corresponding keywords (case-insensitive regex matching). A single post may be assigned to multiple categories. This approach is more interpretable than embedding topic modeling methods, though it relies on predefined category definitions rather than data-driven topic discovery. Figure 9 presents the number of discussions associated with the main topics identified by the model. The results show that a substantial share of discussions revolve around negative themes, including concerns about deceptive or unrealistic food images and calls for avoiding platforms perceived to rely on AI-generated visuals.

Figure 9: Number of Posts and Comments by Topics



The media coverage and social media discourse indicate that Zomato's policy likely served as an information shock that made the issue of AI-generated dish images salient to consumers. Increased awareness could influence consumers' perceptions of platform credibility, potentially improving Zomato's brand image as a platform that safeguards authenticity while simultaneously raising skepticism toward competing platforms perceived to tolerate synthetic imagery.

8.2 Moderating Effect of Restaurants' Dish Image AI Likelihood

We further exploit cross-sectional variation in AI likelihood scores across Swiggy restaurants, building on the three validated AI likelihood measures from Section 7.2. We first calculate the AI likelihood for each dish image im for restaurant r using each of the three detectors k, then we average over all three detectors for each dish image, and then we average over all dish images for restaurant r.

To examine whether the post-policy effects vary with the intensity of AI usage in restaurant imagery, we categorize Swiggy restaurants into *low-*, *moderate-*, and *high-AI-likelihood* groups based on percentiles of the restaurant-level average dish image AI prediction score. Specifically, we use the 33rd percentile (0.2568) and the 66th percentile (0.3993) of the Swiggy AI score distribution as cutoffs. All Zomato restaurants remain in the treated group across specifications, while the composition of the control group varies depending on the AI likelihood category of Swiggy restaurants. We then re-estimate Equation 1 separately for each subsample. We restrict the analysis to restaurants in Kolkata, the city for which we observe comprehensive dish image data. This restriction ensures consistent measurement of image characteristics across platforms and avoids sample composition differences driven by data availability.

A naive subgroup design that pools Zomato and Swiggy restaurants and applies a common AI likelihood cutoff across the two platforms' restaurants would generate an unbalanced comparison, because Swiggy restaurants exhibit systematically higher AI likelihood than Zomato restaurants. Such an approach would mechanically assign a disproportionate share of Swiggy restaurants to the high-AI group and Zomato restaurants to the low-AI group. This imbalance would confound platform effects with differences in image-generation practices. Our approach instead holds the treated group fixed and varies only the composition of the *control* group, allowing us to isolate how treatment effects differ with the AI intensity of Swiggy restaurants' imagery. Conceptually, this design compares Zomato restaurants, none of which can use generative AI post-ban, to Swiggy restaurants that differ in how "AI-like" their dish images appear. Table 7 reports the results.

Table 7: **Moderating Effect of Dish Image AI Likelihood**

Control Group Restaurant Type	Low-AI-Likelihood Swiggy Restaurants	Moderate-AI-Likelihood Swiggy Restaurants	High-AI-Likelihood Swiggy Restaurants
Dependent Variable	Order Volume	Order Volume	Order Volume
Treat × PostPolicy	0.0122	0.0234*	0.0272**
	(0.00845)	(0.0120)	(0.0106)
Constant	0.0408***	0.0357***	0.0334***
	(0.00410)	(0.00583)	(0.00511)
Platform-Restaurant FE	Yes	Yes	Yes
YearWeek FE	Yes	Yes	Yes
Observations	60314	60314	60526
R^2	0.063	0.070	0.062

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We find that when Swiggy restaurants with *low* AI likelihood images are used as the control group (Column 1), the estimated DiD coefficient on *Treat* × *PostPolicy* is positive but statistically insignificant. This suggests that relative to Swiggy restaurants whose images appear largely authentic, Zomato restaurants do not experience a pronounced post-policy change in order volume.[22]

When the control group consists of Swiggy restaurants with *moderate* AI likelihood images (Column 2), the estimated treatment effect becomes larger and marginally statistically significant. Finally, when Swiggy restaurants with *high* AI likelihood images serve as the control group (Column 3), the DiD estimate is both economically larger and statistically stronger. This pattern indicates that the relative demand advantage of Zomato after the ban is driven primarily by Swiggy restaurants whose dish images appear more likely to be AI-generated.

Overall, these results provide consistent evidence of a monotonic moderation effect: the relative post-policy advantage of Zomato increases with the degree of AI manipulation in Swiggy restaurants' dish images. The findings support the interpretation that consumer responses to the policy are concentrated in market segments where AI-generated imagery is most prevalent. This is consistent with behavioral evidence sug-

[22] This null result does not contradict the platform-level awareness mechanism documented in Section 8.1. Rather, this suggests that heightened consumer awareness of AI imagery translates into demand penalties primarily for Swiggy restaurants whose dish images plausibly appear AI-generated. In other words, the awareness only damages restaurants whose images actually look AI-generated, leaving authentic-looking Swiggy restaurants unharmed. This is consistent with a platform-level information shock that activates restaurant-level heterogeneity in consumer responses.

gesting that consumers exhibit greater distrust toward algorithmically generated content when authenticity is salient (Dietvorst et al., 2015; Exner et al., 2025).

As a complementary piece of descriptive evidence on consumer perceptions, we examine the relationship between Swiggy restaurants' dish image AI likelihood and their customer ratings on Swiggy. We find a statistically significant negative association between AI likelihood and restaurant ratings. The Spearman rank correlation is -0.091 ($p = 0.019$) (Sedgwick, 2014). While purely correlational, these patterns are consistent with the interpretation that consumers perceive AI-generated dish images as less authentic, which may translate into lower evaluations.

8.3 Alternative Control Group: Multi-homing Restaurants with Different Dish Images

The AI likelihood analysis demonstrates that the policy's demand effects are concentrated among restaurants whose imagery exhibits stronger generative AI signatures. To complement this classifier-based measure with a sharper behavioral contrast, we next exploit cross-platform variation in dish images among multi-homing restaurants.

Restaurants operating on both platforms typically have incentives to maintain a consistent visual presentation across listings. Reusing the same image set minimizes photography and editing costs, preserves brand coherence, and avoids confusing consumers. When a multi-homing restaurant nonetheless displays different dish images on Swiggy than on Zomato following Zomato's generative AI ban, this divergence plausibly reflects the use of AI-generated images on Swiggy that are not permitted on Zomato.

This setting, therefore, provides a behaviorally grounded comparison between listings constrained from using AI-generated dish images (Zomato) and listings plausibly deploying AI-generated dish images (Swiggy) without relying solely on model-based AI-detection scores. Consistent with this interpretation, Figure G2 in Online Appendix G.1 shows that when multi-homing restaurants display different dish images across platforms, Swiggy listings exhibit significantly higher AI likelihood scores than the corresponding Zomato images based on the average AI likelihood of the three classifiers.

We identify 21 such multi-homing Swiggy restaurants in Kolkata whose dish images differ from those displayed by the same entity for the same dishes (matched by restaurant name and address) on Zomato.[23] These 21 Swiggy restaurants serve as the alternative control group, while all Zomato restaurants in Kolkata remain the treated group. We re-estimate Equation 1 using order volume as the dependent variable.

We do not restrict the treated group to only multi-homing Zomato restaurants. Outcomes for multi-homing restaurants are likely to be correlated across platforms: restaurants that perform well on one platform

[23] In the robustness section, we obtain similar results using a larger, multi-city sample.

tend to perform well on the other. The order volume for these restaurants on either platform may therefore be jointly influenced by unobservable restaurant-level demand shocks rather than by platform-specific image policies. Restricting the treated group to multi-homing restaurants would confound these correlated outcomes with the policy effect. Retaining the full set of Zomato restaurants as the treated group avoids this concern and preserves a clean comparison. Nonetheless, in the robustness check section, we additionally conduct an analysis using only multi-homing treated restaurants, classified based on whether they use different dish images across platforms.

The resulting estimates are shown in Column 1 in Table 8. We find that the policy change's impact on Zomato restaurants' order volume remains significant and positive. This suggests that Zomato's policy banning AI-generated dish images produced meaningful increases in consumer demand for Zomato restaurants, when benchmarked against a behaviorally grounded comparison group of Swiggy restaurants that are likely to have used AI-generated dish images.

8.4 Placebo Test: Multi-homing Restaurants with Identical Dish Images

As a natural placebo test, we next examine multi-homing restaurants that display identical dish images on both Swiggy and Zomato. When a restaurant uses the same image set across platforms, its exposure to Zomato's generative AI ban should be minimal, and the image-authenticity mechanism should not generate differential demand responses across platforms.[24]

Using our cross-platform image-matching procedure, we identify 84 multi-homing restaurants whose dish images are identical across the two platforms in Kolkata. Because these restaurants do not appear to rely on platform-specific image manipulation, comparing their Swiggy performance with that of all Zomato restaurants provides a clean test of whether residual platform-level differences, which are unrelated to imagery, could be driving the main results. If the baseline effects are indeed attributable to image authenticity, the estimated treatment effects in this placebo comparison should be close to zero. We re-estimate Equation 1 for order volume, using this set of restaurants as the Swiggy control group.

[24] To validate this identification strategy, we examine whether restaurants that display identical images across platforms also exhibit similar AI likelihood scores. Figure G2 in Online Appendix G.1 plots the difference in AI likelihood between Swiggy and Zomato dish images across restaurant groups. For multi-homing restaurants that display the same images on both platforms, the estimated difference is close to zero and not significant.

Table 8: **Alternative Control Group Estimation Results**

Control Group Restaurant Type	Different-Dish-Image Swiggy Restaurants as Control	Same-Dish-Image Swiggy Restaurants as Control
Dependent Variable	Order Volume	Order Volume
Treat × PostPolicy	0.0511^{***}	-0.000818
	(0.0194)	(0.0101)
Constant	0.0190^{*}	0.0477^{***}
	(0.0104)	(0.00509)
Platform-Restaurant FE	Yes	Yes
YearWeek FE	Yes	Yes
Observations	54537	57876
R^2	0.063	0.065

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses. Revenue results are consistent with the order volume findings, as shown in Table J6 in Online Appendix J.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As shown in Column 2 in Table 8, the interaction term *Treat* × *PostPolicy* is small in magnitude and statistically insignificant. This null result provides further validation that the demand effects documented in the baseline and heterogeneity analyses are not driven by platform-wide shocks, possible platform-wide dish image resolution differences, differential promotions, or sample composition differences, but arise precisely when Swiggy restaurants present imagery that is plausibly AI-generated or visually distinct from the constrained images allowed on Zomato.

9 Robustness Checks and Alternative Explanations

9.1 Parallel Trends Assumption Check

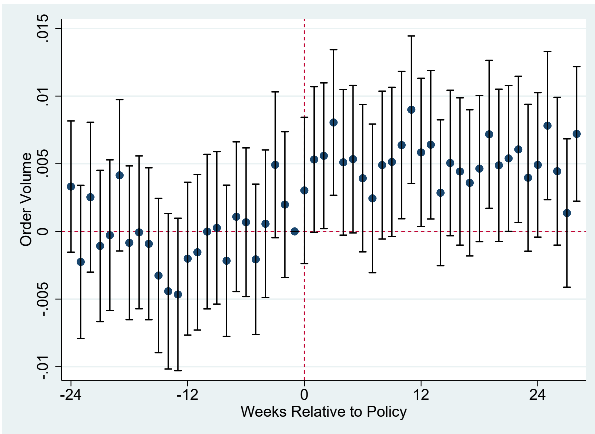
The difference-in-differences analyses rely on the parallel trend assumption. To check the validity of the assumption, following Aral and Dhillon (2021), we create a series of week dummies to indicate the weeks before and after the policy change during the sample period. We then interact each of the dummy variables with the treatment variable and run the following regression:

$$\mathrm{Y}_{rt} = \alpha + \sum_{\tau=-24,\ldots,-2}^{0,1,\ldots,28} \beta_\tau 1[t - event_t = \tau] \times Treat_r + \delta_r + \gamma_t + \varepsilon_{rt} \tag{5}$$

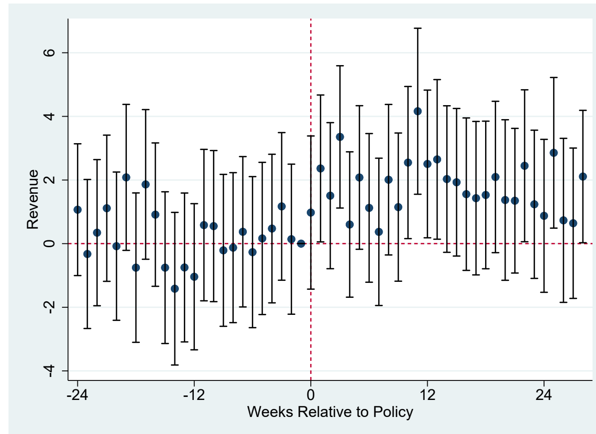
where Y_{rt} includes restaurants' weekly order volume and total revenue. $event_t$ represents the week in which the policy shock occurred. $1[t - event_t = \tau]$ are a series of "event-time" dummies that equal one when the policy shock is τ periods away from $event_t$. The week before the policy shock serves as the baseline, and its event-time dummy variable is omitted. We run the regression for the whole restaurant sample in India and in Kolkata separately. The regression results are shown in Figure 10. As shown in the regression results, the coefficients are not significantly different from 0 before the policy change in the four specifications. These patterns indicate no statistically significant differential pre-treatment trends in order volume or revenue, supporting the parallel trends assumption underlying the difference-in-differences design.

Figure 10: Parallel Trend Assumption Check Results

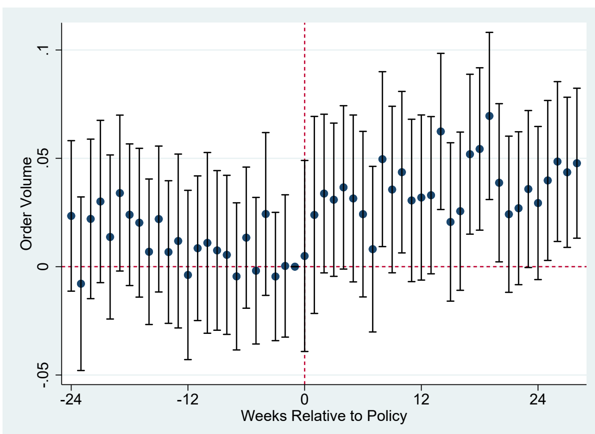
(a) Order Volume - India



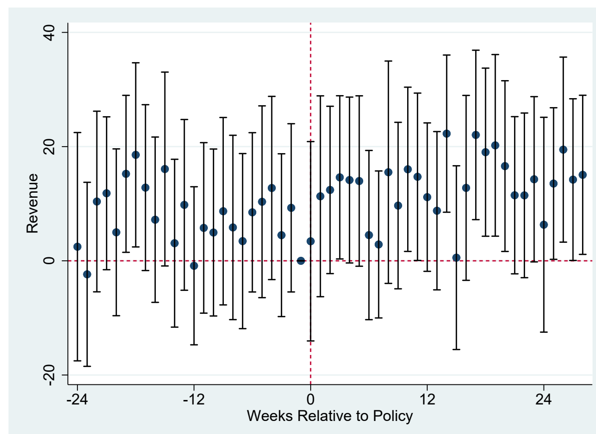
(b) Revenue - India



(c) Order Volume - Kolkata



(d) Revenue - Kolkata



9.2 Single-Homing Restaurants

As discussed in Section 8.3, for multi-homing restaurants, sales performance across the two platforms may be correlated: it is likely that restaurants that perform well on one platform tend to perform well on the other due to unobserved restaurant characteristics. As a result, observed demand outcomes may be jointly driven by unobservable restaurant-level demand shocks rather than by the platform's image policy or their dish images' AI likelihood. These create a potential violation of the Stable Unit Treatment Value Assumption (SUTVA).

To address these concerns, we focus on restaurants that operate exclusively on a single platform, which comprise the majority of the restaurants. We re-estimate Equation 1 using the sample of single-homing restaurants, and report the results in Table J1 in Online Appendix J. Consistent with our main regression results, we find that the post-policy effect remains positive and statistically significant for single-homing restaurants.

9.3 Robustness Check Using Additional Cities

To assess whether the alternative control group results generalize beyond Kolkata and are not driven by idiosyncratic local conditions, we extend the analysis to a broader set of cities. Specifically, in addition to Kolkata, we include Kochi, Kanpur, Madurai, Nagpur, New Delhi, Patna, and Surat. These cities vary substantially in size, market maturity, and consumer demographics, providing a more stringent test of the robustness of our identification strategy.

Using the same cross-platform image-matching procedure described earlier in Sections 8.3 and 8.4, we classify multi-homing Swiggy restaurants into two groups: (i) those displaying identical dish images on Swiggy and Zomato, and (ii) those displaying different dish images across platforms. Across the eight cities, this procedure identifies 264 multi-homing Swiggy restaurants with identical images and 81 multi-homing Swiggy restaurants with different images. All 3,347 Zomato restaurants from these cities serve as the treatment group. While these samples remain modest, which reflects the inherently conservative nature of image-based matching, they represent a meaningful expansion relative to the Kolkata-only analysis.

We re-estimate Equation 1 using these expanded samples, focusing on order volume as the primary outcome. Column 1 of Table 9 reports baseline estimates using all restaurants in the additional cities and confirms a positive and statistically significant post-policy effect. Column 2 uses Swiggy multi-homing restaurants with different dish images from their Zomato listings as the control group. Similar to the estimation results of Column 1 in Table 8, the estimated $Treat \times PostPolicy$ coefficient remains positive and statistically significant, indicating that the treatment effect persists when comparing against multi-homing Swiggy restaurants with different dish images across the two platforms. Column 3 uses Swiggy multi-homing restaurants with identical dish images as their Zomato listings as the control group. Consistent with the placebo logic in Section 8.4, the estimated treatment effect becomes small in magnitude and statistically insignificant. This pattern mirrors the Kolkata results shown in Column 2 of Table 8. Overall, despite the unavoidable noisiness of image-based classification and the limited size of the multi-homing sample, the qualitative pattern of results remains stable across geographies.

Table 9: **Robustness Check Using Additional Cities**

Control Group Restaurant Type	All Swiggy Restaurants	Different-Dish-Image Swiggy Restaurants as Control	Same-Dish-Image Swiggy Restaurants as Control
Dependent Variable	Order Volume	Order Volume	Order Volume
Treat × PostPolicy	0.0172***	0.0209**	0.00922
	(0.00285)	(0.00921)	(0.00636)
Constant	0.0402***	0.0346***	0.0422***
	(0.000890)	(0.00492)	(0.00322)
Platform-Restaurant FE	Yes	Yes	Yes
YearWeek FE	Yes	Yes	Yes
Observations	310845	181684	191383
R^2	0.081	0.067	0.068

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.

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

9.4 Alternative Specification: Multi-Homing Restaurants as the Treated Sample

We examine whether the results presented in Section 9.3 hold when the treated group is restricted to the same set of multi-homing restaurants on Zomato, rather than all Zomato restaurants. This specification provides a more conservative comparison because it focuses on restaurants observed on both platforms.

Similar to the procedures described in Sections 9.3, we divide multi-homing restaurants across the eight cities into two groups based on whether they use the same dish images across Zomato and Swiggy. The first group consists of restaurants whose dish images differ across platforms, where Swiggy listings are more likely to retain visually distinct or plausibly AI-generated images. The second group consists of restaurants whose dish images are identical across platforms, which serves as a placebo comparison because these restaurants should be less affected by Zomato's generative-AI image policy. The regression specification is Equation 1.

Table J2 in Online Appendix J.2 reports the results. Consistent with Table 8, the positive treatment effect is concentrated among multi-homing restaurants that use different dish images across platforms, while the effect is economically small and statistically insignificant among restaurants using identical images.

9.5 Controlling for Image Aesthetics

In Section 7.3, we document a negative correlation between Swiggy dish image AI likelihood and aesthetic score. A natural concern is that consumers may disfavor Swiggy restaurants due to lower image quality, rather than because the images appear AI-generated and thus less authentic. To address this concern, we rerun the subgroup analysis presented in Table 7, additionally controlling for $Restaurant\ Image\ Aesthetics \times PostPolicy$.

We find that restaurant aesthetic quality does not independently predict post-policy demand shifts (Online Appendix Table J3), and the coefficients on $Treat \times PostPolicy$ remain similar to those in Table 7 across all three specifications. These results suggest that the demand effects documented in Table 7 operate through a channel specific to perceived AI generation, rather than through image aesthetics alone.

9.6 Restaurants' Quality-Based Robustness Checks

Our main regression results in Table 2 demonstrate the average treatment effect comparing treated restaurants to the control group restaurants, regardless of whether the restaurants on Swiggy used generative AI to generate dish images or not. We then show that when benchmarked against restaurants with higher-AI-likelihood Swiggy restaurants, Zomato restaurants have a higher order volume uplift after the policy change in Table 7. A remaining concern is that restaurants' propensity to adopt generative AI dish images may be correlated with unobserved characteristics, such as restaurant price categories and quality, that could also generate differential demand trajectories. If so, the control group of Swiggy restaurants might fail to provide a valid counterfactual for Zomato restaurants, even after accounting for restaurant fixed effects.

We examine whether the estimated treatment effects are driven by comparisons with systematically lower-quality or lower-priced restaurants on the control platform. Table J4 in Online Appendix J.4 re-estimates the baseline difference-in-differences specification Equation 1 using alternative Swiggy control groups defined by observable restaurant characteristics. Specifically, we separately restrict the control group to (i) budget restaurants (Price Category: Less than 300 Indian Rupees), (ii) expensive restaurants (Price Category: Higher than or Equal to 300 Indian Rupees), (iii) low-rating restaurants (Rating < 3.57), and (iv) high-rating restaurants (Rating ≥ 3.57).[25]

Across all four specifications, the estimated coefficient on $Treat \times PostPolicy$ remains positive, relatively stable, and statistically significant. Importantly, the treatment effect persists when the control group consists exclusively of high-rating or higher-priced Swiggy restaurants, alleviating concerns that the baseline results are driven by comparisons with low-quality establishments that may be more inclined to adopt AI-generated imagery. Conversely, the effect is also present when restricting attention to lower-rated or budget restaurants, suggesting that the results are not driven by differential quality upgrading or price positioning among weaker restaurants.

9.7 Order Size

We also perform a robustness analysis to rule out the possibility that the observed increase in order volume is driven by temporary promotions or platform- or restaurant-level pricing changes. Specifically, we re-estimate Equation 1 using the average number of dishes per order as the dependent variable. If the post-policy increase in order volume were primarily due to promotions (e.g., “1-for-1” deals or discounts), we would expect to observe more dishes per order on Zomato (Dai and Li, 2025).

As shown in Table J5 in Online Appendix J, the estimated treatment effect on the number of dishes per order is statistically insignificant. These results suggest that the policy change did not affect order size, reinforcing that the observed rise in order volume on Zomato is unlikely to be driven by promotional activities. Because dish-level prices are not observed in our data, we are unable to directly estimate price changes across platforms.

[25] 300 Indian Rupees is the median price category for Swiggy Restaurants in Kolkata. 3.57 is the median rating for Swiggy Restaurants in Kolkata. The rating range is from 1 to 5.

10 Discussion

This study examines how consumers respond to generative-AI–modified visual content in a real marketplace. Exploiting a platform-level policy divergence in India's food delivery market, we use difference-in-differences designs to identify the average treatment effect of banning AI-generated images on restaurant sales. Our results show that banning generative AI dish images leads to a 10.4% increase in restaurant order volume and 9.3% increase in revenue on the platform that adopts the ban, relative to merchants on a competing platform that does not ban AI-generated dish images. These effects are economically meaningful and robust across several alternative specifications, alternative control groups, and geographic settings.

Importantly, the demand response is not uniform across restaurants. The post-policy advantage of Zomato is substantially larger when benchmarked against Swiggy restaurants whose dish images exhibit stronger signatures of generative AI manipulation, as measured using classifier-based AI likelihood scores. In contrast, when Swiggy restaurants display dish images that are not "AI-like" or visually identical to their Zomato listings, the estimated treatment effects are small and not statistically significant. At the user level, we find consistent reallocation of demand toward Zomato following the policy change, reflected in increased order volumes and asymmetric platform switching.

A natural question raised by our findings is why Swiggy did not adopt a similar ban if restricting AI-generated imagery improves platform demand. While we cannot directly observe Swiggy's strategic calculus, several explanations are plausible. First, Swiggy may have positioned AI image tools as a feature that lowers barriers for small restaurants without photography budgets, trading off authenticity against content accessibility. Second, and perhaps most importantly, the relative demand shift we document is only observable through a cross-platform comparison. Without a natural experiment like ours, a platform observing only its own order trends may attribute any slowdown to seasonality, market conditions, or unrelated factors rather than to image policy. We note these explanations are speculative and cannot be tested with our data, but they are consistent with the platform competition literature showing that rivals do not always imitate governance innovations, particularly when switching costs and merchant relationships create path dependence (Armstrong, 2006; Li and Zhu, 2021; He et al., 2023).

This research makes important theoretical contributions. First, it contributes to the literature on algorithms, AI, and consumer trust by examining the impact of platform governance of AI-generated seller content. Prior work has examined how consumers respond to algorithmic decision making and AI-mediated interactions (Kim and Duhachek, 2020). We extend this literature by studying a marketplace setting in which the platform does not deploy AI-generated content itself; instead, it must decide whether and how to govern third-party sellers' use of generative AI in product presentation. In such environments, generative AI may lower content creation costs and improve visual appeal, but it may also make product representations appear less authentic. Our findings suggest that platform restrictions on AI-generated seller content can lead to higher demand. In addition, the paper contributes to the literature on platform competition and marketplace design (Armstrong, 2006; Niculescu et al., 2018). Traditional platform competition research emphasizes prices, network effects, and participation on multiple sides of the market (Mayya and Li, 2025). We show that in digital marketplaces, competition may also depend on how platforms govern the quality and credibility of seller-generated content. In our setting, a platform's policy toward generative AI imagery is associated not only with restaurant-level demand changes but also with user reallocation across rival platforms. This suggests that content-governance choices can function as a strategic dimension of platform differentiation, particularly when consumers face uncertainty about product quality before purchase.

Our research also has important managerial implications. In practice, restaurants may have incentives to use generative AI tools for dish images because these tools can save time and produce more visually appealing images. However, in contexts where consumers rely heavily on the authenticity of images to inform their decisions, the use of AI-generated visuals may backfire and suppress demand. From the platform's perspective, widespread use of generative AI dish images can dilute its brand and undermine consumer trust, potentially driving users toward competing platforms that offer more trustworthy visual content. More broadly, businesses should be cautious when deploying AI-generated content in settings where consumers place a high value on authenticity. Food delivery is the clearest case, but the mechanism plausibly extends to short-term rentals, for example, Airbnb (Zhang et al., 2022), e-commerce product listings, and travel and tourism bookings. Platform operators should therefore carefully govern AI-generated content in marketplaces where visual signals serve as primary pre-purchase quality cues and where information asymmetry between buyers and sellers is substantial.

This paper has several limitations worth acknowledging. First, we do not observe ground-truth information on which restaurants used generative AI to modify dish images prior to the policy change. While this constraint does not undermine the validity of our cross-platform design, since we estimate the average treatment effect of a platform-level generative AI image ban on restaurant sales outcomes, it prevents us from directly examining heterogeneity between adopters and non-adopters. Because some Zomato restaurants may not have used AI-generated images even prior to the ban, and because enforcement and detection classifiers are imperfect, such that some AI images may remain on Zomato post-ban, our estimates should be interpreted as a conservative lower bound on the true demand effect of full AI-image removal.

Second, we do not directly observe the actual reduction or removal of AI images on Zomato following the policy. The restaurant dish images are a snapshot collected after the policy change. Nevertheless, several pieces of indirect evidence support the interpretation that the ban was materially enforced. Following the policy announcement, online discussions continued to highlight concerns about AI-generated images on

Swiggy, whereas comparable complaints about Zomato were rare. In addition, among multi-homing restaurants, roughly 20% display different dish images across platforms, with images on Swiggy being substantially more likely to appear AI-generated than the corresponding images on Zomato, which is a pattern consistent with platform-specific compliance.

Third, we do not observe restaurant entry and exit decisions. Restaurants that previously relied on AI-generated images may have migrated from Zomato to Swiggy following the ban, which would make the post-ban Zomato restaurant pool compositionally different. As a partial check, we restrict the sample to single-homing restaurants, which have purchase records only on one platform. We find results similar to the main results presented in Table 2, which is inconsistent with a composition story driven by cross-platform migration.

Our paper opens several avenues for future work. First, generative AI technologies are evolving rapidly. Although both our study and prior research document consumers' distaste for AI-generated images on platforms and social media (Exner et al., 2025; Hartmann et al., 2025), future generative AI systems may produce images that are only marginally distinguishable from human-taken photographs. As a result, consumer responses to such images may differ from the patterns identified in existing studies. In addition, while we focus on AI-generated images, generative AI is increasingly being used to produce text, video, and interactive content. Understanding whether similar trust and authenticity concerns arise across different content modalities represents an important direction for future research.

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Online Appendix

A News Coverage and Reddit Discussions

A.1 News Coverage of the Generative AI Image Ban

Table A1: Representative Media Coverage of Zomato's Ban on Generative AI Dish Images

Source	Date	Coverage and URL
Economic Times	Aug. 2024	Reports that Zomato banned AI-generated food images following customer complaints and highlights concerns that such images may mislead consumers. Available at: Economic Times article
The Times of India	Aug. 2024	Describes Zomato's decision to prohibit AI-generated dish images and emphasizes the platform's effort to improve authenticity and user trust. Available at: Times of India article
India TV News	Aug. 2024	Covers the customer backlash against AI-generated food images and explains that Zomato responded by removing such images from the platform. Available at: India TV News article
The Indian Express	Oct. 2024	Discusses the broader use of generative AI by Indian consumer platforms, including Zomato's restriction on AI-generated food images. Available at: Indian Express article

Notes: This table summarizes representative news coverage documenting the public salience of Zomato's policy banning generative AI dish images. These sources are used to show that the policy attracted media attention and raised public discussion about the authenticity of food images on delivery platforms.

A.2 Reddit Discussions on AI-Generated Dish Images

Table A2: Representative Reddit Discussions on AI-Generated Dish Images

Platform	Subreddit	Discussion theme	URL
Swiggy	r/swiggy	Users criticize restaurants for posting AI-generated food images and call for restrictions.	`https://www.reddit.com/r/swiggy/comments/1nkf3lv/swiggy_should_restrict_restaurants_putting_ai/`
Swiggy	r/swiggy	Users discuss whether AI-generated burger images on Swiggy are misleading.	`https://www.reddit.com/r/swiggy/comments/1pdslia/so_we_cool_with_ai_burger_images_now/`
Swiggy	r/Chennai	Users react negatively to unrealistic AI-style food images shown on Swiggy.	`https://www.reddit.com/r/Chennai/comments/1k1zlwt/swiggy_out_here_scaring_me_with_ai/`
Swiggy	r/swiggy	Users complain that restaurants use AI to exaggerate food appearance relative to actual delivery.	`https://www.reddit.com/r/swiggy/comments/1qbtzy9/if_restaurants_r_using_ai_to_make_bakwas_food/`

Notes: This table reports representative Reddit discussions illustrating that AI-generated dish images became a salient consumer concern and were more commonly associated with Swiggy after Zomato's policy ban. These discussions are qualitative and illustrative rather than comprehensive measures of AI-image prevalence.

B Examples of Swiggy and Zomato Dish Images

One example is the dish image of "Watermelon Juice" from *Doveton Cafe* [26] The dish image of the watermelon juice on Swiggy is likely to be AI-generated as it is made green, while the Zomato one is red and looks more natural.

Figure B1: Images of "Watermelon Juice" from *Doveton Cafe* (Left Swiggy, Right Zomato)

Another group pair, Figure B2, illustrates forensic diagnostics for representative Chicken Manchow Soup images from the same restaurant (Bombay Seekh Paratha) on Swiggy and Zomato.[27] The Swiggy image exhibits substantially higher sharpness ($\approx$ 124) relative to the Zomato image ($\approx$ 19), indicating stronger edge enhancement and high-frequency amplification. Its residual statistics show a higher mean (1.98 vs. 0.94) and standard deviation (3.71 vs. 1.42), consistent with heavier and more irregular residual structures. In addition, the Swiggy image displays stronger error-level artifacts, with a higher ELA mean (8.39 vs. 6.59) and a larger upper-tail intensity (95th percentile = 30 vs. 20).

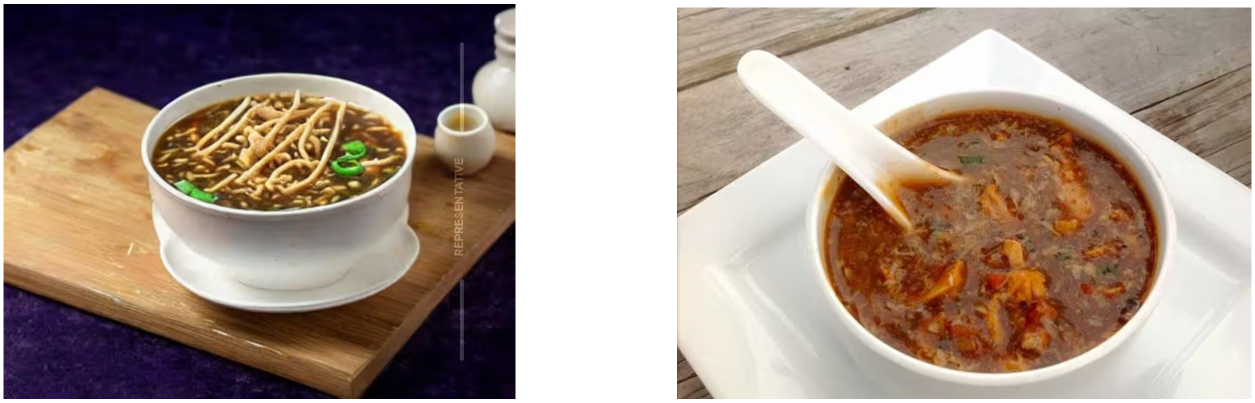
Beyond these statistical diagnostics, the Swiggy image also shows visible qualitative irregularities, including unnatural geometric twists in the background surface and the presence of a "Representative" watermark. Such visual patterns are commonly associated with AI-generated images rather than organic restaurant photography. In contrast, the Zomato image exhibits lower sharpness, weaker residual and ELA signals, and a visually coherent background consistent with casual smartphone photography. Taken together, the forensic evidence and visual cues jointly suggest that the Swiggy image is more likely to have undergone

[26] See `https://www.swiggy.com/city/chennai/doveton-cafe-purasavakkam-purasaiwakkam-rest18341` and `https://www.zomato.com/chennai/doveton-cafe-purasavakkam/order` (accessed December 2025).

[27] URLs: `https://www.zomato.com/pune/bombay-seekh-paratha-kondhwa/order` and `https://www.swiggy.com/city/pune/bombay-seekh-paratha-kondhwa-rest130400` (accessed September 2025).

AI-based generation or enhancement, whereas the Zomato image appears more consistent with an authentic photograph.

Figure B2: Images of "Chicken Manchow Soup" from *Bombay Seekh Paratha* (Left Swiggy, Right Zomato)



C Sample Representativeness Check

We assess the representativeness of our consumer sample by comparing its geographic distribution and revenue trends with those reported in the platforms' investor relations reports.

C.1 Geographic Representativeness of the Consumer Sample

Because our analysis relies on a subset of food delivery consumers, an important concern is whether the geographic distribution of the sample reflects the broader population of India. To assess external validity, we compare the distribution of consumers across Indian states in our dataset with official state-level population statistics for 2024.[28]

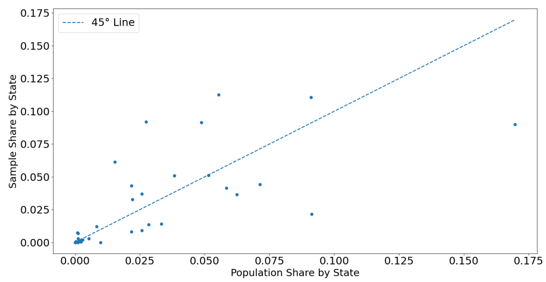
We first aggregate the data at the state level by counting the number of unique consumer accounts in each state, resulting in coverage across 36 Indian states and union territories. We then compute each state's share of consumers in our sample and compare it with the corresponding share of the national population. Figure C1 plots the relationship between population share and sample share. The dashed 45° line represents perfect proportional representation.

Overall, the geographic distribution of consumers closely tracks population distribution across states. The correlation between state population and the number of sampled consumers is 0.7. More developed states are slightly over-represented in the consumer sample, which is natural. Although some deviations remain—which is expected given platform penetration differences across regions—the overall pattern indicates that

[28]See `https://www.noidabusinessguide.com/indian-states-by-population/` (accessed March 2026).

the consumer sample broadly reflects India's population geography, supporting the external validity of our analysis.

Figure C1: Population and Sample Share Comparison by State



C.2 Revenue-Based Representativeness Validation

Beyond geographic coverage, we further assess whether the transaction-level sample captures meaningful platform-level demand dynamics. Because our dataset represents only a subset of platform transactions, the absolute revenue constructed from observed orders is mechanically smaller than the revenue reported in firms' financial statements. Instead of comparing levels, we examine whether revenue movements in the sample track publicly disclosed platform performance.

For both platforms, we aggregate transaction values to the quarterly level and compare the resulting revenue series with food delivery revenue reported in the firms' financial disclosures.[29] Table C1 presents the comparison. Although the sample represents only a small fraction of total platform activity, revenue constructed from transaction-level data tracks publicly reported revenue dynamics closely for both platforms, with correlations of 0.99 for Zomato and 0.89 for Swiggy. Differences in magnitude are expected because platform financial reports include additional monetization channels, such as advertising and subscription services, that are not observable in our dataset.

Table C1: **Quarterly Platform Revenue Comparison (in 10 million Indian Rupees)**

Year–Quarter	Zomato Reported	Zomato Sample	Swiggy Reported	Swiggy Sample
2024Q2	2,256.00	0.64	1,730.00	0.60
2024Q3	2,340.00	0.68	1,808.00	0.63
2024Q4	2,413.00	0.71	1,860.00	0.63
Correlation		0.994		0.896

[29]See `https://www.swiggy.com/corporate/wp-content/uploads/2025/10/Q2-FY2026-Shareholder-letter.pdf` and `https://b.zmtcdn.com/investor-relations/Eternal_Shareholders_Letter_Q3FY26_Results.pdf` (accessed March 2026).

D Seasonality Adjustment

Food delivery demand exhibits pronounced seasonal patterns throughout the year. Factors such as holidays, weather conditions, and vacation periods can systematically influence ordering behavior and generate recurring fluctuations in order volume.

To address this, we construct a seasonality-adjusted outcome using an extended sample spanning August 2023 to February 2025. The longer panel allows us to estimate stable recurring monthly patterns separately for each platform. Specifically, we estimate platform-by-calendar-month fixed effects that capture the typical demand level associated with each month of the year for a given platform.

Formally, the seasonality-adjusted outcome is constructed as

$$\tilde{Y}_{pmt} = Y_{pmt} - \widehat{\lambda}_{p,m} + \overline{Y}_p,$$

where Y_{pmt} denotes the raw average monthly order volume on platform p in calendar month m at year-month t, $\widehat{\lambda}_{p,m}$ is the estimated calendar-month effect for platform p, and $\overline{Y}_p$ is the platform-specific mean order volume over the extended sample period. The term $\widehat{\lambda}_{p,m}$ captures recurring month-of-year demand patterns (e.g., higher demand during festive seasons or lower demand during off-peak months). Subtracting this component removes predictable seasonal variation. We then add back the platform-specific mean $\overline{Y}_p$ to preserve the overall level of the series, ensuring that the adjusted outcome remains directly comparable to the original scale.

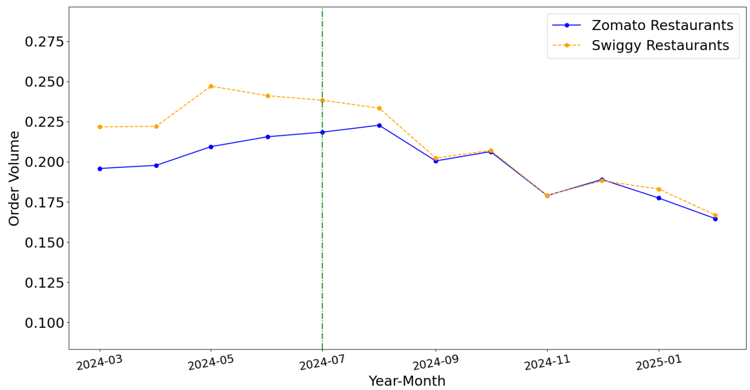
Intuitively, this procedure isolates deviations from a platform's typical seasonal demand pattern. As a result, differences observed in the adjusted series primarily reflect structural changes in demand rather than predictable seasonal fluctuations. This adjustment allows us to interpret post-policy changes in order volume as policy-related divergence between platforms rather than artifacts of seasonal demand shifts.

Our approach follows standard seasonal adjustment practices widely used in macroeconomic time-series analysis, such as those employed by the U.S. Bureau of Labor Statistics and the International Monetary Fund, which remove recurring calendar patterns while preserving the underlying level and trend of the series (Lee, 2017).

We do not use an extended panel in the regression because it would include periods in which AI image tools were either not yet available or only recently introduced.

D.1 Model-Free Evidence before Adjusting Seasonality

Figure D1: Average monthly order volume per restaurant on two platforms in India (raw series)



Notes: This figure shows the raw monthly averages without seasonality adjustment. The overall pattern is similar to Figure 3, but both platforms exhibit a mild decline after the summer break months, reflecting common seasonality in food delivery demand as well as the intermittent nature of food delivery usage, rather than a response to the policy change (U.S. Department of Agriculture, 2025). July 2024, which is the last month before the policy change, is marked by the green dotted vertical line.

E Restaurants' Customer Number

This subsection analyzes the policy change's impact on consumer traffic. The dependent variables that we employ include the number of total consumers, which is measured by the number of unique consumer IDs that have purchase records on platform j in week t, the number of new consumers, and the number of returning consumers. New and returning consumers are defined as discussed in Section 5.2, depending on whether they are first-time buyers from restaurant r or not. We re-run the regression model 1 and the results are presented in Table E1. We find that the policy change has a positive impact on the number of total, new, and returning consumers. The effect is larger for the number of new consumers, in line with the order source analysis results presented in Section 5.2.

Table E1: **Consumer Source Analysis**

	(1) Num Customers	(2) Num New Customers	(3) Num Returning Customers
Treat × PostPolicy	0.00507***	0.00390***	0.00117***
	(0.000629)	(0.000385)	(0.000449)
Platform-Restaurant FE	Yes	Yes	Yes
YearWeek FE	Yes	Yes	Yes
Observations	3112690	3112690	3112690
R^2	0.069	0.013	0.120

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F Validation of Image Forensic Measures on Human-made and AI-generated Images

Before applying image forensic measures to platform restaurant images, we first assess the reliability and discriminative power of these measures in a controlled setting with known ground truth labels. Specifically, we compare forensic statistics computed on human-generated food photographs against images generated by a state-of-the-art text-to-image model.

Our human image benchmark consists of 75,750 dish images drawn from the training split of the Food-101 dataset available via Hugging Face. Created in the pre-GPT era of the 2010s, food-101 contains high-quality, real-world food photographs spanning 101 dish categories and is widely used in computer vision research. These images serve as a clean reference set of human-captured food photographs with no generative manipulation.

We generate a synthetic dataset of 12,000 food images using Stable Diffusion XL (SDXL). The goal is to create images that resemble food delivery platform listing photos (i.e., centered dishes, clean backgrounds, realistic lighting) while maintaining systematic variation in dish types. The generation procedure is as follows.

Step 1: Construct a dish-name seed list from platform data. We start from our merged dish-level dataset and standardize menu metadata collected from Swiggy and Zomato websites. We clean the raw "Item Category" strings and map them into canonical menu buckets (e.g., *Beverages, Desserts & Bakery, Rice & Biryani, Fried Rice & Noodles, Pizza, Rolls, South Indian, Chinese, Main Course*), dropping purely promotional/UI sections (e.g., "Recommended," "Top Picks," "Offers"). We then clean dish names by removing non-informative tokens (e.g., "combo," "deal," "free"), truncating trailing add-ons (e.g., "with . . ."), and removing punctuation. Within each bucket, we rank dishes by frequency and select a diverse seed set that combines (i) the top 30 most frequent dish names and (ii) 20 additional dishes sampled from the remaining tail. Finally, for each selected dish name, we assign a *primary cuisine* label based on the most common cuisine associated with that dish in the underlying data (using the first cuisine tag when multiple cuisines are listed). This procedure yields a broad set of dish prompts spanning multiple buckets and cuisines, consisting of 13 buckets corresponding to 626 unique dish names.

Step 2: Prompt templates designed to mimic delivery-app photography. For each dish, we generate multiple images using a rotating set of prompt templates that explicitly request photorealistic, smartphone-like menu photos. The templates vary in composition and context, but keep the photographic intent constant. The four typical prompt take the form:

- "A realistic food delivery app menu photo of {dish}, {cuisine} cuisine, {bucket}, served in a takeaway container, {angle}, natural lighting, plain background, high detail, sharp focus",
- "A smartphone photo for a food delivery listing: {dish}, {cuisine} cuisine, {bucket}, in a plastic takeaway box, {angle}, realistic colors, slight JPEG compression",
- "A restaurant listing photo of {dish} ({cuisine} cuisine), {bucket}, {angle}, appetizing, studio lighting, no people, no text, realistic food photography",
- "A realistic food delivery platform dish image of {dish}, {cuisine} cuisine, {bucket}, {angle}, centered composition, clean background, photorealistic".

We rotate across four such templates and three camera angles (*top-down, 45-degree, close-up*) to avoid over-fitting to a single visual style.

For each image, we compute three complementary forensic statistics commonly used in digital image forensics: (i) the mean Error Level Analysis (ELA) value, which captures compression inconsistencies indicative of post-processing; (ii) image sharpness, which reflects high-frequency edge content and texture; and (iii) the standard deviation of GAN residuals, which measures dispersion in model-specific noise patterns rather than mean bias.

Figure F1 compares the distributions of these three measures across human and AI-generated images. Across all dimensions, AI-generated images exhibit clear and systematic shifts relative to human photographs. SDXL images display substantially higher ELA means, consistent with non-uniform compression artifacts introduced during generation. They are also significantly sharper on average, reflecting the tendency of generative models to over-emphasize high-frequency detail. Finally, GAN residuals for AI images exhibit greater dispersion, indicating stronger synthetic noise signatures even when images appear visually realistic.

Collectively, these results demonstrate that the forensic measures used in our analysis reliably distinguish AI-generated food images from human-captured photographs in a controlled benchmark. This validation provides confidence that subsequent variation in forensic scores observed in real-world restaurant images reflects meaningful differences in generative manipulation rather than noise or dataset artifacts.

Table F1: **Sample Descriptive Statistics of Forensic Image Measures**

Dataset	Variable	Count	Mean	Median	Min	Max
Food101 (Human-Made)	ELA Mean	75750	8.880	8.674	1.170	28.361
AI-Generated	ELA Mean	12000	20.788	20.707	8.371	38.222
Food101 (Human-Made)	Sharpness	75750	657.542	485.757	5.081	13362.858
AI-Generated	Sharpness	12000	745.670	674.055	40.923	6979.533
Food101 (Human-Made)	Residual Std	75750	5.298	5.053	0.450	21.351
AI-Generated	Residual Std	12000	5.553	5.434	1.536	16.819

Figure F1: Distribution of forensic image statistics for human and AI-generated food images.

Notes: The figure reports boxplots of (i) mean Error Level Analysis (ELA), (ii) image sharpness, and (iii) standard deviation of GAN residuals. Human images are drawn from the Food-101 training dataset, while AI images are generated using SDXL based on real dish names. Boxes indicate interquartile ranges.

It is worth noting that many images deployed on food delivery platforms may not be generated from text prompts, but are instead produced via image-to-image generative pipelines that modify an existing photograph. These workflows, including background replacement, lighting normalization, style transfer, and image blending, preserve a foreground dish while algorithmically synthesizing other visual elements.

From a forensic perspective, however, such AI-modified images remain generative outputs: the final pixels are produced by diffusion-based models rather than captured directly by a camera sensor. As illustrated and documented in platform disclosures, these approaches substitute text-to-image generation with image-conditioned generation, without altering the underlying generative mechanism.[30] In other words, "AI-modified" dish images are still "AI-generated" images; the difference lies only in whether generation occurs via text-to-image or image-to-image models.

G Validation of AI Likelihood Scores on Human-made and AI-generated Images

In addition to low-level forensic statistics, we further validate the behavior of AI likelihood detectors using the same benchmark images with known ground truth. The goal is to assess whether detector outputs exhibit systematic and interpretable separation between human-captured food photographs and AI-generated images, rather than to claim perfect classification.

We apply three independent AI likelihood detectors to all images in the benchmark dataset described in Section 7.2. Each detector produces a continuous score in $[0, 1]$, where higher values indicate a higher likelihood that an image is AI-generated. Detectors differ in architecture and training data, allowing us to assess robustness across detection approaches. Importantly, all detectors are applied *out-of-sample* to Food-101 human-taken dish images and SDXL-AI-generated dish images.

Figure G1 reports violin plots of the detector score distributions for human and AI images. Across all three detectors, the distributions exhibit clear and systematic shifts in central tendency between the two image sources.

For Detector 1, AI-generated images have a noticeably higher mean AI likelihood score than human images (median $\approx$ 0.31 vs. 0.20), despite substantial overlap in the lower tail. This pattern suggests a conservative detector that assigns moderate AI probability even to some human images, but still exhibits meaningful mean separation. Detector 2 exhibits much stronger separation: the mean AI likelihood score for AI-generated images is effectively one, while the corresponding mean for human images is approximately 0.54. This pattern reflects a detector that is highly sensitive to generative artifacts but assigns nontrivial AI probability to some high-quality human food photographs, likely due to stylization or professional lighting. Detector 3 displays the largest mean gap between human and AI images, with human images having a mean AI likelihood close to zero and AI-generated images having a mean of 0.75. At the same time,

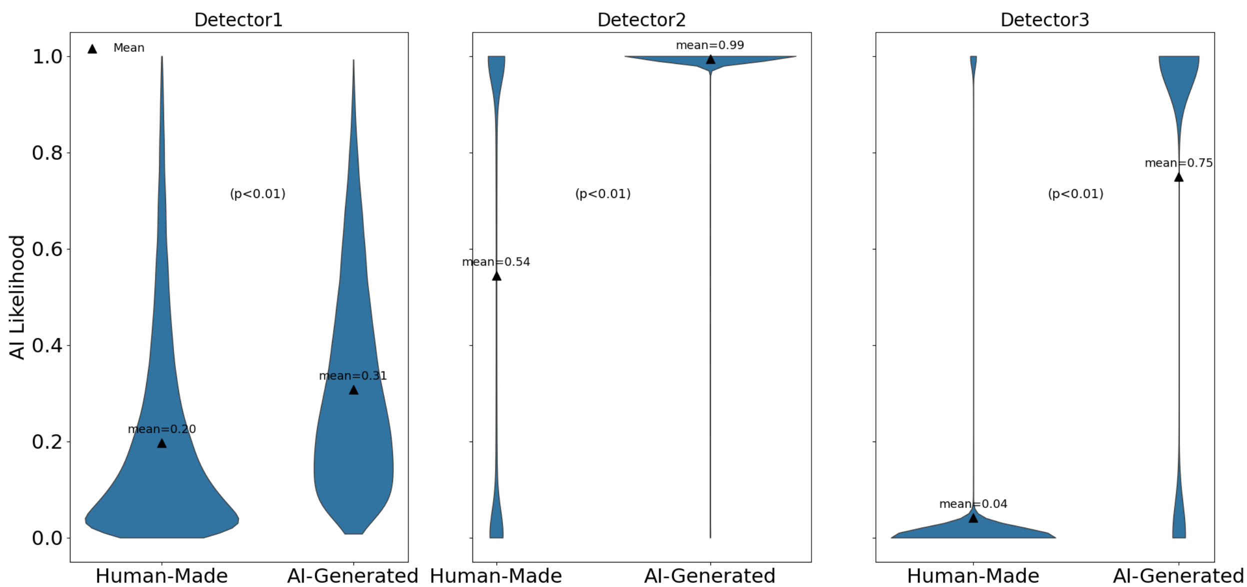
[30] e.g., Swiggy's generative AI photo enhancement pipeline in `https://bytes.swiggy.com/reflecting-on-a-year-of-generative-ai-at-swiggy-a-brief-review-of-achievements-learnings-and-13a9671dc624` (accessed January 2026).

the distribution exhibits heavier tails for both image types, indicating occasional false positives and false negatives. This behavior suggests strong discrimination on benchmark data, but also highlights potential calibration sensitivity outside controlled settings.

Across detectors, the mean AI likelihood score consistently ranks AI-generated images well above human photographs. While the full distributions overlap, which reflects both detector conservatism and visual similarity between photorealistic AI images and professional food photography, the mean separation is large and stable. This property is particularly important for our empirical analysis, which relies on relative variation in AI likelihood scores across restaurants and images rather than binary classification.

Overall, this validation confirms that AI likelihood scores behave in an economically and statistically meaningful way when applied to food images, supporting their use as continuous measures of generative intensity in real-world platform data.

Figure G1: Distribution of AI likelihood scores for human and AI-generated food images.

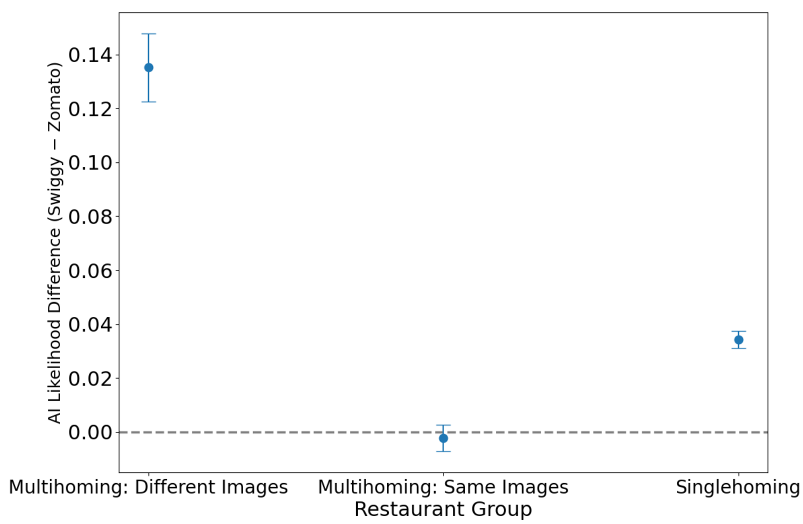


Notes: The figure reports violin plots of AI likelihood scores from three detectors applied to Food-101 human images and SDXL-generated images. Black dots indicate mean values. Scores range from 0 to 1, with higher values indicating a higher likelihood of AI generation.

While Detector 3 exhibits the strongest separation on this benchmark dataset, we retain all three detectors in our main analysis rather than selecting a single preferred detector. First, this section is intended as a validation exercise using images with known ground truth, not as a model-selection or accuracy comparison. Our objective is to verify that *multiple* independently trained detectors exhibit systematic and interpretable differences between human and AI images. Second, detectors are known to vary in calibration, conservatism, and false-positive behavior across image domains. In particular, detectors that perform extremely well on controlled benchmark images may be less stable when applied to heterogeneous, real-world restaurant imagery. Consistency of results across detectors therefore provides stronger evidence that observed patterns reflect genuine generative artifacts rather than the idiosyncratic behavior of any single model. Importantly, all three detectors point in the same direction, showing statistically meaningful and economically interpretable differences between human and AI images, which motivates our use of multiple AI likelihood measures in the main empirical analysis.

G.1 AI Likelihood Comparison by Restaurant Multi-homing Status and Image Consistency across Platforms

Figure G2: AI Likelihood Difference



H LLM Prediction Details and Results

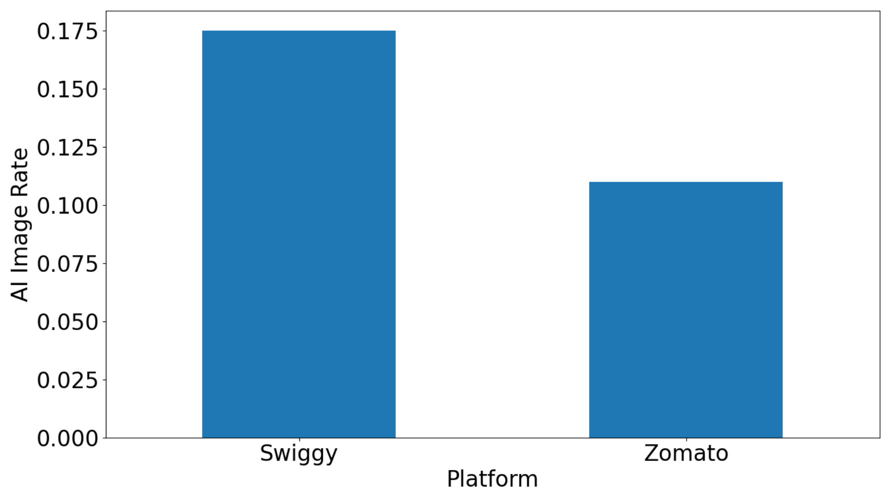
To complement the classifier-based and forensic analyses, we implement an LLM-based image labeling approach to assess whether dish images are likely to be generated by generative AI. We use a vision-enabled large language model (LLM) in a zero-shot setting, prompting the model to classify each image as either AI-generated or not, and to provide a brief explanation based on visual cues.[31] The backbone Large Language Model that we employ is GPT-5.4.

[31] We adopt a zero-shot setting because ground-truth labels for AI-generated dish images on the two platforms are not available. Using few-shot examples constructed from platform-specific images could introduce unintended biases and reduce the generalizability of the classification across platforms.

We apply the LLM-based classification to a random sample of 200 dish images from each platform (Swiggy and Zomato).[32] The model is prompted with a standardized instruction to evaluate whether an image appears AI-generated, based on characteristics such as texture consistency, lighting realism, object boundaries, and overall visual coherence. All classifications are conducted independently for each image, without using platform identifiers.

Figure H1 presents the share of images classified as AI-generated by the LLM for each platform. We find that Swiggy images are more likely to be labeled as AI-generated than Zomato images (17.5% vs. 11.0%), consistent with the patterns documented using classifier-based detection methods. This provides additional evidence that images on Swiggy exhibit stronger signatures associated with AI generation or heavy post-processing.

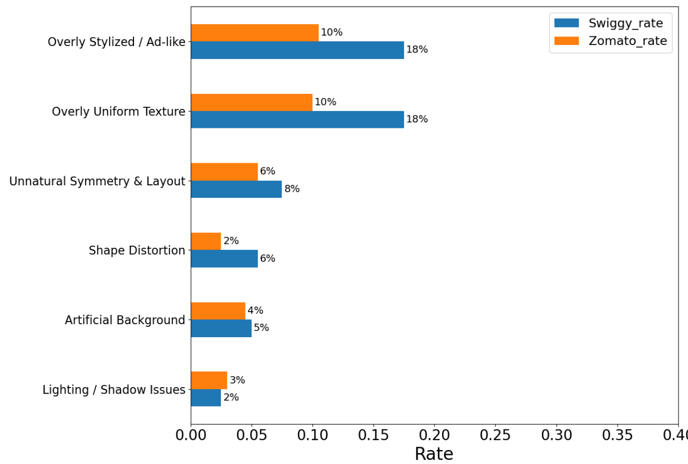
Figure H1: AI Image Rate Prediction by LLM



Beyond binary classification, the LLM also provides structured explanations highlighting the visual features that contribute to its predictions. Figure H2 summarizes the frequency of key visual indicators identified by the model across platforms. The most commonly cited features are "overly stylized or advertisement-like appearance" and "overly uniform texture," both of which appear more frequently for Swiggy images (18% vs. 10% for each). Swiggy images are also more frequently associated with unnatural symmetry (8% vs. 6%) and shape distortion (6% vs. 2%). Differences for other features, such as artificial background (5% vs. 4%) and lighting or shadow issues (2% vs. 3%), are relatively small.

[32] This sample size reflects a tradeoff between labeling cost and coverage, as LLM-based image evaluation incurs non-trivial computational expenses. Despite the relatively small sample, the random sampling design ensures representativeness of the underlying image distribution.

Figure H2: Visual Features Associated with AI-Generated Images



These patterns align closely with the forensic diagnostics and AI detection models reported in the main text. In particular, features such as uniform texture and symmetry are consistent with the high-frequency amplification and residual patterns observed in synthetic images. Importantly, the visual features identified by the LLM are salient and interpretable, suggesting that they may also be observable to consumers when browsing dish images. This provides a potential mechanism through which AI-generated images could influence consumer perceptions of authenticity and quality.

I Construction of CLIP and Aesthetic Image Measures

To characterize visual properties of restaurant dish images, we construct two complementary measures based on pretrained vision–language models.

I.1 CLIP Embeddings

A defining feature of AI-generated dish images relative to human-taken photographs is that they are produced by systems optimized to closely condition on textual prompts. Modern image-generation models are trained on large-scale image–text pairs and are explicitly optimized to produce visuals that semantically match a given description. As a result, AI-generated images tend to exhibit a high degree of consistency with menu text, often presenting dishes in an idealized and literal manner. Anecdotal evidence also suggests that Swiggy restaurants may just use dish names and descriptions when generating AI-images.[33] Hence, theoretically, on Swiggy, higher consistency between dish images and dish text descriptions may potentially indicate a higher possibility of generative AI usage of the dish images.

[33]See `https://tinyurl.com/mryrvcef` (accessed December 2025).

To examine this mechanism, we leverage a multi-modal similarity measure based on CLIP embeddings, which capture the semantic alignment between dish images and their corresponding text descriptions. CLIP (Contrastive Language–Image Pre-training) is a state-of-the-art multi-modal representation learning framework proposed by a group of researchers at OpenAI (Radford et al., 2021). The core idea of CLIP is to jointly embed unstructured data from different modalities, most commonly images and text, into a shared latent space, such that semantically aligned image-text pairs are positioned closer together than mismatched pairs.

Formally, let I denote an image and T denote its corresponding textual description. CLIP consists of an image encoder $f(\cdot)$ and a text encoder $g(\cdot)$, which map the two modalities into a common d-dimensional embedding space:

$$\mathbf{v}_I = f(I), \quad \mathbf{v}_T = g(T). \tag{I1}$$

The semantic alignment between an image and a text description is measured using cosine similarity:

$$\text{CLIPScore}(I, T) = \cos(\mathbf{v}_I, \mathbf{v}_T) = \frac{\mathbf{v}_I^\top \mathbf{v}_T}{\|\mathbf{v}_I\| \, \|\mathbf{v}_T\|}. \tag{I2}$$

CLIP Scores range from -1 to 1. Higher cosine similarity indicates stronger semantic consistency between the image and its associated text, while lower similarity reflects weaker alignment or potential mismatch across modalities.

For each restaurant, we compute the average CLIP similarity score across all dish image–text pairs, capturing the overall degree of AI-likeness in menu presentation.

I.2 Aesthetic Score

While CLIP similarity captures semantic alignment between dish images and textual descriptions, it does not directly measure perceived visual quality or stylistic appeal. To complement the semantic measure, we construct an aesthetic ("beauty") score that proxies for perceived photographic quality using a pretrained model developed on large-scale internet image datasets.

The aesthetic predictor follows a two-stage architecture widely adopted in the computer vision literature. First, each image is encoded into a high-dimensional representation using a pretrained CLIP image encoder. Let $\mathbf{v}_I = f(I)$ denote the CLIP embedding of image I, where $f(\cdot)$ maps the image into a shared semantic feature space learned from large-scale image–text pairs. Second, a lightweight regression head $h(\cdot)$ is applied to the frozen CLIP embedding to predict human aesthetic ratings:

$$\text{BeautyScore}(I) = h(\mathbf{v}_I). \tag{I3}$$

The regression head is trained on datasets in which images receive human-provided aesthetic scores, allowing the model to learn visual attributes commonly associated with perceived photographic quality, such as composition, lighting, color balance, and depth-of-field.

The aesthetic model is not trained to detect generative AI content. Instead, it predicts how closely an image resembles visual styles that are prevalent and positively rated in large-scale internet photography. As a result, the Aesthetic Score reflects "web-native" aesthetic preferences rather than an objective measure of beauty or authenticity. Images that conform to stylized online conventions, such as highly saturated colors, exaggerated textures, or overly symmetric plating, may receive higher or lower aesthetic scores depending on how closely they resemble human-photographed examples in the training data.

For each restaurant, we compute the average aesthetic score across all dish images to capture its overall visual presentation style. Conceptually, this measure allows us to distinguish between two mechanisms. High CLIP similarity indicates that an image closely matches prototypical food representations conditioned on text descriptions, while the aesthetic score reflects perceived photographic realism and stylistic quality. Because generative AI systems often optimize for semantic alignment rather than authentic photographic signals, AI-generated dish images may exhibit high CLIP similarity without corresponding increases in aesthetic ratings.

This distinction is particularly relevant in the context of food delivery platforms. Consumers rely on dish images as credibility signals regarding taste, portion size, and preparation quality. If AI-generated images emphasize idealized or standardized visual patterns at the expense of authenticity, consumers may interpret them as less trustworthy even when they appear visually polished. The aesthetic measure, therefore, complements the CLIP-based alignment score by capturing how closely restaurant imagery resembles human-photographed food visuals rather than algorithmically stylized renderings.

J Robustness Check Results and Additional Regression Result Tables

J.1 Single-Homing Restaurant Sub-Sample Estimation Results

Table J1: **Single-Homing Restaurants**

	(1) Order Volume
Treat × PostPolicy	0.00567***
	(0.000832)
Platform-Restaurant FE	Yes
YearWeek FE	Yes
Observations	2749004
R^2	0.082

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J.2 Alternative Specification: Multi-Homing Restaurants as the Treated Sample

Table J2: **Policy Impact on Multi-Homing Restaurants: Alternative Specification**

Image Type Across Platforms	Different-Dish-Image Restaurants	Same-Dish-Image Restaurants
Dependent Variable	Order Volume	Order Volume
Treat × PostPolicy	0.0211*	0.00655
	(0.0118)	(0.00898)
Constant	0.0434***	0.0637***
	(0.00340)	(0.00250)
Platform-Restaurant FE	Yes	Yes
YearWeek FE	Yes	Yes
Observations	9116	28461
R^2	0.054	0.088

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J.3 Controlling for Image Aesthetics

Table J3: **Moderating Effect of Dish Image AI Likelihood Controlling for Dish Image Aesthetics**

Control Group Restaurant Type	Low-AI-Likelihood Swiggy Restaurants	Moderate-AI-Likelihood Swiggy Restaurants	High-AI-Likelihood Swiggy Restaurants
Dependent Variable	Order Volume	Order Volume	Order Volume
Treat × PostPolicy	0.0121	0.0229*	0.0265**
	(0.00866)	(0.0121)	(0.0107)
Restaurant Image Aesthetics × PostPolicy	0.00211	0.000284	0.00511
	(0.00436)	(0.00428)	(0.00444)
Platform-Restaurant FE	Yes	Yes	Yes
YearWeek FE	Yes	Yes	Yes
Observations	49396	49396	49608
R^2	0.068	0.075	0.066

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J.4 Robustness Check on Restaurant Quality

Table J4: **Robustness Check on Restaurant Quality**

Control Group Restaurant Type	Budget Swiggy Restaurants	Expensive Swiggy Restaurants	Low-Rating Swiggy Restaurants	High-Rating Swiggy Restaurants
Dependent Variable	Order Volume	Order Volume	Order Volume	Order Volume
Treat × PostPolicy	0.0219**	0.0195***	0.0411***	0.0108*
	(0.00859)	(0.00711)	(0.0122)	(0.00568)
Platform-Restaurant FE	Yes	Yes	Yes	Yes
YearWeek FE	Yes	Yes	Yes	Yes
Observations	62540	68476	61109	69907
R^2	0.066	0.065	0.066	0.066

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J.5 Order Size

Table J5: **Impact of the Policy Change on Restaurants' Order Size**

	(1) Avg Number of Dishes Per Order
Treat × PostPolicy	-0.0461
	(0.0321)
Platform-Restaurant FE	Yes
YearWeek FE	Yes
Observations	93482
R^2	0.538

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J.6 Alternative Control Group - Revenue as the Dependent Variable

Table J6: **Alternative Control Group Estimation Results - Revenue**

Control Group Restaurant Type	Different-Dish-Image Swiggy Restaurants as Control	Same-Dish-Image Swiggy Restaurants as Control
Dependent Variable	Revenue	Revenue
Treat × PostPolicy	17.55***	-1.265
	(6.566)	(5.575)
Constant	9.491***	20.21***
	(3.520)	(2.816)
Platform-Restaurant FE	Yes	Yes
YearWeek FE	Yes	Yes
Observations	54537	57876
R^2	0.076	0.080

Notes: Robust standard errors, clustered at the restaurant level, are presented in parentheses.

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