

When Social Proof Becomes Demand: Price Resistance and Consumer Behavior in Viral Food Trends

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ABSTRACT: Recently, certain foods like Dubai chocolate have exploded in popularity across social media platforms, despite these viral products being more expensive than normal products. But what exactly is the driving force behind participating in these viral food trends? This study examines whether social proof, defined as trying a viral food because others posted about it, talked about it, or recommended it, reduces price resistance in viral food markets. This study is grounded in theories such as informational cascades, social influence, media richness, and fear of missing out, along with surveying 271 students and adults in the Chicago area in a short survey with questions involving social media, price resistance, and what influenced participation in food trends. The survey data were then put into logistic regression models to determine significance and correlation. The analysis supports that social proof is strongly associated with lowering consumers' price resistance. However, social proof was found not to be a statistically significant predictor of repeat purchasing or posting and sharing behavior. Instead, purchase frequency was found to be the strongest predictor of both repeat purchasing and sharing, suggesting that long-term demand, unlike short-term demand, which depends on social proof, depends more on consumer habit and experience. Overall, the findings show that social proof is most powerful in generating initial demand for viral food products, but its effects weaken after the first purchase.

KEYWORDS: Economics, Behavioral Economics, Consumer Behavior, Social Proof, Viral Food Trends.

■ Introduction

The year 2025 saw the rise of certain viral food trends such as matcha, Dubai chocolate, Crumbl cookies, and protein snacks. More recently, even simple products like Dot cakes, which are just plain cakes with sprinkles, are exploding online. These foods became so widespread that they were and still are widely circulated across platforms such as TikTok, Instagram, and YouTube, and businesses and consumers alike were trying their best to participate in these trends. However, these food items are usually priced higher than items that aren't viral but otherwise similar in taste. For example, Dubai chocolate generally costs between \$15 and \$30, whereas a normal Hershey's bar costs just \$1.50. Crumbl cookies can cost up to almost \$7 a cookie, compared to one of their competitors, Insomnia Cookies, which only charges \$3.50 per cookie. Yet, despite these high prices, the consumer demand does not seem to be slowing down. Looking through an economics lens, the high demand and widespread adoption of these foods reflect how social media is able to influence consumer demand. Consumers are not just influenced by taste but also by visual appeal and peer influence.

This study focuses on social proof as a central driver of consumer behavior in viral food markets. Social proof is defined here as trying a viral food because other people posted about it, talked about it, or recommended it. The main research question is whether social proof reduces consumers' price resistance in viral food markets. To answer this question, surveys were sent out to high school students and adults in the Chicago area, and their responses were collected, measuring exposure to viral

food trends, social proof, perceived overpricing, repeat purchasing, willingness to pay, and social media influence.

This study is grounded in several theories combining ideas like consumer utility theory, informational cascades, social influence, media richness, scarcity, prospect theory, and fear of missing out (FOMO). In a simple utility framework, a consumer purchases when the perceived utility of buying exceeds the perceived cost:

$$\text{ConsumerUtility}_i = \text{TasteUtility}_i + \text{SocialParticipationUtility}_i + \text{Scarcity/FOMOUtility}_i + \text{InformationSignal}_i - \text{PriceCost}_i$$

Social proof can increase the nonprice utility of a purchase by making a product appear more popular, trustworthy, urgent, and socially meaningful. Herd behavior and informational cascade theories explain why consumers may rationally imitate others when product quality is uncertain. Because cascades can form from a small number of early signals, they also help explain why viral food products can become popular quickly and then lose attention just as quickly.^{1,2}

Social influence theory adds that consumers may respond to others through compliance, identification, and internalization. In viral food markets, internalization occurs when consumers treat reviews, ratings, and influencer recommendations as useful information; identification occurs when consumers try foods to feel connected to a broader trend community; and compliance occurs when consumers respond to perceived social pressure or urgency.³ Media richness theory further helps explain why short videos, photos, and influencer posts are powerful for food products: these formats can communicate taste, texture, atmosphere, and emotional reaction more effectively than text-only information.⁴

Empirical studies provide added support for these theories. Prior research on digital engagement suggests that social media advertisements, electronic word of mouth (e-WOM), and social media influencers can increase consumer responsiveness in the food and beverage industry.⁵ Viral marketing research also suggests that useful, credible, and informative content can strengthen consumer attitudes and purchase intentions.⁹ These mechanisms matter because they show how consumers may use posts, comments, reviews, and ratings as external signals of product value, because they are initially unable to fully evaluate taste, quality, or experience themselves.

Viral food purchases may also provide additional utility from participation. Consumers may buy a product to post about it, discuss it with peers, or feel included in a trend. Research on coffee shops, for example, shows how businesses use social media to build brand awareness, trust, and loyalty, while using their visually appealing spaces to encourage customers to visit, take photos, and post about it online.⁶ As these posts gain views, they increase the visibility of the product and the experience associated with it, making more people want to participate. Social media can also intensify FOMO by making other people's purchases and experiences highly visible, creating urgency and an increasing desire to participate. When a food product is framed as limited in time or quantity, consumers may interpret not buying as losing a desirable opportunity. Prospect theory helps explain this behavior because anticipated losses may feel more psychologically powerful than equivalent gains.^{7,8}

This study contributes to the literature and previous studies by testing whether social proof is associated with lower price resistance in a specific consumer context: viral food markets. It also separates initial purchase from repeat purchase and posting behavior. The study tests three hypotheses: H1, social proof is positively associated with purchasing a viral food despite perceiving it as overpriced; H2, social proof is positively associated with repeat purchasing; and H3, social proof is positively associated with posting or sharing viral food content.

■ Methods

Using a cross-sectional survey design, two Google Form surveys were sent out, one to high school students and one to adults in the Long Grove/Chicago, Illinois, area. The combined consumer sample includes 271 respondents, consisting of 79 students and 192 adults. Due to a few respondents skipping specific questions, some variables have smaller observation counts. The survey was designed to measure whether social proof is associated with three consumer outcomes: purchase despite perceived overpricing, repeat purchase, and posting or sharing behavior.

The survey design was informed by three case examples of viral food trends: Dubai chocolate, matcha, and Crumbl. Dubai chocolate illustrates how online visibility and scarcity can transform a niche product into a high-demand viral item, with major retailers and food chains later responding to the trend.¹⁰ Matcha illustrates a trend that combines visual appeal, health identity, and sustained market growth, shown through the long-lasting attention and continued product adoption by food businesses.^{11,15} Crumbl illustrates how rotating flavors,

distinctive packaging, and frequent social media reviews can turn limited-time flavors into recurring engagement, despite criticism that the product may be overhyped.^{16,17}

Table 1 defines the consumer variables and reports descriptive statistics. For binary variables, the mean represents the proportion of respondents coded as 1. Variable coding was harmonized across student and adult survey files so that similar concepts with different question wording were represented by standardized binary or ordinal variables (Table 2).

Table 1: Consumer variable definitions and descriptive statistics. Descriptive statistics show that social proof and social media exposure were common in the sample, as 75.2% of valid respondents reported that they tried a viral food because others posted, talked about, or recommended it, and 68.3% first encountered viral food trends through social media. However, only 19.0% reported posting or sharing viral food content, suggesting that consumers were more likely to be influenced by viral food trends than to actively spread them.

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
OverpricedPurchase	Whether the respondent purchased a viral food even though they believed it was overpriced.	269	0.595	0.492	0	1
SocialProof	Whether the respondent tried a viral food because others were posting about it, talking about it, or recommending it.	270	0.752	0.433	0	1
RepeatPurchase	Whether the respondent continued buying a viral food at least occasionally after the first purchase.	265	0.577	0.495	0	1
FOMO/Urgency	Whether the respondent said food trends feel limited-time, urgent, or time-sensitive.	266	0.549	0.499	0	1
FirstSocialExposure	Whether the respondent first learned about or saw viral food trends through a social media platform.	271	0.683	0.466	0	1
PostShare	Whether the respondent posted or shared a trending food on social media.	269	0.190	0.393	0	1
TasteReason	Whether taste was selected as a reason for continued purchasing.	271	0.878	0.328	0	1
Student	Whether the respondent belongs to the student survey sample.	271	0.292	0.455	0	1
SocialMediaInfluence	Self-reported level of social media influence on food-trend decisions, coded from 0 to 4.	270	1.348	1.004	0	4
PurchaseFrequency	Frequency of purchasing viral or trending foods, coded from 0 to 4.	270	1.548	0.860	0	4
MaximumWTP	Maximum willingness to pay for a viral food item, coded in dollars.	270	13.778	7.843	0	40

Note. For binary variables, the mean represents the proportion of respondents coded as 1. For example, the mean of SocialProof is 0.752, meaning approximately 75.2% of valid respondents reported trying a viral food because others posted, talked about, or recommended it. MaximumWTP is coded as follows: adult responses of 0 are coded as 0; "under \$5" = 5; "~\$10" = 10; "~\$20" = 20; "~\$30" = 30; student "no limit" responses are coded as 40.

Table 2: Variable construction and coding.

Variable	Coding
OverpricedPurchase	1 = purchased despite believing item was overpriced; 0 = did not
RepeatPurchase	1 = purchased again after first trial; 0 = did not
PostShare	1 = posted/shared viral food online; 0 = did not
SocialProof	1 = tried because others posted/recommended/talked about it; 0 = no
Student	1 = student respondent; 0 = adult respondent
PurchaseFrequency	0 (never) to 4 (very often)
MaximumWTP	0–40 scale from willingness-to-pay categories
SocialMediaInfluence	0 (not influential) to 4 (extremely influential)
FirstSocialExposure	1 = first learned via social media; 0 = otherwise

The primary model tests whether social proof reduces price resistance by increasing the probability that consumers purchase a viral food despite perceiving it as overpriced. Let $P_{op,i}$ represent the probability that respondent i purchased a viral food despite perceiving it as overpriced:

$$P_{op,i} = \Pr(\text{OverpricedPurchase}_i = 1)$$

The model is specified as:

$$\ln(P_{op,i} / (1 - P_{op,i})) = \beta_0 + \beta_1 \text{SocialProof}_i + \beta_2 \text{Student}_i + \beta_3 \text{PurchaseFrequency}_i + \beta_4 \text{MaximumWTP}_i + \beta_5 \text{SocialMediaInfluence}_i + \beta_6 \text{FirstSocialExposure}_i + \varepsilon_i$$

The repeat purchase model examines whether the same viral demand factors that encourage initial purchase also sustain consumer demand over time. Let $\text{Pr}_{p,i}$ represent the probability that respondent i purchases a viral food again after the initial trial:

$$P_{rp,i} = \Pr(\text{RepeatPurchase}_i = 1)$$

The model is specified as:

$$\ln(P_{rp,i} / (1 - P_{rp,i})) = \alpha_0 + \alpha_1 \text{SocialProof}_i + \alpha_2 \text{Student}_i + \alpha_3 \text{PurchaseFrequency}_i + \alpha_4 \text{MaximumWTP}_i + \alpha_5 \text{SocialMediaInfluence}_i + \alpha_6 \text{FirstSocialExposure}_i + u_i$$

The sharing and diffusion model evaluates whether participation in viral food trends extends into online posting or sharing behavior. $P_{ps,i}$ represent the probability that respondent i posted or shared viral food content:

$$P_{ps,i} = \Pr(\text{PostShare}_i = 1)$$

The model is specified as:

$$\ln(P_{ps,i} / (1 - P_{ps,i})) = \delta_0 + \delta_1 \text{SocialProof}_i + \delta_2 \text{Student}_i + \delta_3 \text{PurchaseFrequency}_i + \delta_4 \text{SocialMediaInfluence}_i + \delta_5 \text{FirstSocialExposure}_i + \varepsilon_i$$

In each model, the left-hand side represents the log odds of the corresponding outcome occurring. All three outcomes are binary. Therefore, the models are estimated as logistic regressions. Results are reported as coefficients, odds ratios, average marginal effects, and p-values. Because the survey is cross-sectional and self-reported, the models identify associations rather than causal effects.

■ Results and Discussion

Descriptive statistics:

The survey results show that viral food behavior is common among both students and adults. Across the combined sample, many respondents reported exposure to viral food trends through social media, and 75.2% of valid respondents reported trying a viral food because others posted, talked about, or recommended it (Table 1). The main outcome variable, *OverpricedPurchase*, measures whether a respondent purchased a viral food even though the respondent believed it was overpriced. This variable is used as the study's measure of reduced price resistance. The secondary outcomes are *RepeatPurchase*, which measures whether respondents continued buying the product after the first trial, and *PostShare*, which measures whether respondents posted or shared viral food content on social media.

Price resistance:

Table 3 presents the logistic regression results for the price resistance model. The dependent variable is *OverpricedPurchase*, equal to 1 if the respondent purchased a viral food despite believing that it was overpriced.

Table 3: Logistic regression predicting purchase despite perceived overpricing. Social proof is strongly and significantly associated with purchasing despite perceived overpricing. Respondents exposed to social proof had about 3.09 times higher odds of buying an overpriced viral food, and social proof was associated with a 21.6 percentage-point increase in the probability of purchase.

Predictor	Coefficient	Odds Ratio	Marginal Effect	p-value
Social Proof	1.127	3.087	0.216	0.0015
Student	-0.151	0.860	-0.029	0.6575
Purchase Frequency	0.652	1.918	0.125	0.0015
Maximum WTP	0.013	1.013	0.003	0.5444
Social Media Influence	0.398	1.489	0.076	0.0311
First Social Exposure	-0.504	0.604	-0.097	0.1421

Note. N = 268. McFadden pseudo R^2 = 0.163. AUC = 0.756. Marginal effects are average marginal effects.

The results support H1. Social proof is statistically significant and positively associated with reduced price resistance (p = 0.0015, Table 3). After controlling for student status, purchase frequency, maximum willingness to pay, social media influence, and first exposure through social media, respondents who experienced social proof had approximately 3.09 times higher odds of purchasing a viral food despite perceiving it as overpriced (Table 3). The average marginal effect suggests that social proof is associated with a 21.6 percentage-point increase in the probability of buying despite perceived overpricing (Table 3). Purchase frequency is also statistically significant (p = 0.0015, Table 3), indicating that respondents who buy trending foods more often are more likely to purchase despite overpricing. Social media influence is positive and statistically significant as well (p = 0.0311, Table 3).

Student status, maximum willingness to pay, and first exposure through social media are not statistically significant in the full model (Table 3).

Repeat purchase:

Table 4 presents the logistic regression results for the repeat purchase model. The dependent variable is *RepeatPurchase*, equal to 1 if the respondent continued buying a viral food after the first purchase.

Table 4: Logistic regression predicting repeat purchase. Social proof does not significantly predict repeat purchasing after the first trial. Instead, purchase frequency is the strongest predictor, suggesting that continued demand depends more on existing buying habits than on social proof alone.

Predictor	Coefficient	Odds Ratio	Marginal Effect	p-value
Social Proof	0.251	1.286	0.054	0.4631
Student	0.034	1.035	0.007	0.9149
Purchase Frequency	0.694	2.003	0.150	0.0004
Maximum WTP	0.028	1.028	0.006	0.1823
Social Media Influence	0.105	1.111	0.023	0.5438
First Social Exposure	-0.286	0.751	-0.062	0.3765

Note. N = 264. McFadden pseudo R^2 = 0.091. AUC = 0.699. Marginal effects are average marginal effects.

The repeat purchase results do not support H2. Social proof has a positive coefficient, but it is not statistically significant (p = 0.4631, Table 4). Therefore, the data do not provide strong evidence that social proof alone predicts whether consumers continue buying a viral food after the initial trial. The strongest

predictor of repeat purchase is PurchaseFrequency ($p = 0.0004$, Table 4). Each one-point increase in the purchase frequency scale is associated with approximately 2.00 times higher odds of repeat purchase and a 15.0 percentage-point increase in the probability of repeat purchase (Table 4). This suggests that repeat purchasing is more closely related to existing food-trend buying habits than to social proof alone. Student status, maximum willingness to pay, social media influence, and first exposure through social media are not statistically significant in the full model (Table 4).

Posting and diffusion:

Table 5 presents the sharing and diffusion model. The dependent variable is PostShare, equal to 1 if the respondent posted or shared a trending food on social media.

Table 5: Logistic regression predicting posting or sharing behavior. Social proof is positively related to posting or sharing behavior, but the relationship is not statistically significant. Purchase frequency is the only statistically significant predictor, suggesting that consumers who buy viral foods more often are also more likely to share them online.

Predictor	Coefficient	Odds Ratio	Marginal Effect	p-value
Social Proof	0.755	2.128	0.099	0.1958
Student	0.120	1.127	0.016	0.7461
Purchase Frequency	0.736	2.088	0.097	0.0012
Social Media Influence	0.246	1.278	0.032	0.2369
First Social Exposure	0.640	1.897	0.084	0.1946

Note. $N = 268$. McFadden pseudo $R^2 = 0.137$. AUC = 0.733. Marginal effects are average marginal effects.

The sharing model provides limited support for H3. Social proof is positively associated with posting or sharing behavior, with an odds ratio of 2.13, but the relationship is not statistically significant ($p = 0.1958$, Table 5); therefore, it cannot be concluded that differences in sharing are actually due to social proof. First exposure through social media and social media influence are also positive, but not statistically significant (Table 5). The only statistically significant predictor is PurchaseFrequency ($p = 0.0012$, Table 5). Because posting or sharing may happen after purchase, this model should be interpreted as a diffusion outcome rather than as evidence that sharing causes demand. The available data suggest that sharing behavior may describe how viral food trends spread, but the timing of the survey does not allow a stronger causal claim.

Interpretation:

Taken together, the findings support a two-stage interpretation of demand in viral food markets. Social proof appears to be the most powerful in the early stage by reducing price resistance and encouraging consumers to try viral foods even if they perceive them as overpriced (Table 3). This pattern is consistent with the idea that visibility, endorsement, and trend participation can temporarily increase perceived utility. In later stages, however, social proof weakens as a predictor. Repeat purchasing and posting behavior depend more on consumers' existing engagement with food trends, as measured by purchase frequency (Tables 4 and 5). Therefore, this also explains

why some trends die out quickly, especially if consumers originally didn't purchase the product frequently.

These findings are consistent with the theoretical predictions discussed earlier, particularly informational cascade theory and social influence theory. The strong association between social proof and purchasing despite perceived overpricing (Table 3) suggests that social information and participation value may increase consumers' perceived utility enough to offset the higher price. The fact that social proof predicts initial but not repeat purchasing (Table 4) is also consistent with informational cascade theory. Cascades can be fragile because they only rely on a small number of earlier decisions rather than independent evidence of product quality. Once consumers gain firsthand experience, these external signals may become less influential. Prospect theory, particularly loss aversion, may further explain this behavior when consumers view missing a limited or popular product as a loss, while FOMO may intensify the urgency to participate. However, because the survey did not directly measure loss aversion or experimentally manipulate scarcity, the results should not be interpreted as a direct test of prospect theory.

These findings can also be used as insight and a foundation for food businesses and marketers who are looking to utilize social media to attract more attention. Businesses should use marketing and product strategies that make use of social proof rather than just introducing new items that fit the current trends in order to attract more customers. Utilizing things like influencers, customer content, and reviews can be useful in helping spark initial demand for a product, even if pricing is on the higher end (Table 3). However, to turn these customers into repeat ones requires more emphasis on product quality and value (Table 4). In other words, online hype may attract attention, but long-term demand depends on product experience.

Limitations and future research:

Several limitations should be considered when interpreting the results. For starters, all survey respondents came from the Chicago area, which means the findings really only represent this one specific area and do not provide the greatest generalizability to other regions or cultural contexts. Additionally, the data is self-reported, which risks biases and certain respondents not being one hundred percent truthful. The study is also cross-sectional, which means it cannot determine causation. Next, posting and sharing outcomes present a timing issue because sharing may occur after purchase. As a result, the sharing model should be interpreted cautiously. The models may also be affected by unobserved confounding factors. For example, income, general price sensitivity, impulsivity, personality traits, or a desire for social belonging could influence both a consumer's responsiveness to social proof and willingness to purchase an overpriced viral food. Because these characteristics were not measured, the estimated relationship between social proof and price resistance may partly reflect differences among respondents that are not captured by the included control variables. Finally, these findings may only reflect the specific products and social media environment at the time of the survey, because viral food trends tend to change quickly.

To combat these limitations and add to this study, future research should consider surveying larger samples with respondents from different areas, not just one. Future research could collect measures of income, baseline price sensitivity, impulsivity, and social conformity. Experimental studies that randomly vary the amount of social proof shown to participants could also provide stronger evidence about causality. In addition, to distinguish between short-term trial and long-term repeat purchasing, future research can consider using longitudinal designs that could track consumers before and after exposure to a viral food product. Another idea could be comparing differences between social proof on different platforms like TikTok, Instagram, and YouTube, and their effects on price resistance. Future studies can also compare differences between short-lived trends and more prevalent trends, such as matcha, to pinpoint why some trends fade quickly while others last longer.

■ Conclusion

This study investigated how social proof shapes consumer behavior in viral food markets, with a particular focus on whether social proof reduces price resistance. Through surveys and models, the study found that social proof is significantly associated with reduced price resistance, which helps explain why consumers who were exposed to social proof were more likely to purchase viral foods even though they were overpriced. This suggests that social influence can temporarily weaken traditional price sensitivity when a product feels popular, urgent, or socially valuable, explaining why demand for viral foods is so high even though they are more expensive.

However, at the same time, the findings also show that social proof has its limitations. In the full models, social proof was found not to be a significant factor when it comes to customers purchasing again or posting and sharing online afterward. Instead, purchase frequency was found to be the strongest predictor. These findings suggest that social proof may contribute to initial purchases of viral foods, but long-term demand depends more on consumer habits and the actual product experience, reflecting why trends sometimes die out after a few months. Still, these findings can provide valuable insight for businesses, reflecting how social media visibility may be useful for attracting attention and creating initial demand for a product, but long-term success still depends on whether the product can satisfy consumers after the hype.

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