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The price of attention: An analysis of the intersection of media coverage and public sentiments about eggs and egg prices

Sachina Kagaya, Nicole Olynk Widmar, Valerie Kilders *

Department of Agricultural Economics, Purdue University, 403 Mitch Daniels Blvd. West Lafayette, IN 47906, United States

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A B S T R A C T

Retail prices for eggs surged during the period from early 2022 to mid-2023 in the U.S. We investigate the impact of egg price fluctuations on online and social media discourse, analyzing the relationship between egg prices and public sentiment. Utilizing online and social media listening data from September 2019 to August 2023, we explore how the total number of statements (i.e., mentions) and sentiment respond to changes in egg prices in the U.S. We find a significant association between increases in egg prices and both the volume of mentions and the sentiment of online discussions. Notably, mentions increased and sentiment became more negative as egg prices rose, highlighting a clear public response to price changes. However, the relationship between egg prices and online and social media attention is complex, which becomes apparent when studying the timing of increased concern with the timing of online news media coverage. Importantly, using regression discontinuity in time, we show that online and social media conversations about eggs and egg prices tend to increase after the rapid rise in online news coverage. Similarly, online and social media conversations about eggs and egg prices tend to decrease after the rapid rise in online news coverage.

Introduction

Eggs are not only an important source of protein and other nutrients (Ruxton, 2013; Zahed, 2022), but, given their low cost, they are also one of the top items of SNAP household expenditures (Garasky et al., 2016). Thus, the more than 136% increase in prices during the period from early 2022 to mid-2023 (U.S. Bureau of Labor Statistics, n.d.), posed a significant access barrier to this good. Given the substantial impact of these rising costs on consumer access to affordable nutrition, it becomes crucial to explore how these changes are reflected in the broader public discourse. To do so, we leverage social media listening as a proxy for capturing the public's attention and sentiment towards this issue.

While there are plenty of studies that focus on relationships between egg prices and product attributes of eggs (Chang et al., 2010; Gracia et al., 2014; Karipidis et al., 2005; Kim and Chung, 2011), studies aimed at exploring the relationship between egg prices and consumer sentiment are scarce. In our analysis, we focus on two measures of online and social media. The first measure is the total number of statements (i.e., mentions) to capture the levels of collective attention toward a particular topic. We hypothesized that egg prices are positively associated with the number of mentions in online and social media. That is, people pay more attention as egg prices increase. The second measure is the degree of positivity vs negativity to understand people's sentiment towards the topic. We hypothesize that rising egg prices are negatively associated with net sentiment. In other words, perceptions and feelings of people become negative as egg prices increase.

To test these hypotheses, we collected weekly social listening data from September 2019 to August 2023. We then deployed ordinary least squares (OLS) regression to estimate the impact of egg prices and other factors on online and social media reactions in the U.S. The results using the dataset from the price-specific search suggest that the number of online mentions increased as egg prices increased, and that online sentiment decreased as egg prices increased. To better understand the relationship observed, we leveraged a regression discontinuity in time (RDiT) design (Hausman and Rapson, 2018) to explore the effects of the rapid rise in online news coverage on social listening data.

Previous research has shown that news about a topic can at least partially explain the intensity of online activity (Araujo et al., 2020) leading us to investigate whether online and social media conversations about egg prices were driven by the increased news attention regarding rising egg prices. Specifically, we hypothesize that the rapid rise in online news coverage about egg prices and egg availability led to sudden

* Corresponding author.
E-mail address: vkilders@purdue.edu (V. Kilders).

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increases in the number of mentions in the social media listening data. Correspondingly, we also posit that the rapid rise in online news coverage led to sudden decreases in net sentiment in the social media listening data. Indeed, our results show that online and social media conversations about eggs and egg prices tend to increase after the rapid rise in online news coverage.

This study will contribute to the literature in three ways. First, for the agri-food business, analyzing social media listening data will provide retailers with information on public perceptions and insights into pricing. This can help producers decompose the effects of different factors on public sentiment and attention levels and plan accordingly. Second, policymakers can utilize online and social media listening data in decision-making. By observing social media listening data, they can capture the degree of public awareness of price fluctuations or product availability over time. Moreover, the data can be used to think about efficient communication when consumers are at risk of price increases or product shortages. Third, research on online sentiment using social media listening is a relatively new method and there is still no "best" way to quantify that kind of data. We will provide examples of how social media listening data can be applied, using the recent events that attracted broad attention from the public.

Background

Egg demand/supply and egg prices

The nutritional value of eggs has been highlighted by many articles and studies (McNamara, 2015; Ruxton, 2013; Zahed, 2022). Ruxton (2013) highlighted the roles of several nutrients of eggs in maternal health, fetal development, weight management during pregnancy, and the growth and development of infants. Fernandez (2006) suggested that eggs are a good source of antioxidants known to protect the eye. Moreover, Mottet and Tempio (2017) state that poultry birds, including egg-producing aspects, are not associated with major religious or cultural taboos.

The per capita use of eggs in the U.S. increased from 254 eggs in 2002 to 279 eggs in 2022 (USDA WAOB, 2003, 2023) creating a total sales value of $19.4 billion in 2022 according to the USDA Economic Research Service (USDA ERS, 2023a). The increase in per capita use of eggs prevailed despite an increase in egg prices over the last two decades, which saw the price per dozen eggs increase from 0.97 dollars in January 2002 to 1.93 dollars in January 2022 (U.S. Bureau of Labor Statistics, n.d.). Indeed, Andreyeva et al. (2010) found that the own-price elasticity of eggs was about 0.27, the lowest among all 16 examined categories. The inelasticity of demand is likely due to the characteristics of eggs (i.e., there are scarce sources of protein that can be purchased at a lower price than eggs).

While the rate of increase in prices has been relatively consistent over the recent two decades, several price spikes over the last several decades stand out including the 2014-2015 price spike where prices rose by more than $1.30 per dozen Grade A eggs in the span of about five months (USDA ERS, 2016). The spike was caused by an outbreak of the avian flu, which is also considered to be one of the main driving forces behind the rapid price rise in 2022/2023, when egg prices peaked at $4.82 in January 2023 following 10 month of consistent, above-average price-growth rates (USDA ERS, 2023b). According to the Centers for Disease Control and Prevention (CDC, 2023), highly pathogenic avian influenza viruses have been detected in the U.S. beginning in January 2022. The number of birds affected in commercial and backyard flocks was 59.4 million in total as of October 24, 2023 (USDA Animal and Plant Health Inspection Service [APHIS], n. d.). This is equivalent to 15 % of average layers during September 2023 (USDA National Agricultural Statistics Service [NASS], 2023), thus constituting a tremendous supply shock that was carried through to the consumer.

The effects of the outbreak were compounded by a high inflation rate driving up prices (U.S. Bureau of Labor Statistics, 2023), the rise in production inputs including feed costs and fuel costs[1], and the lingering effects of the COVID-19 pandemic (Malone et al., 2021).

Use of online and social media data in food and agriculture

A host of previous studies have focused on egg prices in relation to consumer preferences. The objectives are often to learn about consumer attitudes towards specific product attributes and to estimate how much egg prices were determined by those attributes (Chang et al., 2010; Gracia et al., 2014; Karipidis et al., 2005; Kim and Chung, 2011). In these studies, surveys (Gracia et al., 2014; Patel et al., 2014) or scanner data (Chang et al., 2010; Kim and Chung, 2011) are widely used.

These are important to understanding consumer behavior. However, they do not touch on the bigger picture of what public sentiment is towards eggs and how it changes over time. Social media listening lends itself to capturing such sentiments as the internet and social media have become pervasive and indispensable (Gottfried, 2024). The method of social media listening itself, is a relatively new method for data collection in academic research, enabling us to efficiently search and quantify data from online and social media platforms (Widmar et al., 2020c).

Despite its recent emergence, it has successfully been used in the food and agricultural space to examine a range of topics. For example, Jung et al. (2023) examined online media reactions to baby formula shortage, finding changes in reactions over time were in response to supply shortfalls rather than the recall announcement. Likewise, Ortez et al. (2023) analyzed potential relationships between online media-derived data and dairy futures prices and concluded social media listening data could be utilized to glean insights into financial markets, along with food and agricultural markets. Most closely related to our study, Widmar et al. (2020c) examined social and online media perceptions of hen housing. We built upon these previous studies by utilizing online and social media data to study reactions to changes in egg prices.

Material and methods

Data

Social media listening data

To facilitate the collection of social media listening data, we employed the Quid platform (formerly known as NetBase and then NetBase Quid) for our data collection and preliminary analysis in line with earlier studies such as Ortez et al. (2023), and Widmar et al. (2020a,b,c). The Quid platform is a consumer and market intelligence platform (Quid, n.d.-a) that enables organizations (or researchers) to "harness data-driven insights, deepening their understanding of consumers and markets" (Quid, n.d.-c). By using it, we can search both online news media and social media platforms, most notably Twitter (recently renamed "X"), but also blogs, reviews, and so on. It is utilized in business contexts (Quid, n.d.-b) as well as academic research (Ortez et al., 2023; Widmar et al., 2020a,b,c).

To test our hypotheses, we first developed search terms for a "general search" to amass online and social media posts related to table eggs which are consumed as human food and egg-laying hens. Second, we conducted a "price sub-search", which is a subset of the data collected in the general search. By obtaining these two datasets, we are able to parse out what share of online and social media conversations on eggs are attributable to discussions about egg prices specifically. It also allows us to compare public sentiment towards table eggs in general and the price of eggs in particular. We describe the detailed process below.

[1] Feed costs jumped from 156.2 in 2020 to 223.3 in 2021, with the reference value of 1998-2000=100 (USDA ERS, 2023b). Fuel costs, represented by propane prices, remained at high levels for the 2021 and 2022 periods (U.S. Energy Information Administration, n.d.)

Search term development

The basis for the collection of social media listening data is the definition of search terms. The program underlying Quid allows researchers to directly determine which terms to include and exclude from the search process and even permits the exclusion of specific authors. The inclusionary/exclusionary terms and authors provided to Quid are used by the platform to identify relevant posts that contain either one or multiple of the selected search terms.

For the general search about eggs, we generated a set of terms that allowed us to capture online talks about eggs in a range of contexts independent of their potential association with prices. Referring to and taking ideas from the study of Widmar et al. (2020c), we defined 10 inclusionary terms: "egg, hen, pullet, eggs, #eggs, #egg, #hen, #pullet, laying hen, #laying hen". In addition, 85 exclusionary terms and 8 excluded authors were set in this stage. For the precise list of exclusionary terms and authors, see Appendix A. Exclusionary terms and authors were carefully developed after the researcher's review of the initial search findings to eliminate irrelevant posts to the objectives of this study. For example, as Widmar et al. (2020c) outlined, in the context of computer software, video games, or entertainment such as movies and television, an "Easter egg" could be an expression indicating an intentionally hidden message or secret feature. Another example would be the idioms such as "egged on". As these talks are not about real commodity eggs, we tried to exclude those from the datasets by setting exclusionary terms without losing relevant information about actual table eggs.

Given our specific interest in the impact of price increases on online and social media conversations, for our "price sub-search", we narrowed the results down to focus on price-related media within the results of the general search. As such we utilized the same 10 initial terms which had to appear in combination with at least one of 21 additional terms related to price aspects. The included terms were "price, cost, expense, spend, expensive, cheap, money, budget, dollars, dollar, cents, cent, SNAP, WIC, TEFAP, pay, affordable, food stamps, sale, discount, promotion". No additional terms were excluded due to assuming that the terms we needed to exclude were already excluded in the general search.

Following the search term development, we also performed sentiment tuning of our results. The Quid platform possesses an integrated natural language processing[2] (NLP) model, which conducts a preliminary analysis of each post, deciding for each post whether it reflects a positive or negative sentiment. As the assignment is based on the phrases and individual words contained within the post, it is important to consider the designation within the context of the topic under consideration. Quid's NLP allows researchers to control the sentiment of specific words and phrases. Therefore, we checked the preliminary results of the keywords that drive sentiment and had the sentiment on "deviled, devil, beaten, beat, crack, cracked" set to neutral[3] (using the "Neutral Insight" feature of the Quid platform), so that we can confirm "contextual correctness" within the subject.

In conjunction, the definition of search terms and the sentiment tuning allow us to collect two types of metrics: mentions (i.e., a total number of statements) and net sentiment (i.e., a score representing the ratio of positive to negative sentiment). The net sentiment is necessarily bounded between -100 and +100. The extreme values can be interpreted as most/all relevant posts carrying a negative or positive sentiment as identified by the NLP following tuning (See Appendix B for the graphs of these two metrics gained by our data collection.).

The geographical areas of interest for our study included the United States and the United States Minor Outlying Islands. The language of interest was set as English. These geography and language parameters were put into place because cultural context and language use, including slang, differ across countries.

Social media listening data was collected for the period from September 1, 2019, to August 31, 2023 meaning a for each variable 209 observations were gathered. Data collection took place through the Quid platform on November 15, 2023[4]. The number of mentions and net sentiment for both searches are reported in Fig. 1.

USDA data

We used two types of USDA data to augment our online and social media data collected and enable integration of our data with real-life occurrences in egg production and markets, namely egg prices and the number of birds affected by avian flu. The latter was collected given the relationship between the increase in egg prices and the avian flu outbreak, meaning conversations about eggs and egg prices might have been stimulated by the severity of the outbreak at said time.

We obtained *Weekly Combined Regional Shell Eggs* data from the USDA Agricultural Marketing Service (USDA AMS, n.d.). These are average prices (cents per dozen) on sales to volume buyers of USDA Grade A and Grade A, large, white eggs in cartons. Retail prices would be preferred, rather than wholesale prices, because our research interests are in consumers' reactions through online and social media. However, given the publication frequency of data (i.e., daily, weekly, or monthly) and data completeness (i.e., whether there is missing data during our research period), favored the average prices to volume buyers.

For the number of birds affected by the avian flu, we obtained the *2022-2023 Confirmations of Highly Pathogenic Avian Influenza in Commercial and Backyard Flocks* data from USDA APHIS (n.d.). Daily data (as provided) was aggregated into weekly data to match with the frequency of social media listening data[5] (see Appendix C). We collected data with confirmation dates of the period from September 1, 2019, to August 31, 2023. No cases were reported for 2019, 2020, and 2021 (CDC, 2023).

Online news data

To understand the relationship between online news coverage and public attention, we also collected data about the intensity of news coverage regarding egg prices in the weeks prior and following the peak of mentions in January 2023. To capture this, we used the news feature of the Google search engine. Google functions as the leading online search engine and provides users via the "News" tab with an index of online news articles about a pre-specified topic. Importantly, according to Google (n.d.) the News tab is not personalized so everyone within a particular country sees the same results preventing our results from being biased due to previous search activity on the devices used to collect the data. We acknowledge that this limits us to electronic articles and does not capture print or television media. However, most of the major news companies also tend to own their online news websites where they publish similar or even more extensive content than can be found in their print or TV coverage. Moreover, previous studies also found that online news media have come to play a more dominant role in controlling news agendas than print media (Vargo and Guo, 2017; Vonbun et al., 2016).

We limited our search to just using the search term "eggs" rather than the collective terms applied in the web scraping in an effort to simplify the search process and reflect how conversation about eggs

[2] According to the blog post of Quid (Pace, 2023), "Natural Language Processing (NLP) can process every post that consumers upload, extracting insights like sentiment (positive or negative), emotions, behaviors, names of people, and other relevant data, and then indexes these posts for reference."

[3] Researchers set the terms "devil" and "deviled", for example, to be neutral in sentiment; in the context of eggs, the sentiment of deviled is neutral in the sense that it refers to a specific egg dish or recipe, not anything devilish or overtly negative in tone.

[4] The precise timing of data collected needs to be recorded due to the fluid nature of social media data, that is, both each post and account can be deleted or edited by the author or the social media platform itself.

[5] For this research, we use the weekly online media listening data which starts on Sundays through Saturdays.

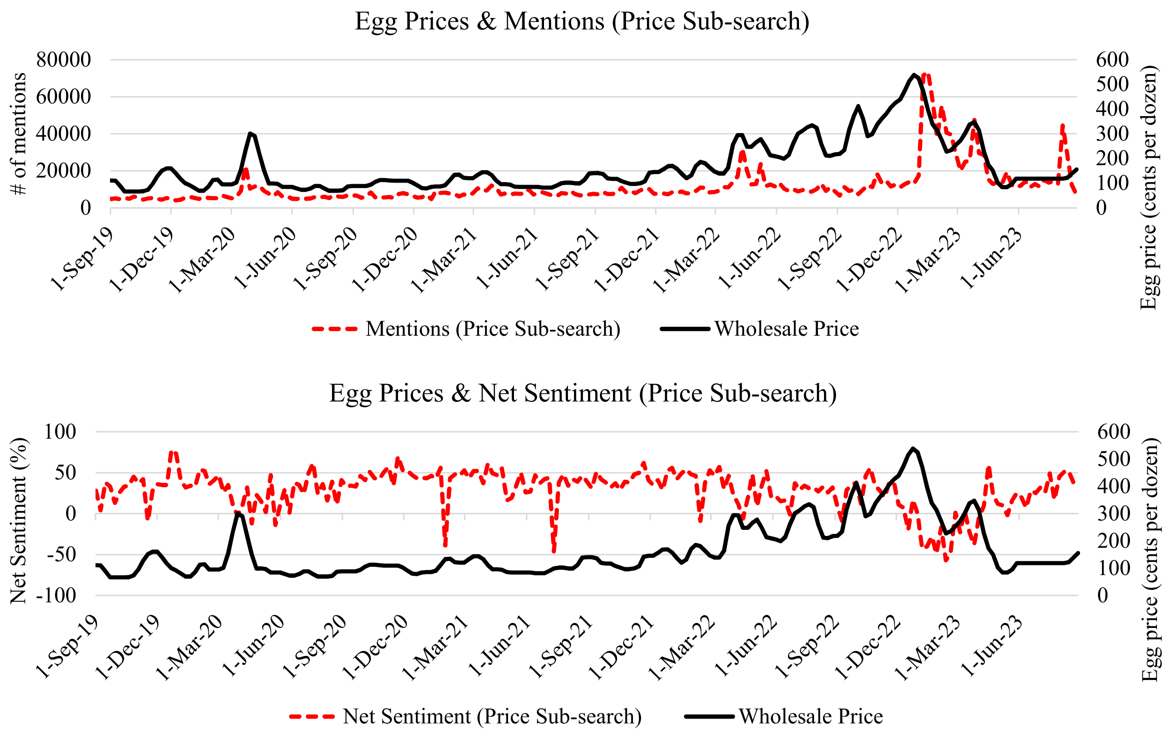

Fig. 1. Wholesale prices for eggs in comparison with mentions and net sentiment in the price sub-search.

altered across time. We did not use terms such as "laying hen" for this Google search, which is differentiated from the broad and inclusive search terms used for the social media listening data collection. We intentionally limited the Google search results to ensure clear understanding of search results and interpretation of changes in search volumes over time.

The data collection was conducted on November 9, 2023, and January 17, 2024. The target period was set as from August 28, 2022, to August 31, 2023, using the custom date range feature integrated into Google. This period was selected to overlap with the final year of our research period, which attracted huge online and social media attention to eggs, and extracted it to better align with the other weekly data. After choosing "Sorted by relevance" instead of "Sorted by date" to grasp people's interests or popular articles, we manually recorded how many of the top 20 results for each week focused on egg prices or availability. The results are shown in Fig. 2 (see Appendix D for a tabular breakdown and Appendix E for a side-by-side display of the google search data with the social media data).

Statistical analysis

To assess the relationship between mentions and egg prices as well as net sentiment and egg prices, we first ran four sets of OLS models with four different independent variables: *GeneralMentions, GeneralNetSent, PriceMentions,* and *PriceNetSent*. Respectively, these variables describe the number of mentions in the general search, the net sentiment in the general search, the number of mentions in the price sub-search, and the net sentiment in the price sub-search. For each, we tested two separate models. Model 1 only includes the egg price variable as an independent variable:

$$online_t = \beta_0 + \beta_1 \, price_t + \varepsilon_t \tag{1}$$

where $online_t$ represents the four dependent variables, and t denotes week. $price_t$ is the wholesale price for eggs.

Model 2 expands upon Model 1 and permits us to test the influence of the number of birds affected by the avian flu (flu_t) and Easter[6] ($easter_t$). These variables are included primarily to control for epidemical and cultural events' effects on social media listening data. Model 2 is defined as follows:

$$online_t = \beta_0 + \beta_1 \, price_t + \beta_2 \ln(flu_t + 1) + \beta_3 \, easter_t + \varepsilon_t \tag{2}$$

where the variables are defined as in Model 1, with β_i representing the respective coefficient.

By incorporating the recorded avian flu cases in the form of a natural logarithm we can directly interpret the results as proportional differences, which given the wide range of values (0 to 8.6 million cases) is more suitable for our purpose[7]. We added +1 to the number of flu cases in our model because we have several weeks where no flu cases were reported. Since the natural logarithm of zero is undefined, adding +1 ensures that all weeks, including those with zero cases, can be included in the analysis.

We specified Easter as a dummy variable that took the value 1 if according to the Gregorian calendar, it is the week before or after Easter (including Easter itself) and 0 otherwise. The decision to expand the range to capture the week before and after Easter was based on the test of model fit using different settings of the Easter dummy variable. The test results lead us to choose "two weeks before Easter" and "one week after Easter including and starting with Easter Sunday", which is supported by the improved fit of the model relative to alternative time ranges tested.

We then employed a RDiT design following Hausmann and Rapson

[6] Eggs are used in the preparation and celebration of Easter, for instance, by boiling and painting eggs or kids doing Easter egg hunt. Thus, we assumed that people would talk more about eggs (or also about egg prices) specifically at the time around Easter.

[7] As the avian flu was only affecting birds for a subset of the measured time period, the $log(x+1)$ transformation was applied to handle the zero values in the dataset though we have to be aware of some limitations along with it (Bellégo et al., 2022).

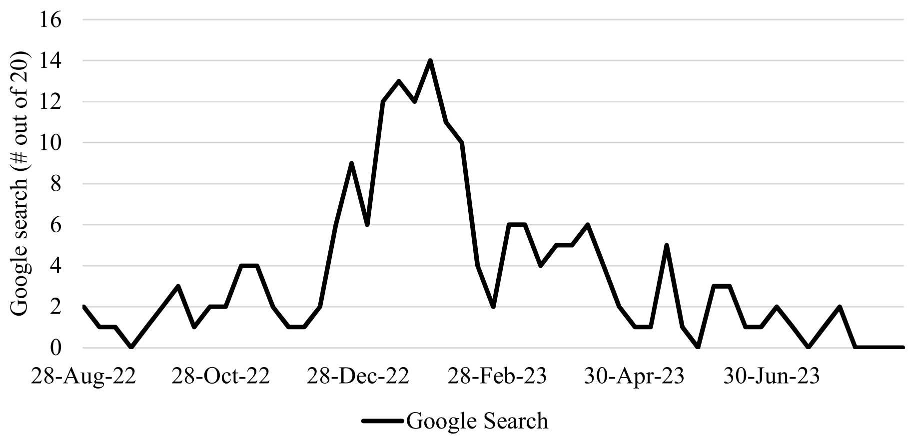

Fig. 2. Google search results.

(2018) to test the impact of increased news coverage on the intensity of social media attention. Generally, regression discontinuity designs are used to measure the causal effects or treatment effects of an intervention with an assigned cutoff value. It is typically used in situations in which candidates are selected for treatment based on whether their value for a numeric rating exceeds a designated threshold (Jacob et al., 2012). In an RDiT design, time functions as the running variable, which lends itself to our context as the running variable determines whether people were exposed to increased online news coverage.

Similar to standard regression discontinuity designs, the RDiT requires researchers to determine a cutoff point. To determine our cutoff point, we assessed the Google news search data we collected. Given our hypotheses, we wanted to select a cutoff after which we could safely assume that news coverage was noticeably higher relative to other periods. Thus, we defined two conditions that were to be met: 1) More than 5 of the top 20 search results for "eggs" dealt with egg prices and 2) the number of topical articles had to more than doubled compared to the maximum value found in the previous calendar month. Our first criterion ensures that a substantial portion of the news coverage about eggs is focused on egg prices, indicating heightened public and media attention. Our second one confirms that the increase in coverage is not only noticeable but also substantial, reflecting a significant shift in media attention from usual egg related conversations. The week of December 25, 2022, fulfilled both of these criteria leading to us selecting it as the cutoff date.

To validate our chosen cutoff date and ensure the robustness of our results, we conducted several robustness checks and sensitivity analyses following the procedures outlined by Hausman and Rapson (2018), with detailed findings presented in Appendix F.

Regression discontinuity model

To test our hypotheses that the increase in media attention was associated with the increase in mentions and decrease in net sentiment, we first used a basic regression discontinuity model focusing on the impact of the rapid increase in online news media attention. Thus, the regression can be expressed as:

$$\boldsymbol{online_t} = \beta_0 + \beta_1\ \boldsymbol{treat_t} + \beta_2\ \boldsymbol{run_t} + \beta_3\ \boldsymbol{treat_t} * \boldsymbol{run_t} + \boldsymbol{\varepsilon_t} \tag{3}$$

where $treat_t$, is a binary treatment variable, that equals 1 during and after the week of December 25, 2022, and 0 prior to the week of December 25, 2022. Meanwhile, run_t represents the running variable, which measures the distance between t and the cutoff week. For example, the variable equals 1, one week after the cutoff week and it takes a negative value before the cutoff week. The interaction term between the treatment variable and the running variable is represented by $treat_t * run_t$. All other components of (3) are defined as above.

To isolate the effect of prices, we used an additional model in which we integrated an additional interaction effect between the treatment and the price variable:

$$\boldsymbol{online_t} = \beta_0 + \beta_1\ \boldsymbol{treat_t} + \beta_2\ \boldsymbol{run_t} + \beta_3\ \boldsymbol{treat_t} * \boldsymbol{run_t} + \beta_4\ \boldsymbol{price_t} + \beta_5\ \boldsymbol{treat_t} * \boldsymbol{price_t} + \boldsymbol{\varepsilon_t} \tag{4}$$

The interaction term is used to capture how consumers reacted to the egg prices under the condition that the rapid increase in online news coverage of the egg prices/availability had already occurred.

To account for the effects of other factors than prices, our final model also incorporated the controls for avian flu cases and Easter:

$$\boldsymbol{online_t} = \beta_0 + \beta_1\ \boldsymbol{treat_t} + \beta_2\ \boldsymbol{run_t} + \beta_3\ \boldsymbol{treat_t} * \boldsymbol{run_t} + \beta_4\ \boldsymbol{price_t} + \beta_5\ \boldsymbol{treat_t} * \boldsymbol{price_t} + \beta_6\ \ln(\boldsymbol{flu_t} + 1) + \beta_7\ \boldsymbol{easter_t} + \boldsymbol{\varepsilon_t} \tag{5}$$

Results and discussion

Summary statistics, data sources, and top terms

In total, 32,699,457 mentions were retrieved for the entire period for the general search and 2,380,941 for the price sub-search. Across all years, the majority of mentions for the general search came from Twitter (see Table B.1 in the Appendix), which differs to the results by Widmar et al. (2020c), who used data from the time period of December 2015 through February 2018 and observed that News accounted for 69% of the sources of the general egg-specific dataset. The difference might be partly attributable to the slightly different search terms adopted for this study. For the price sub-search, blogs are the top source for Year 2 and Year 3 while Twitter is the top source for Year 1 and Year 4 (see Table B.2 in the Appendix).

Table 1 reports the summary statistics. Overall, all variables show significant flux across the study period. This is most pronounced for the variable *flu*, which due to the absence of recorded cases of the avian flu prior to January 2022 was zero for the majority of the study period. It peaked at more than 8.6 million cases in the week of March 13, 2022, more than nine months earlier than the peak of the egg prices in the week of December 25, 2022 at $5.38.

In total, 32,699,457 mentions were retrieved for the entire period for the general search and 2,380,941 for the price sub-search. Across all years, the majority of mentions for the general search came from Twitter (see Table B.1 in the Appendix), which differs to the results by Widmar et al. (2020c), who used data from the time period of December 2015 through February 2018 and observed that News accounted for 69% of the sources of the general egg-specific dataset. The difference might be partly attributable to the slightly different search terms adopted for this study. For the price sub-search, blogs are the top source for Year 2 and Year 3 while Twitter is the top source for Year 1 and Year 4 (see Table B.2 in the Appendix).

Table 1
Summary statistics.

Variable	Definition	N	Mean (SD)	Min	Max
GeneralMentions	Mentions in general search	209	156,456.7 (63,468.9)	96,483	524,245
GeneralNetSent	Net sentiment in general search	209	37.3 (11.6)	-36	55
PriceMentions	Mentions in price sub-search	209	11,380.6 (10,280.1)	3,980	73,463
PriceNetSent	Net sentiment in price sub-search	209	28.5 (23.9)	-57	76
price	Wholesale prices	209	165.57 (103.25)	66.28	538.33
Avian flu	Birds affected by avian flu	209	281,298.7 (1,063,138.2)	0	8,621,696

NOTE: Our research period contains 209 weeks, and all statistics above are on a weekly basis.

According to Chawinga (2017), who studied the benefits of Twitter and blogs in the educational context, Twitter has characteristics of instant communication and content sharing while blogs have benefits in reading and reflecting on the contents. Thus, the increased proportion of blogs in the price sub-search results might suggest that talks related to egg prices contain more complex discussions or explanations compared to the general talks about eggs and egg-laying hens.

Looking more closely at what people were talking about, we also evaluated the top attributes and things mentioned annually in the context of eggs for both the general search and price sub-search (see Tables B.3 and B.4 in the Appendix). Consistent with our hypotheses, we find a rise in price-related terms among the top sentiment drivers from late 2022 onwards for both searches. In the general search, "price" ranked among the top three disliked terms for the first time in year 3. In year 4, all top three disliked terms are related to price.

For the price sub-search, the top two disliked terms are "price" or "expensive" for all years. However, the number of mentions for those two terms stands out in year 4, with a more than 640% increase in the mention of "price" relative to the previous year. Similarly, in the 'things' category, mentions of 'price' and 'egg price' surged in year 4, increasing by over 830% and 1330%, respectively, compared to the previous year.

Regression results

Table 2 describes the OLS regression results for the general search dataset. We observe that while *price* is significant in model 1, it is not in model 2, suggesting that in the general conversation about eggs, price does not play as much of a role especially when considering other factors, such as *Easter*, which is highly significant. The variable capturing the influence of the avian flu on mentions is not significant, suggesting that the outbreak was not a conversation driver in the study period. However, when looking at *GeneralNetSent, flu* has a significantly positive influence on general net sentiment. Perhaps, the positive impact can be attributed in-part to expressions of sympathy or supportive discussions during the outbreak.

Meanwhile, the impact of egg prices on sentiment is consistently significant across both models. Specifically, in Model 2, a coefficient of -0.043 implies that, on average, a $1 increase in egg prices leads to a 4.3% decrease in net sentiment. This finding highlights the negative sentiment associated with rising egg prices, reflecting consumer concerns or frustrations over affordability.

Table 3 describes the OLS regression results for the price sub-search dataset. For the number of mentions (*PriceMentions*), the coefficients of egg price are positive and statistically significant at the 99% confidence level for both Model 1 and Model 2. This indicates that online mentions of egg prices are significantly associated with egg prices, which is consistent with our hypothesis. Correspondingly, an increase in egg prices also has a statistically negative impact on net sentiment, which corresponds with our second hypothesis.

Interestingly, changes in avian flu cases across the US did not influence the number of mentions in this sub-search, suggesting that most people did not appear to link the flu outbreak to egg price fluctuations at least in their public discourse. This lack of association could be due to a time lag between the rise in avian flu cases and any subsequent changes in egg prices, which may not be immediately apparent to consumers.

Regression discontinuity results

While our above analysis shows that there is a significant association between egg prices and mentions and net sentiment, when compared to the egg price data, the pattern of price increases does not directly correspond with the increase in mentions and decrease in net sentiment for eggs. Specifically, while prices experienced a more gradual increase in 2022 leading up to 2023, mentions in the price sub-search exploded at the beginning of January 2023 and the average net sentiment dropped by 42 percentage points in January 2023 compared to December 2022 (see Fig. 1) [8]. We used a RDiT design to more closely assess the nature of the observed relationship by leveraging the social media listening data in combination with the online news data.

Regression results for the general search dataset

Table 4 provides the results of the regression discontinuity models for the general search dataset.

In line with our hypothesis, we find a positive and significant relationship between the cutoff (*Treat*) and online and social media mentions in models 1, 2, and 3. The results indicate that people's online conversations about table eggs or egg-laying hens did indeed increase relative to our cutoff point (i.e., the week of December 25, 2022). This finding is consistent with Araujo et al. (2020), who observed a positive relationship between news coverage and the intensity of online activity.

The impact of time, as expressed through the running variable, is less clear, as the variable is not significant in Model 1 but is indeed significant with negative coefficients in models 2 (-257.13) and 3 (-171.91) suggesting that the effect of time alone is not consistently robust. Moreover, the interaction between the treatment and the running variable is not significant in any of our model, meaning the increase in general mentions due to the treatment remains relatively stable over the weeks following the cutoff.

Regarding the impact of egg prices on mentions, we find that the price variable is positive and significant in Model 2 but not in Model 3. This suggests that the direct effect of price on mentions diminishes when additional controls are included. Interestingly, the interaction between the cutoff and egg prices ($Treat * Price$) is significant and negative in both Models 2 and 3. This indicates that the increase in mentions due to higher egg prices diminishes after the cutoff. In other words, after the news coverage spike, the sensitivity of mentions to price changes decreases, implying that additional increases in social media intensity are not solely attributable to the actual price of eggs.

Looking at the net sentiment (*GeneralNetSent*), the treatment variable is negative and significant across all three models meaning that sentiment dropped after public coverage of the egg price increase was widely covered in the media. The result corresponds with findings by McCombs (2015) stating that news media has among other things an influence on the focus of public attention.

We further find that the net sentiment seems to be slightly improving over time as expressed via the positive and significant coefficient for the

[8] Also, see Appendix G for the graphs using the general datasets.

Table 2
Results for the general search dataset

Variable	*GeneralMentions* Model 1	*GeneralMentions* Model 2	*GeneralNetSent* Model 1	*GeneralNetSent* Model 2
Price	115.959***	0.959	-0.021***	-0.043***
	(41.956)	(56.641)	(0.008)	(0.012)
(ln) Avian flu cases		1,440.480		0.471**
		(1,058.749)		(0.219)
Easter		136,509.383***		6.788**
		(16,525.562)		(3.421)
Constant	137,257.511***	143,377.401***	40.803***	42.328***
	(8,181.329)	(7,827.446)	(1.494)	(1.620)
Observations	209	209	209	209
R-squared	0.036	0.277	0.035	0.070

NOTE: *, **, and *** represent statistically significant coefficients at the p = 0.10, 0.05, and 0.01 levels, respectively.

Table 3
Results for the price sub-search dataset.

Variable	*PriceMentions* Model 1	*PriceMentions* Model 2	*PriceNetSent* Model 1	*PriceNetSent* Model 2
Price	49.953***	37.823***	-0.097***	-0.093***
	(5.986)	(9.203)	(0.015)	(0.023)
(ln) Avian flu		245.179		-0.021
		(172.028)		(0.425)
Easter		5,634.621**		-6.476
		(2,685.108)		(6.628)
Constant	3,109.824***	3,929.523***	44.587***	44.441***
	(1,167.222)	(1,271.820)	(2.847)	(3.140)
Observations	209	209	209	209
R-squared	0.252	0.273	0.176	0.180

NOTE: *, **, and *** represent statistically significant coefficients at the p = 0.10, 0.05, and 0.01 levels, respectively.

running variable. Strikingly, the interaction between the running variable and the treatment variable is highly significant and positive. The result suggests that sentiment substantially increased over time following the cutoff, i.e., there is a "recovery" from the initial negative shock.

We further find a negative and significant coefficient for egg prices, but no significant coefficient for the interaction between prices and the cutoff. Hence, it appears that higher prices are associated with a more negative sentiment with the relationship remaining fairly stable even after news media attention increased.

Regression results for the price sub-search dataset

Table 5 presents the results of regression discontinuity models for the price sub-search dataset. For the number of mentions (*PriceMentions*), the coefficients of the treatment variable are positive and statistically significant for all models. This can be interpreted egg price related mentions increasing significantly after the surge in news coverage aligning with our hypothesis.

While the running variable is positive across all three models, it is only significant in model 1 but not models 2 and 3, meaning there does not appear to be a robust change in mentions over time once we control for other factors. However, the interaction between the treatment variable and the running variable is negative and highly significant across models. The result suggests that the effect of the treatment on mentions decreases over time, implying an initial spike in interest that gradually diminishes as time progresses. This kind of "erosion of attention" can also be seen in previous studies (Widmar et al., 2020b).

We do not find a robust effect of egg prices on price mentions and also do not observe a significant change in the relationship between the two after our cutoff (as expressed by the insignificant coefficient for *treat ∗ price*).

Looking at net sentiment (*PriceNetSent*), the coefficients of the treatment variable are negative and significant for all models indicating that online conversations about egg prices are more negative after the cutoff than before it, consistent with our hypothesis. But, as for the general search, the positive and significant coefficient of the interaction term between the cutoff and the running variable, suggests that we have a mellowing out of the initial negative feedback.

The significant negative coefficients in both models 2 and 3 confirm

Table 4
Regression discontinuity results for the general search dataset.

Variable	*GeneralMentions* Model 1	*GeneralMentions* Model 2	*GeneralMentions* Model 3	*GeneralNetSent* Model 1	*GeneralNetSent* Model 2	*GeneralNetSent* Model 3
Treat	116,889.806***	223,112.859***	207,412.160***	-24.667***	-33.565***	-35.587***
	(16,379.742)	(46,019.827)	(34,125.585)	(3.829)	(10.939)	(10.970)
Run	-58.671	-257.130***	-171.909**	0.033**	0.066***	0.065***
	(69.180)	(94.052)	(75.558)	(0.016)	(0.022)	(0.024)
*Treat*Run*	395.301	-1,084.249	-1,260.709	0.768***	0.786**	0.827***
	(732.325)	(1,272.670)	(968.062)	(0.171)	(0.303)	(0.311)
Price		151.217***	-12.205		-0.026**	-0.039***
		(49.833)	(43.205)		(0.012)	(0.014)
*Treat*Price*		-318.560***	-263.802***		0.031	0.037
		(116.008)	(86.686)		(0.028)	(0.028)
(ln) Avian flu			1,726.159**			0.241
			(720.312)			(0.232)
Easter			131,854.744***			7.644**
			(9,985.673)			(3.210)
Constant	131,082.701***	90,365.869***	110,841.663***	41.522***	48.399***	49.294***
	(6,939.775)	(15,033.802)	(11,235.914)	(1.622)	(3.574)	(3.612)
Observations	209	209	209	209	209	209
R-squared	0.495	0.522	0.747	0.171	0.190	0.216

NOTE: *, **, and *** represent statistically significant coefficients at the p = 0.10, 0.05, and 0.01 levels, respectively.

Table 5
Regression discontinuity results for the price sub-search dataset.

Variable	*PriceMentions* Model 1	*PriceMentions* Model 2	*PriceMentions* Model 3	*PriceNetSent* Model 1	*PriceNetSent* Model 2	*PriceNetSent* Model 3
Treatment	30,508.050***	23,754.496***	21,442.305***	-65.583***	-107.530***	-105.557***
	(2,361.789)	(6,691.284)	(6,591.281)	(6.932)	(19.139)	(19.444)
Running	42.444***	21.646	17.559	-0.024	0.092**	0.095**
	(9.975)	(13.675)	(14.594)	(0.029)	(0.039)	(0.043)
Treat*Run	-1,021.582***	-718.486***	-654.481***	2.351***	2.697***	2.645***
	(105.594)	(185.046)	(186.979)	(0.310)	(0.529)	(0.552)
Price		15.847**	2.211		-0.089***	-0.077***
		(7.246)	(8.345)		(0.021)	(0.025)
Treat*Price		12.306	19.824		0.135***	0.128**
		(16.868)	(16.743)		(0.048)	(0.049)
(ln) Avian flu			280.834**			-0.239
			(139.127)			(0.410)
Easter			6,219.813***			-5.645
			(1,928.711)			(5.690)
Constant	12,133.596***	7,866.739***	8,419.934***	31.089***	54.954***	54.419***
	(1,000.644)	(2,185.915)	(2,170.192)	(2.937)	(6.252)	(6.402)
Observations	209	209	209	209	209	209
R-squared	0.600	0.615	0.641	0.361	0.417	0.421

NOTE: *, **, and *** represent statistically significant coefficients at the p = 0.10, 0.05, and 0.01 levels, respectively.

that higher egg prices are associated with more negative public sentiment, which could reflect consumer's concerns over affordability and access to a staple food item. The effect is moderated after the spike in media coverage, as indicated by the positive coefficient of the interaction term between price and the treatment variable. Our finding suggests that the extensive media coverage around the cutoff period may have led to substantial negative sentiment in the beginning. Sentiment then appears to stabilize as the public becomes less sensitive to further price increases and further media coverage about the price increases.

In summary, all results above indicate that the rapid rise in online news stories about egg prices caused discontinuities in social media listening data at the peak of coverage and resulted in increased mentions and decreased net sentiment after the cutoff point. Compared to the results from the simple OLS regressions, we found that egg prices are less associated with mentions and net sentiment in online and social media when we include the influence of online news coverage suggesting that people's public outrage might have been fueled by temporary media attention rather than the gradual price increases.

Conclusion

We analyzed relationships between online and social media conversations and egg prices in the U.S. Our regression results indicate that while egg prices are positively associated with the volume of mentions and negatively with sentiment about them, this association is less clear when considering more general conversations about eggs, where other variables such as *Easter* drive the interest.

Our findings suggest that the 2022/2023 increases in online news coverage is associated with a rapid rise in online and social media attention towards eggs and egg prices. Interestingly, when accounting for the increased news attention, egg prices themselves are not significantly associated with shifts in mentions meaning the news coverage itself drove attention. In practice, our results imply that retailers and policymakers need to pay attention not only to the pricing but also to the amount and timing of news reporting on recent events to better understand consumer responses to shifts in prices.

To build on our study, future research should more closely assess seasonality and the long-term impacts of price fluctuations. While we partially addressed seasonality by including an Easter dummy variable, there is room for further consideration of handling the characteristics of time series data. Relatedly, the validity of our results should be assessed in other countries, and in multiple languages, which would help to assess whether our results are universal or specific to the context in which we studied eggs.

Moreover, regarding social media listening data, we must be aware that opinions on social media platforms can be biased due to the socio-demographic composition of users[9] and there could be some overlap between the Google search data used to decide a cutoff week and social media listening data. For example, a particular online news article might be hit in both searches. In this same context, it is possible and likely that online media mentions on social media platforms are about news articles, thus increased news media may drive increased social media, although by how much it is very difficult or impossible to measure as social media users often do not reveal why they posted or what they looked at prior to posting (unless it is a retweet with original content cited/linked). Future studies should examine this interplay more closely.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Dr. Nicole Widmar reports financial support was provided by USDA National Institute of Food and Agriculture, Hatch Project 7007883. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psj.2024.104482.

[9] For example, 78% of 18- to 29-year-olds say they use Instagram, while only 15% of those 65 and older say they use it (Gottfried, 2024).

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