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Quantifying the effect of striking with picketing on grocery store foot traffic

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Abstract

Unionized workers often use striking and picketing to raise attention to their grievances, dissuade customers from patronizing a business, and pressure employers in negotiations. Despite its wide use and recognition in popular culture, the effects of picketing and striking on retail business are not well understood. Adjacent literature has used cell phone tracking and other digital geo-tagging techniques to measure the effects of factory closures, COVID-19 restrictions, and stimulus payments on store patronage and economic activity. This article provides a case study using mobile geolocation data to quantify the loss of store foot traffic due to striking with picketing by analyzing the 2022 King Soopers strike in Colorado, USA. Using the historic foot traffic data of the past two years for 118 King Soopers locations, 78 of which went on strike, two SARIMA models were trained, and their predicted foot traffic values were compared to the actual values during the strike period. This technique indicates an average 47% decrease in foot traffic for striking stores and a 14% decrease in foot traffic for nonstriking locations.

Keywords: Foot Traffic; Cellular Location; Geospatial

1 Introduction

To the best of the author's knowledge, no existing literature has leveraged modern tracking data to quantify striking with picketing's effect on store patronage. This study applies the established use of SafeGraph, a data aggregation company that quantifies foot traffic in areas of interest, geolocation data to a strike of a large regional grocer, quantifying any measurable changes in tracked persons entering and leaving the stores. In this case, all stores that went on strike also had physical picket lines outside their entrances, so the terms will be used interchangeably throughout this paper. The central question is whether striking has a measurable effect on store foot traffic, and if so, to what degree. To answer this question, we apply a similar technique to Dong et al., who used seasonal autoregression models based on historic map queries to predict the resulting revenue to public businesses [7]. By training a model on all per-store foot traffic data well before the strike, we predict what store visitations should have occurred if a strike had never happened, which is then compared to the SafeGraph values to find the resulting difference. This paper will first cover the details of the strike itself, followed by our methods and their limitations, and finally, the results of the model compared to the real-world data. When compared to the values predicted by our seasonal models, we found an average 47% decrease in foot traffic for striking stores and a 14% decrease in foot traffic for nonstriking locations.

1.1 Colorado King Soopers strike of 2022

On January 12th, 2022, 8,700 King Soopers grocery store employees across 78 stores of 118 total locations went on strike, which had been formally announced on January 6th due to failed contract negotiations [16]. King Soopers is a large grocery store chain owned by the Kroger Company, with 118 locations split between 117 in Colorado and 1 in Wyoming. During the strike, King Soopers leveraged Kroger's national presence to bring in employees across the country and hired temporary staff to keep all stores open [3]. Members of the striking United Food and Commercial Workers (UFCW) Local 7 union demanded higher wages, better healthcare benefits, increased COVID protections, and an end to alleged unfair labor practices [19]. All King Soopers stores did not go on strike because some of the union contracts are on a separate schedule and expired at a later date, so these stores will be referred to as nonstriking stores throughout the paper [5].

Local reporting described the resulting picket lines to be in front of all striking locations whenever the store was open with two to over twenty workers standing outside the entrance to the stores [16]. These picketers carried prominent signs asking customers to not patronize King Soopers and were typically pictured standing right outside the entrance so potential customers would have to physically cross the picket line [16]. Local reporting also noted that this strike was prominently known in the community due to King Soopers being a large regional grocer, with people interviewed by local media saying they would avoid shopping at the chain [5]. Figure 1 provides a map of all the striking and nonstriking stores open in Colorado during the strike period. For clarity, the Wyoming location has been excluded from analysis for this study.

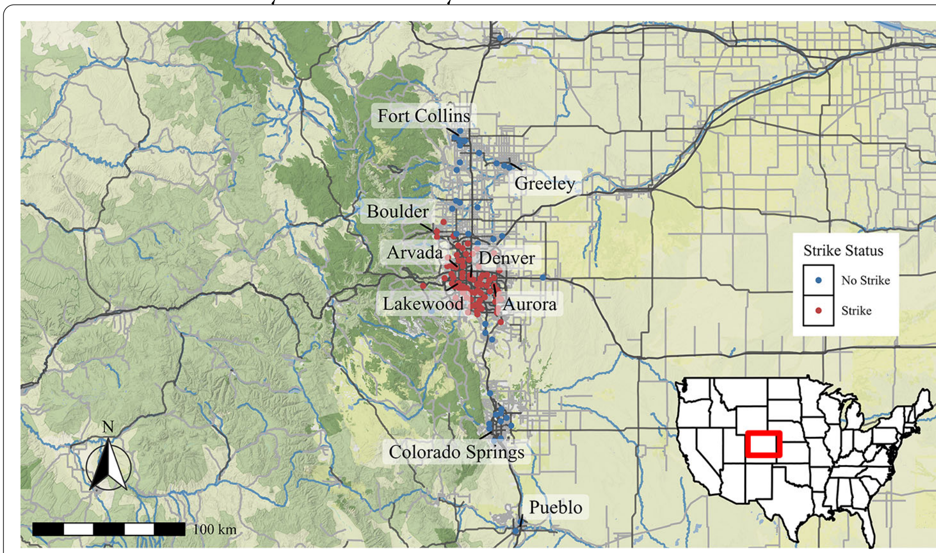

Figure 1 Map of striking stores (red) and nonstriking stores (blue) in 2022

The majority of King Soopers locations are in the immediate proximity of Colorado's major cities with all of the cities labeled having a minimum population of forty thousand persons. The timeline of strike events is illustrated in Fig. 2.

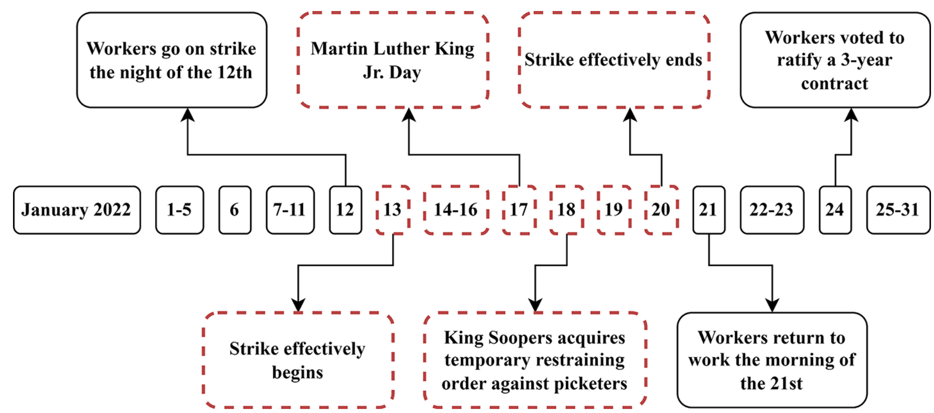

Figure 2 Timeline of strike events with dashed boxes representing strike period

On January 18th, King Soopers acquired a temporary restraining order against picketers, prohibiting impeding the movement of anyone entering or exiting the store, picketing in groups larger than ten people in front of or near King Soopers locations, interfering with or shouting within 20 feet of another person, and following anyone leaving King Soopers premises [2]. However, this order was short-lived as the strike came to an end in the early morning of January 21st, and workers returned to their jobs that same day [6]. On January 24th, the union voted to ratify a 3-year labor contract, ensuring an end to the ten-day picket and marking an end to the first grocery store strike in Colorado since the late 1990s [1].

1.2 Literature review

While established research has examined the relationship between striking and company share price, there are no peer-reviewed studies that measure the effect of striking or picketing on the patronage of a business (i.e. foot traffic). However, a wide assortment of adjacent literature uses cell phone data to quantify the economic and human mobility impact of factory closures and travel restrictions implemented during the COVID-19 pandemic. The use of cell phones to measure foot traffic is common and well-established. Two papers in 2017 outlined how human mobility can be accurately modeled using geolocation data [7, 12]. In China, researchers noted that "foot traffic is one of the most critical metrics for service sector businesses such as retail stores, restaurants, movie theatres, and hotels [7]." They observed that the number of digital map queries (i.e. searching an address in a map engine) is highly correlated with offline foot traffic [7]. When examining four separate industries and using digital map queries as their foot traffic metric, the authors found a strong correlation (R-squared > 0.7) and statistically significant relationship ($p < 0.001$) between foot traffic and auto sales, as well as between foot traffic and restaurant spending [7]. Although not a direct measurement, this finding is consistent with the assumption that foot traffic provides a strong indicator of consumer spending, particularly at businesses such as restaurants and grocery stores with relatively low-priced items. In Singapore, a similar connection between mobile data and offline foot traffic was found with location data extracted from phone call proximity to cell towers: "phone users with different phone usage patterns do not have systematic differences in travel behavior," meaning their data could be applied to the broader population [12].

Numerous studies have also performed foot traffic analysis utilizing consumer geolocation data from SafeGraph, a location data aggregation company [8, 13, 20]. One paper observed how the COVID-19 lockdown in New York City affected stay-at-home behavior, using each person's home census tract demographics to ascertain how education, race, and income may relate to rule adherence [8]. An adjacent study examined COVID-19 cases and restrictions in Houston, Texas, comparing SafeGraph data with unemployment claims, COVID-19 cases, and mobility sector data from Google [13]. It found that foot traffic shifts lagged actual COVID-19 cases, and that grocery store and pharmacy visits were the least affected by COVID-19 [13]. A similar paper that cross-validated SafeGraph data with data from Apple and Google examined the effectiveness of lockdown measures across the entire United States [10]. It established that stay-at-home orders induced a 3.5%-7.9% foot traffic decline whereas reopenings had a 1.6%-5.2% foot traffic increase, noting that counties with a higher proportion of essential businesses experienced less of a decline in foot traffic [10]. One interesting observed phenomenon was that foot traffic reduction only ever lasted for a month followed by a rapid rebound, no matter the level of COVID-19 infections [10]. A further article used SafeGraph and card spending data to scrutinize how COVID-19 measures affected consumer spending and foot traffic, specifically the effect of reopenings and stimulus checks [20]. Researchers found a significant increase in both foot traffic and card spending at nonessential businesses before lockdown measures were implemented and an immediate sink in foot traffic afterward [20]. Overall, SafeGraph's foot traffic data and its application to economic activity are well-established in academia.

1.3 Methods & limitations

For this study, cell phone positioning data was acquired from SafeGraph, a data aggregation company. SafeGraph identifies Points of Interest (POIs), which are clear geographical areas associated with a store or otherwise important location [17]. Once a POI is defined, there are a wide variety of ways to know whether or not a cellphone and by extension its owner has entered a POI. For SafeGraph, these methods include but are not limited to internet protocol (IP) addresses, available or connected Wi-Fi networks, available or connected Bluetooth networks, and beacon proximity [18]. These techniques are similar in that they know someone's general position because they are connected to or visible to geographically known connection points. For example, if a customer walks into a grocery store and their phone connects to the complimentary Wi-Fi that has unique identifiers for that store, the customer's relative position is surmised. Even if the customer never connects to the network, their device still performs digital handshakes with the devices around them, providing constant opportunities to identify their location. Companies like SafeGraph acquire these types of interactions en masse and then aggregate them into datasets [17]. It is important to note that the data for this research was aggregated and anonymized, but cell phone geolocation tracking data without these safeguards poses countless privacy and ethical concerns. For this paper, SafeGraph's researcher program provided hourly foot traffic sums to every King Soopers location from January 1st, 2020, to September 5th, 2022, at no cost.

It is important to note that Kroger, the owner of King Soopers, does not break down its revenue data by store, and due to having ∼2,800 locations, it is impossible to calculate the impact of the King Soopers strike on total revenue. Furthermore, this case study is most relevant to the impact on service-sector businesses that rely on customer foot traffic, as picketing in industrial or similar industries is not meant to deter a customer from physically entering a location. This study excluded any store that was closed or opened around the time of the strike and split the stores between those that went on strike and did not.[1] This analysis also examined relationships between daily foot traffic and local COVID-19 confirmed cases and deaths, local weather daily averages, and local air quality data to account for confounding factors. Table 1 summarizes all data used and their corresponding sources.

Table 1 Summary of variables and sources [9, 21]

Name	Source	Measure(s)	Resolution
Visits or Foot Traffic	SafeGraph	Daily smartphones that entered a King Soopers location	Per Store
COVID-19 Cases	COVID-19 Data Hub	Daily confirmed COVID-19 cases	County
COVID-19 Deaths	COVID-19 Data Hub	Daily confirmed COVID-19 deaths	County
Air Quality	Environmental Protection Agency	Daily Air Quality Index (AQI) score	Per Store
Snowfall	Open Meteo	Daily snowfall sum (cm)	Per Store
Rainfall	Open Meteo	Daily rainfall sum (mm)	Per Store
Mean Temperature	Open Meteo	Daily 2-meter resolution average temperature (°C)	Per Store
Wind Speed	Open Meteo	Daily 10-meter resolution max wind speed (km/h)	Per Store

For further context, the numerical mean and standard deviation for every variable was calculated during the strike period. These values are divided between the striking and nonstriking stores as well as the year from which they were calculated, either 2021, the year prior to the strike, or 2022, the year of the strike. The results are presented in Table 2.

Table 2 Yearly standard deviation and numerical mean for each variable during strike period

Name	Stores	Mean		Standard Deviation	
		2021	2022	2021	2022
Foot Traffic	Striking	40.48	25.77	24.51	18.26
	Nonstriking	62.26	59.41	33.25	30.04
COVID-19 Cases	Striking	39,584	111,415	19,680	51,699
	Nonstriking	23,769	77,120	16,478	52,407
COVID-19 Deaths	Striking	554	882	262	414
	Nonstriking	334	693	242	517
Air Quality (AQI)	Striking	4.2	8.3	2.1	4.6
	Nonstriking	5.3	8.6	2.5	4.1
Snowfall (cm)	Striking	0.05	0.29	0.21	0.66
	Nonstriking	0.08	0.27	0.24	0.67
Rainfall (mm)	Striking	0.01	0.01	0.05	0.03
	Nonstriking	0.02	0.01	0.07	0.09
Mean Temperature (°C)	Striking	0.87	-0.22	2.53	3.31
	Nonstriking	0.08	-0.57	2.76	3.71
Wind Speed (km/h)	Striking	18.64	16.70	7.09	4.82
	Nonstriking	20.34	16.54	9.42	7.38

There are several events (e.g. high disease transmission or a local forest fire) and variables (e.g., ambient temperature) that might explain a change in foot traffic to a grocery store. Therefore, the most likely confounding variables were compared to store foot traf-

[1] The striking King Soopers stores on Havana Street and Pierce Street were excluded from any calculations as their data was incomplete or they closed during the strike period.

fic. The Pearson correlations were computed between daily foot traffic and each of the variables in Table 1 for each store and each year – 2021, the year prior to the strike, and 2022, the year of the strike. Figures 3a and 3b average these daily correlations across all days of the year and all stores in the category, for striking stores and nonstriking stores, respectively. Any variable pair that did not have a significant relationship was plotted with an X over it in Fig. 3.

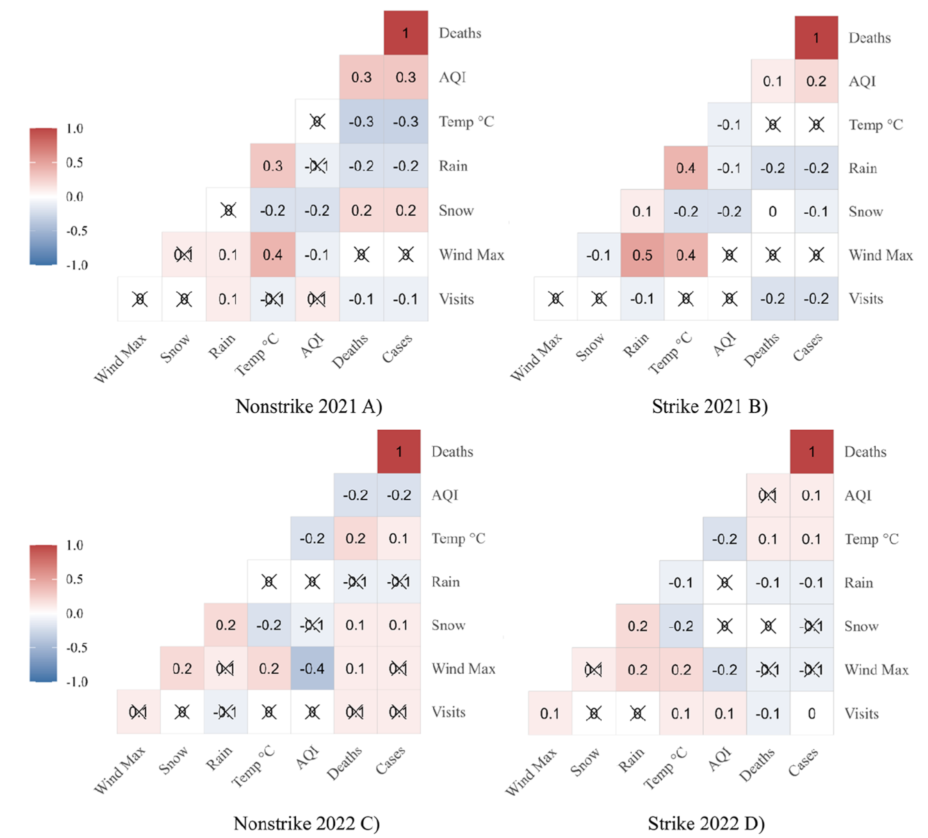

Figure 3 Correlations averaged across all days in the year and all stores

All variables that had a significant relationship (p-value < 0.05) with store visits had a very weak correlation. The strongest, significant correlations with store visits being COVID-19 cases or deaths. These correlations were always negative, implying that elevated numbers of COVID-19 cases or deaths may have dissuaded customers from visiting King Soopers or consolidating to fewer visits. Surprisingly, of the four correlation plots, only the striking stores of 2022 had a significant relationship between the Air Quality Index (AQI) score, which serves as a proxy for forest fires, and store visits with a very weak positive correlation. Overall, no variable presented a strong correlation, but all were considered when analyzing whether any of them could explain a shift in store visits.

Another confounding variable is that the striking stores are geographically concentrated in the Denver area, as pictured in Fig. 1. This poses the issue of differences between the control nonstriking group and the striking group being due to regional differences. While this study is unable to rule out all regional effects, this was mitigated by only comparing stores to their own historical foot traffic (i.e. normalizing any changes on a per-store basis). And, as with the variables explored in Fig. 3, local news reports were checked within the period of the strike that could widely impact foot traffic to grocers (e.g., a terror attack or natural disaster), of which none were found. It is also possible that some decrease may have been due to fewer employees in the stores, but this sum is likely small due to Kroger reporting that they would bring in staff from across the country and hire temporary workers to keep all stores operating normally [3].

2 Analysis and findings

The primary goal of this work is to quantify the effect picketing had on customers entering King Soopers locations. During the month of the strike, Fig. 4 provides a visual overview of the overall average foot traffic for striking and nonstriking stores as well as every individual store's traffic normalized by their foot traffic for January 1st. This day was arbitrarily chosen for ease of comparison of any traffic drop relative to the new year holiday with a ratio of one reflecting equal foot traffic to new years day.

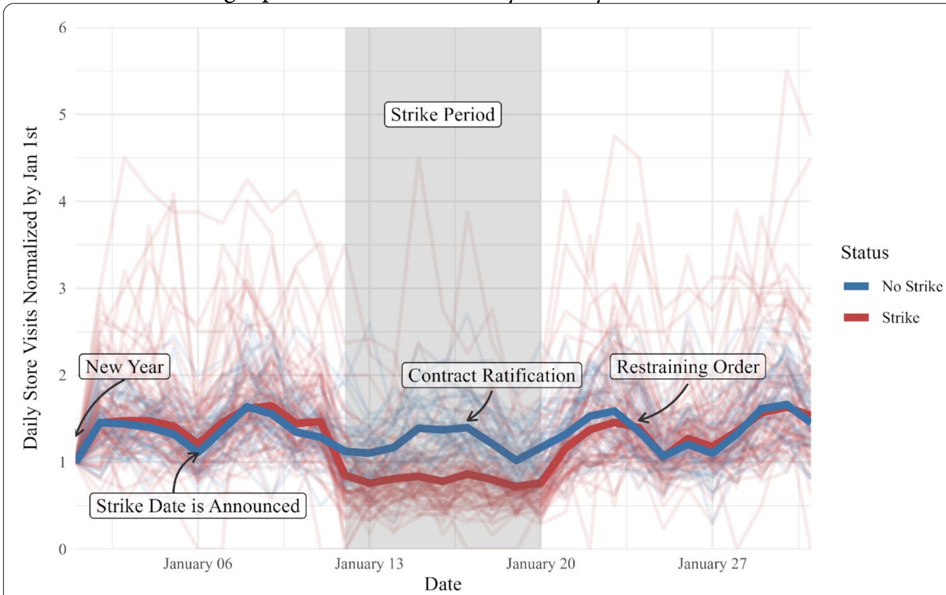

Figure 4 Overview of normalized store visits in 2022 for all striking (red) and nonstriking stores (blue) during the month of the strike period (gray)

Broadly, it can be observed that normalized average foot traffic was lower across the strike period for striking stores with similar declines on notable dates such as New Year, the day the imminent strike was announced, and when King Soopers won its restraining order against the picketers. However, these values cannot be directly compared to previous years due to seasonal changes and other general trends. Therefore, average foot traffic values of one year preceding the strike, 2021, were used to train two weekly Seasonal Autoregressive Integrated Moving Average (SARIMA) models to project what the average foot traffic values would have been for striking and nonstriking stores if a strike never occurred [4].

The SARIMA model works by summing a combination of historical values to make predictions for the future. Specifically, the model is separated into three main parts: the time offset, also referred to as the backshift, the autoregressive components, and the moving average components. In the case of the models trained, they are making predictions around weekly foot traffic trends where the day of the week is a strong foot traffic predictor, so the backshift was looking at the value of the previous week, seven days offset. For example, to predict the value for next Monday, the model would first look to the last Monday as the basis of its prediction. The autoregressive component makes linear combinations of back-shifted data points scaled by constants for the best fit. The moving average component adds back-shifted white noise based on the uncertainty at the previous point, enabling the model to have range and flexibility in its predictions in line with the historical data. All of these components use the historical daily foot traffic values to generate a prediction of a future value with a range of uncertainty.

The forecast package in R was used to automatically fit the best fitting SARIMA equation to the training data, which functions by fitting as many combinations of autoregressive and moving average components as possible to find the one with the best fit to the historical data [11]. Equation (1) defines the general form of the best fitting (2,0,0)x(0,1,1) SARIMA model where $\{w_t\}$ represents white noise.

$$x_t = x_{t-7} + \Phi_1(x_{t-1} - x_{t-8}) + \Phi_2(x_{t-2} - x_{t-9}) + w_t + \Theta w_{t-7} \tag{1}$$

The resulting model can be broken down into its core components where the (2,0,0) represents the non-seasonal components and the (0,1,1) represents the seasonal parts of the SARIMA model. The two in the (2,0,0) means that there are two autoregressive components, Φ_1 and Φ_2, which are combined with seasonal differencing and moving average, Θ, from the (0,1,1) part of the equation. In the resulting equation, the model solves for the foot traffic of a specific date, x_t, by first looking at the foot traffic value of the same weekday one week back x_{t-7}, which is then combined with the autoregressive components times the seasonal differencing of the days next to x_{t-7}; hence, the $(x_{t-1} - x_{t-8})$ and $(x_{t-2} - x_{t-9})$. This implies that the best-fitting model is a combination of the value one week back plus the scaled difference of the one to two days immediately preceding the current day the model is solving for, as well as the value of the prior week. Lastly, the $w_t + \Theta w_{t-7}$ represents the present white noise as well as the scaled white of the prior week that adds uncertainty to the result. The coefficients fit for the striking and nonstriking models are summarized in Table 3.

Table 3 Summary of SARIMA model coefficients

Model	Φ_1	Φ_2	Θ
Striking	0.447	-0.179	-0.879
Nonstriking	0.463	-0.212	-0.903

The larger Φ_1 coefficient for both models when compared to Φ_2 implies that the difference between the day before and the day before a week prior are the main determinants of the predicted foot traffic based on the $\Phi_1(x_{t-1} - x_{t-8})$ portion of Equation (1). Where x_t is the current day's foot traffic that is being solved for. The sign of the coefficients is not important, since they are being multiplied by a day-by-day difference that can be either positive or negative. Further, the white noise coefficient Θ is arbitrary to what yielded the best fit to the training data. Both SARIMA models were assessed using the Ljung-Box test, which tests the null hypothesis that the residuals are white noise (i.e. independently distributed) [15]. The striking and nonstriking models had a p-value > .90, so the null hypothesis cannot be disproven. Although a high p-value is generally worrisome, in this case, it is reassuring because if the residuals were not white noise, this would mean that the models may be consistently mispredicting values in a certain way. This would imply that the models were missing an important trend in the training data, but because we are unable to disprove the null hypothesis, this suggests our residuals are behaving like white noise and therefore our model is properly capturing its training data.

However, this does not test how well the models fit to their training data. To do this, the Mean Absolute Percent Error (MAPE) and Mean Absolute Scaled Error (MASE) tests were applied. The MAPE test averages the difference between the actual and forecasted value, which was 14.4% for the strike model and 19.4% for the nonstriking model. A MAPE score between 10-20% is considered a good forecasting model [14]. However, researchers have noted that while simple and widely used, this model is flawed as near zero values lead it to approach infinity [4]. Therefore, the MASE model was also applied, which compares the predictions of the SARIMA models versus a naive model (i.e. one that predicts the previous day's value for the next day). This yielded 65.0% for the strike model and 72.0% for the nonstriking model. Based on the definition of the MASE model, a value of 100% would mean that the models are identical to a naive model with any value less than 100% being more accurate, closer to the actual values, than a naive model [4]. Both models were over 25% more accurate at predicting foot traffic when compared to the naive model. Figure 5 compares the values predicted by the SARIMA models to the actual average foot traffic of striking (a) and nonstriking (b) stores.

During the strike period, foot traffic values for striking King Soopers locations were consistently lower than the values projected by its SARIMA model, but nonstriking stores' average foot traffic rebounded for three of the nine days during the strike period. This suggests that even if a store did not have an active picket line in front of it, some of the customers nonetheless avoided shopping at King Soopers albeit to a lesser degree. On average, during the strike period, not inclusive of January 21st, as workers had returned to work, striking stores saw a 47% average decrease in foot traffic compared to projected values. Nonstriking stores experienced a 14% average decrease in foot traffic. It should be noted that Martin Luther King Jr. Day occurred on January 17th, which saw the highest average foot traffic for both striking and nonstriking stores during the strike period, potentially lessening the effects of the strike. When considering the 95% confidence interval of the predictions, striking stores saw a minimum of 35% to a maximum of 55% decrease in average foot traffic, whereas nonstriking stores ranged from a 6% increase in average foot traffic to a 27% decrease. Striking stores saw a dramatic rebound in foot traffic the same day workers stepped off the picket line to return to work, January 21st, with a 28% decrease compared to the projected value, and only a 5% decrease the next day. As for nonstriking stores, they experienced a 15% decrease from projected levels the first day employees returned and a 7% increase the day after.

Another observation is that average striking store foot traffic remained consistently down at a similar level throughout the striking period. In contrast, the foot traffic at nonstriking stores was far more sporadic, rebounding on January 15th to only 3% below project levels. This difference may be attributed to nonstriking stores not having the physical disincentive of crossing an active picket line with their only deterrent being a person's own moral beliefs. Whereas the announcement of the future strike seems to have decreased foot traffic, the inverse did not occur when King Soopers successfully won a restraining order against the strikers. On January 18th, when the restraining order was announced, foot traffic decreased by 44% and 25% for striking and nonstriking stores compared to predicted values, respectively. This implies that the publicity of the restraining order may have worsened the effects of the strike. Fascinatingly, the day news of the con-

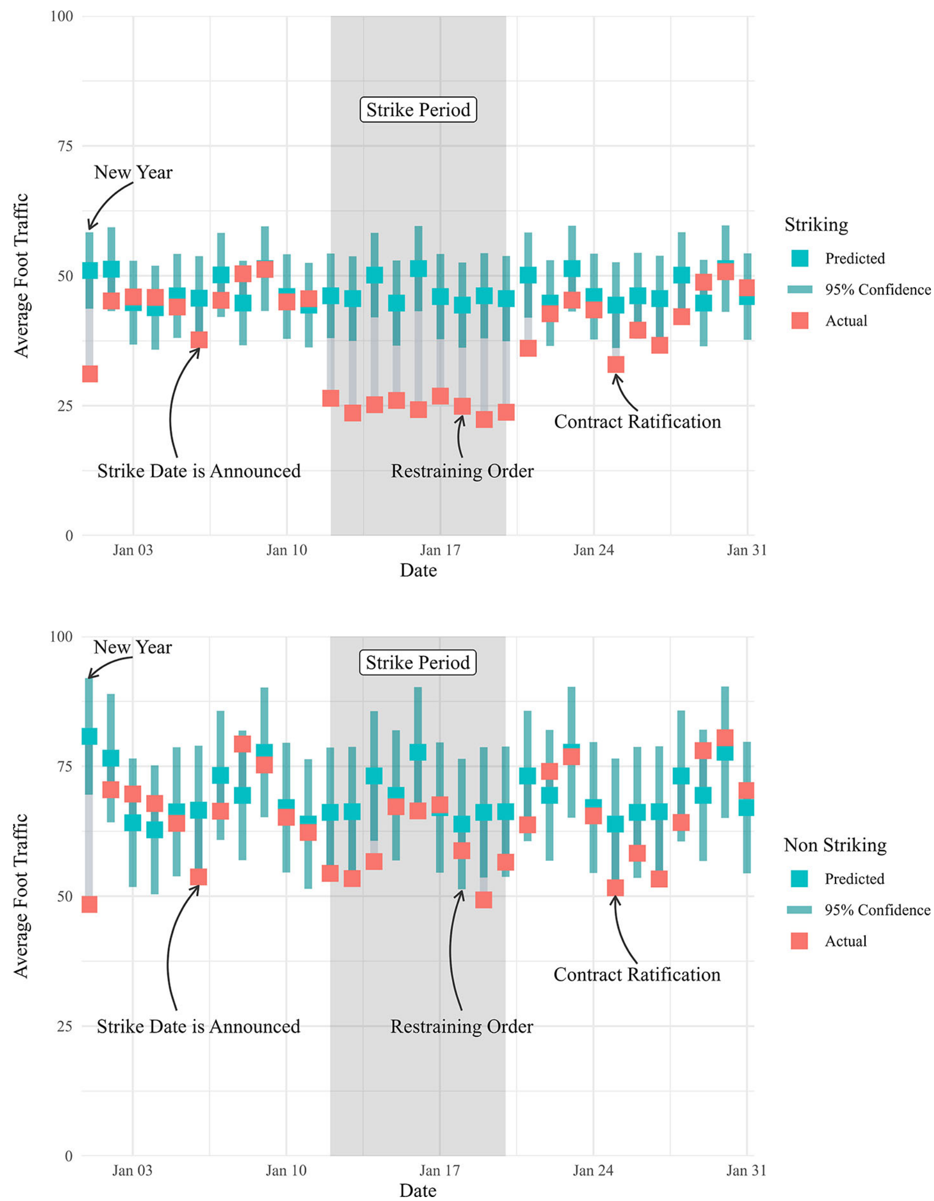

Figure 5 Difference between SARIMA predicted average daily foot traffic values and actual average daily foot traffic values in 2022 for striking (a) and nonstriking (b) stores during the month of the strike with 95% confidence interval for predicted values. (a) Striking Stores. (b) Nonstriking Stores

tract ratification, which occurred on January 24th but wasn't widely publicized until the 25th, seems to have depressed foot traffic to striking stores by 26% and 19% at nonstriking stores on average [1]. But, this is close to the 95% confidence interval of expected values, so it is uncertain is the announcement had any real effect. The SARIMA models present good accuracy to their fitted data and no explicit confounding variable could explain the observed foot traffic decline during the strike period. Therefore, it can be concluded that the strike and resulting picket lines had a measurable effect on foot traffic to King Soopers locations with physical picket lines roughly tripling the resulting decrease.

3 Discussion & conclusion

To the best of our knowledge, this work is the first to use mobile tracking data to quantify the effect of a strike and resulting picket lines on store foot traffic. Further, this King Soopers strike provides the unique scenario where there was a roughly even split between striking and nonstriking stores, which are otherwise similar and located in the same state, helping to isolate the effect of a physical picketing line. This paper provides a framework for modeling and evaluating potential loss in foot traffic that could be applied by other researchers to quantify the effects of other strikes on public retail businesses.

Even though the direct economic cost born by King Soopers due to this strike may never be known, quantifying the strike's effect on foot traffic comes close. Dong, et al. found that restaurant foot traffic in China had a strong correlation and significant relationship to spending, so it can be inferred that the up to 47% decrease in foot traffic incurred some burden on store sales [7]. This takes for granted that King Soopers sells essential goods and services while restaurants are discretionary. However, having a relative number for the cost of picketing can empower future negotiations for both unions and businesses. This research hopes to help shift this cost from an abstract to a tangible sum, which can be factored into better negotiations and avoid costly disputes for both sides in the future. We believe our research is also the first to use this type of data to demonstrate that picketing lines can have an appreciable effect on store traffic with 33% less foot traffic observed on average at stores that had them. Lastly, although other research has found that mobile geolocation data applies to the broader population, it should be noted that the elderly and young were probably undercounted in this study due to these groups generally having fewer mobile phones [12]. Future works could combine cell phone data with physical polling to rectify this issue, but that would be a costly endeavor.

Abbreviations
SARIMA, Seasonal Autoregressive Integrated Moving Average; AQI, Air Quality Index; POI, Point of interest; UFCW, United Food and Commercial Workers; MAPE, Mean Absolute Percentage Error; MASE, Mean Absolute Scaled Error.

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Author contributions
Phillip Post was the sole author of this paper. The author read and approved the final manuscript.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
All data received from SafeGraph was aggregated and anonymized.

Competing interests
The author declares that he has no competing interests.

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