Invited presentation at the 2018 Southern Agricultural Economics Association Annual Meeting, February 2-6, 2018, Jacksonville, Florida

Nowcasting Food Stock Movement using Food Safety Related Web Search Queries

Mahdi Asgari

University of Kentucky, Email: mahdi.asgari@uky.edu; Address: Dept. of Agricultural Economics, 302 C.E. Barnhart Bldg. University of Kentucky, Lexington, KY 40546-0276. Phone: (859) 536-1465

Mehdi Nemati

University of Kentucky, Email: mehdi.nemati@uky.edu; Address: Dept. of Agricultural Economics, 302 C.E. Barnhart Bldg. University of Kentucky, Lexington, KY 40546-0276.

Yuqing Zheng

University of Kentucky, Email: yuqing.zheng@uky.edu; Address: Dept. of Agricultural Economics, 317 C.E. Barnhart Bldg. University of Kentucky, Lexington, KY 40546-0276

Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2018 Annual Meeting, Jacksonville, Florida, February, 2-6 2018

Nowcasting Food Stock Movement using Food Safety Related Web Search Queries

Abstract

Predicting financial market movements in today's fast-paced and complex environment is challenging more than ever. For many investors, online resources are a major source of information. Researchers can use *Google Trends* to access the number of search queries of a particular topic by internet users. The search volume index provided by Google then can be used as a proxy for importance of that topic. To predict the collective response to a particular news, we can use the search index for relevant search terms in our forecasting model. The focus of our study is forecasting food stock movement. A unique feature of the food industry is that besides common fundamental information, stakeholders are responsive to food safety news. In this study, we test whether including relevant search terms would reduce the forecasting error and improve the predictive power of traditional models. We use the market data and Google Trends index for 46 listed food companies. The empirical results show that on average the use of search terms reduces forecasting error by 2 to 31 percent for predicting trading volume, and reduces forecasting error by 3.5 to 77 percent for predicting the closing price, depending on the company. We also applied a model confidence set (MCS) to create a set of specifications that have statistically least forecasting error. The average forecasting error of the models in the set is lower than all models with search terms which implies that the MCS approach is efficient in identifying models with best predictive power.

Keywords: food poisoning, food safety, Google trends, nowcasting, outbreak, stock market

JEL codes: C53, E27, G41, L66

Introduction

Financial markets react to socio-economic incidents. Food safety outbreaks and the news may tarnish the image of the food manufacturing companies. The correlation between such news and investors' concerns and decisions in the food industry has not been investigated in the literature. In this study, we test whether food safety concerns can be an indicator of trading decisions in the near future in the food stock market. Approximately 25 percent of total episodes of illnesses in the U.S. is due to foodborne illnesses (Scallan et al., 2011). Centers for Disease Control and Prevention (CDC) detect foodborne outbreaks and issue public health recommendations with regard to the source of contamination. Food contamination can occur at the production, processing, distribution, or preparation level. We focus our study on the publicly traded companies in food processing and preparation industry. When CDC identifies and announces a product as the contamination source, we expect investors to shift away from the producing company and the stock price to decline and trading volumes change. However, our main objective in this study is not to determine the extent to which food safety news explain the variation in the market indicators but to test whether including such information in the forecasting analysis would improve our understanding of market movements in the near future. Since a considerable share of information transfer involves online activities, we use the aggregate index for related search terms as a measure of the societal sensitivity to outbreak incidents.

The internet has considerably lowered the cost of data collection for researchers in many fields of social sciences. Online published data and web-scraping techniques provided economists with an ever-increasing amount of information which enables them to answer a vast range of questions (Askitas & Zimmermann, 2009, 2015; Edelman, 2012). In recent studies, the relationship between web search volume indexes and social behavior, especially in the context of health and economic decisions, has become more prominent. The correlations between Google Flu Trends and prevalence of influenza has been investigated in various studies (Ginsberg et al., 2009; Goel, Hofman, Lahaie, Pennock, & Watts, 2010; Lazer, Kennedy, King, & Vespignani, 2014). Chunara, Andrews, and Brownstein (2012) used HealthMap news media reports and Twitter postings to estimate the epidemiological pattern of the 2010 Haitian Cholera Outbreak. Public health studies show that syndromic surveillance can complement the traditional monitoring and improve the early detection of epidemiological patterns (Brownstein, Freifeld, & Madoff, 2009; Cooper, Mallon, Leadbetter, Pollack, & Peipins, 2005; Wilson & Brownstein, 2009). Although we are testing the application of the same methods to financial markets, one should consider the difference between the implications for epidemics and financial markets. In the latter, the primary factor that spreads panic is news and we expect that all the agents (market participants) become "affected" at the same time (Bordino et al., 2012).

The significance of online search counts in forecasting consumer behavior has been tested in various studies. Goel et al. (2010) used Yahoo! Web search query to predict the opening weekend box-office revenue for movies, the first-month sales of video games, and Billboard weekly rank of songs. In all three cases, they found that search count data is a good predictor of future. They suggest that including such information in the model increases the forecasting power, especially when other data sources are lacking. Looking at the labor and housing markets in the United Kingdom, McLaren and Shanbhogue (2011) suggest that online search data can complement existing surveys in economic analysis. Perhaps one of the latest improvements in the application of search engine data in forecasting economic indicators is offered by Google Inc. as "Google Trends" which provides an index of search query counts and dates it back to 2004.

Choi and Varian (2012) explain how Google trends can be used to predict economic decisions. They use automobile sales, unemployment claims, tourist demand, and consumer confidence as the empirical examples to examine the goodness of fit in models that includes web queries. Results show that including relevant Google trends data increases forecasting performance by 5 to 20 percent in those cases. Following Choi and Varian (2012) many studies employed Google trends data to nowcast other economic variables. Artola and Martínez-Galán (2012) applied internet search data to predict British tourist inflow to Spain and conclude that the improvements in the forecasting by Google indicators depend on the benchmark model. Vosen and Schmidt (2012) and Vosen and Schmidt (2011) compared out-of-sample nowcasting performance of Google indicators with survey-based indicators on private consumption in Germany. They found that the former model outperforms all alternative models. Yao and Zhang (2017) found a negative correlation between the Google index and crude oil prices. However, Google index data did not improve the forecasting power of their model.

Clearly, internet search data including Google data are more frequent, accessible, and less time consuming to collect compared to surveys and thus a cost-effective source of information for economic analysis (Smith et al., 2016). Using Google trends data, many studies construct an index to include in the model and lower the forecasting error. Antenucci, Cafarella, Levenstein, Ré, and Shapiro (2014) developed a social media index to track the relationship between Tweeter posts related to job loss and unemployment claims in the U.S. and suggested that the proposed index is a high frequency, real-time indicator of job loss in the economy that can be used by policy makers to respond to such events. Similarly, D'Amuri and Marcucci (2017) examined whether an index of Google job-search intensity can predict the U.S. unemployment rate. They found that Google based models generally perform better than the other models. Similar results derived by Askitas and Zimmermann (2009) who found a significant correlation between internet activity and unemployment rates in Germany. Though internet penetration rate is lower in emerging markets, the application of internet-based indexes as a predictor of economic activities is not limited to the developed economies. Carrière-Swallow and Labbé (2013) construct an index of Google searches for automobile purchase in Chile and evaluate the power of forecasting models with and without the index. Estimation results show that their proposed Google Trends Automotive Index nowcast automobile sales better than the benchmark model.

Accuracy and efficiency of the forecasting of the near future are critical to policymakers and market participants. The complexity of the financial and commodity markets today requires a reliable approach to identify the current movements. Previous studies show the correlation between search volume data and financial market fluctuations (Bordino et al., 2012; T. Preis, Reith, & Stanley, 2010). Investors can interpret the changes in the online query volume as the "early warning signs" and therefore identify the systemic financial risk (Bordino et al., 2012; Tobias Preis, Moat, & Stanley, 2013).

Our proposed research builds on the previous works which investigated the predictive power of search volumes on the stock returns, trading volumes, and the investor attention (Andrei & Hasler, 2014; Bordino et al., 2012; Joseph, Wintoki, & Zhang, 2011). Our objective is to test whether including search engine data improve predicting the movements in the stock market. To empirically test this hypothesis, we will use historical data on the stock price and trading volume of 46 leading companies in the food industry. In addition, by using Google Trends, we will obtain longitudinal query volume of searches related to the companies under the study and food safety concerns. We will define various data generating processes using a different combination of lagged variables and follow Hansen, Lunde, & Nason (2011) to construct a model confidence set that includes the best models based on the desired criteria.

The literature has focused on using online queries to nowcast economic decisions on one hand and epidemiologic patterns on the other hand. However, to best of our knowledge, the implication of food safety issues on food stock market has not been included in any previous analysis. Our study bridges the two sides by applying similar methods to financial markets and including search terms related to foodborne outbreaks.

Methods and Data

In this paper, we estimate thousands of models for each company and compare their predictive power to select a model (or a set of models) with least forecasting error. Let y_t be the log of the dependent variable (trading volume and closing prices in our case) at time t. Similar to Choi and Varian (2012) we define a simple autoregressive model as follows

$$y_t = \sum_{q=1}^{k} \beta_q y_{t-q} + \sum_{d=1}^{h} \alpha_d X_{jt-d} + \varepsilon_t \qquad t = 1, \dots, T \tag{1}$$

where q is the number of lag returns for the dependent variable and d is the number of optimum lags for search terms. The second term on the right-hand side is online query volume, defined by X_{jt} which indicates the Google Trends index for search term j at time t. It is evident that if we have n independent variables, we can test the forecasting error for $(2^n - 1)$ different specifications. To examine the predictive power of competing forecasts we can compare Mean Squared Forecast Error (*MSFE*) of the models. Models with lower *MSFE* are more favorable than rest of the estimated models. Thus, if we find *MSFE* of specifications that exclude search terms to be higher than other specifications, we can infer that online search terms improve forecasting accuracy.

This approach is consistent with our objective of identifying a suitable predictive model of the dependent variable as opposed to identifying a causal interpretation of the explanatory variables. The goal of our study is to improve the accuracy of forecasting trade volume and price changes in the stock market, using available online search information. We can evaluate the performance of estimated models using in-sample or out-of-sample criteria. In-sample measures of model performance such as R^2 and Akaike Information Criteria (*AIC*) suggest models that best fit existing data. However, such criteria are better suited for econometric models. To conduct an out-of-sample evaluation, we segment the underlying data into a training set and a prediction set in the spirit of machine learning. The training set is truncated at week t while the prediction set includes the last p observations where $p = t+1, \ldots, T$.

To obtain *MSFE* for each model, we generate predicted values of the dependent variable $\hat{y}_t$ for each company in the sample and for each of the observations in the prediction set using the regression coefficients that are estimated with the observations in the training set. Then, we calculate the forecast error (*FE*) for each week as the difference between the predicted value and the actual value

$$FE_t = (\hat{y}_t - y_t) \tag{2}$$

and finally, the MSFE for each model (m) can be computed as

$$MSFE_m = \frac{\sum_{t=1}^{S}(\hat{y}_t - y_t)^2}{S} \qquad (m = 1,2,3) \tag{3}$$

where S is the number of observations in prediction set. The model with the lowest *MSFE* shows least forecasting error and therefore is our preferred specification. However, the difference between *MSFE*s should be tested statistically.

Since we are not estimating a causal effect but rather trying to predict a variable of interest with minimum MSFE, it is not our purpose to identify the "*True*" specification. Hansen, Lunde, & Nason (2011) propose an approach that constructs a model confidence set which contains the best model(s) with a given level of confidence.[1] This procedure suits our objective best for two reasons. First, it is flexible in terms of defining a user-specified criterion for model selection. In our case, we will use minimum *MSFE* to compare and select models. Second, we specify the model using search terms that are selected somewhat arbitrarily, and other researchers may consider an expanded or limited set of search terms compared to our study. Therefore, we do not assume that one particular specification is representing the true data generating process.

Following Hansen, Lunde, & Nason (2011), we compare and evaluate models in terms of a loss function. Therefore, starting with the set of M^0, that contains m^0 objects, we assign loss function L_{et} to the object e in period t. The relative performance of two models can be defined as

$$R_{ef,t} \equiv L_{e,t} - L_{f,t}, \qquad \text{for all } e,f \in M^0$$

If we assume that $\mu_{ef} \equiv E(R_{ef,t})$, then alternative e is preferred to alternative f when $\mu_{ef} < 0$. If we define MSFE as the loss function, then model e would have lower MSFE and be chosen. Then, the set of superior objects is defined by $M^* \equiv \{e \in M^0 : \mu_{ef} \leq 0 \text{ for all } f \in M^0\}$ where M^* is

[1] In the same sense that a confidence interval covers a population parameter (Hansen Lunde, & Nason, 2011).

determined through a set of significance tests at a certain probability level. Hansen, Lunde, & Nason (2011) refer to any subset of M^0 that contains all M^* as the model confidence set.[2]

Data utilized in this study are trading volume and closing price for leading food companies and also google trends index for company names, and other search terms related to food safety. We obtained daily data on trading volume and closing price of companies in the food industry using *Google Finance* website. Google Finance provides trading information for 64 companies that are specialized as Quick Service Restaurants, Food Processing firms, and Animal Slaughtering & Processing firms. We focused on these three industries because food contamination happens mostly at the processing and preparing levels of the supply chain. We suspect that as the news of an outbreak caused by foodborne illness spreads, the whole market is impacted at the same time. Although the outbreak may involve only one brand, there might be a spillover effect to the whole industry as consumers, even in a very short-term, start to behave more cautious. Investors might react by shifting away from the specific brand or the whole industry to avoid unanticipated loss. We expect such concerns reflect in market trading and price. The online search index for the company name is not available for all companies, and therefore we only used the information from 46 companies, listed in Table 1, to match market information with available online search data.

<< **Table 1 here** >>

We obtained search volume index for each company's name and the search terms related to food safety concerns from the *Google Trends* for the same period. In this study, we focused on two main search terms, *outbreaks* and *food poisoning*, which we think are most related to food

[2] Details on the MCS algorithm and construction of the hypothesis test and elimination rules can be found in Hansen, Lunde, and Nason (2011).

safety issues. Future research can focus on developing an algorithm to identify all related terms with predictive power in this context. For instance, Afkhami, Cormack, and Ghoddusi (2017) propose a multistage filtering process to select search terms that best predict price volatility of crude oil and use the terms as a proxy for the investor attention in their forecasting model.

Google search query volume (SQV) is appealingly accessible, but there is a caveat that needs to be pointed out. As Choi and Varian (2012) note, "Google Trends provides an index of the volume of Google queries by geographic location and category. Google Trends data does not report the raw level of queries for a given search term. Rather, it reports a query index. The query index starts with the query share: the total query volume for a search term in a given geographic region divided by the total number of queries in that region at a point in time. The query share numbers are then normalized so that they start at 0 on January 1, 2004. Numbers at later dates indicated the percentage deviation from the query share on January 1, 2004." Thus, the query shares change every week, and the search index numbers relatively depend on the time of retrieving the data. Hence, forecasting performance of a model using data retrieved on one occasion might be different from a model using a periodic sample of queries (Rivera, 2016). Finding the best strategy to retrieve SQV and the impact of sampling methods on the forecasting efficiency is beyond the scope of this study and can be the subject of future research. In this study, we use a series of data that was retrieved on one occasion.

All time series data are collected from 1 January 2013 to 30 April 2017 period.[3] In this study, we use the observations from January 2013 to the end of February 2017 as the training set to build our prediction model. Next, we predict the variable of interest for the rest of the

[3] Daily stock market data did not date back to 1 January, 2013 for some of the companies. We matched google trends data to the new starting date for those companies. Since each company would have separate estimations, unequal length of data would not impact our conclusion.

observations, i.e., March and April 2017, in all models. We assume that investors are interested in near future and thus we only predict 9 weeks. Google trends data is obtained at the weekly level while the stock market data is daily. Using the same start date, we matched weekly average of the trading volume data with Google Trends data. In the case of the stock price, we assume that the closing price on the first business day of each week is the best indication of the impact that news, during the past week and over the weekend, have on the market. Therefore, we matched the online search index of each week with the closing price of the first trading day at the next week. For instance, in January 2013 the search term index for the week of Monday 7th to Friday 11th is matched with the closing price on Monday 14th which is the start of the following week. Thus, the total number of 226 observations is used for companies with complete data set.

Empirical Results

To compare forecasting power of models with and without search terms, we create an algorithm that produces all possible specifications given a set of independent variables. We define 11 variables to be included in the right-hand side of estimations. These 11 variables are first and second lag of dependent variable, company name search index, first and second lag of company name search index, food poisoning search index and its first and second lag, outbreak search index, and its first and second lag of outbreak. Therefore, we can create 2047 specifications for each company. For instance, we could estimate $y_t = \beta y_{t-1} + \varepsilon_t$ (y = TV and P) which is equivalent to equation (1), q is set to be equal to one and no search term is included. Or we could only use the second lag of the dependent variable, and estimate $y_t = \beta_2 y_{t-2} + u_t$. We could, instead, add the search index for the company's name, GTn_t, to the first model and estimate $y_t = \beta_1 y_{t-1} + \beta_2 GTn_t + \varphi_t$. Finally, the specification that includes all independent variables is $y_t = \beta_1 y_{t-i} + \beta_2 GTn_{t-j} + \beta_3 GTout_{t-j} + \beta_4 GTfp_{t-j} + \mu_t$ in which i = 1, 2 and j = 0,1,2. In this model, $GTout_t$ and $GTfp_t$ denote search index for *Outbreak* and *Food Poisoning*, respectively. As mentioned above, we estimate 20,47 models for each company. In total we estimate 94,162 models.

When comparing the estimations for all companies, if we find that including food poisoning and (or) outbreaks search terms significantly improve forecasting power of the model, we can conclude that food safety concerns may have an impact on investor decisions in this industry. Since we are using general as oppose to incident-specific terms to represent food safety concerns, if the improvement in predictive power is repeated for a considerable number of companies, we suggest that the negative impact of food outbreaks is not limited only to the contaminated product (brand) and the whole industry might be impacted.

Only three specifications (model with only the first lag of dependent variable, with only the second lag, and with both lags) does not include any search terms. The other 2,044 specifications have at least one search term variable. Similar to confidence interval that higher level of probability of error, α, results in a narrower interval, we used $\alpha = 0.6$ to create the model confidence set (MCS) with a lower number of models. This implies that we are 40 percent confident that the set includes the best models regarding forecasting error.

Table 2 reports the average *MSFE* for different forecast groups when trading volume is the dependent variable. Comparing the first two columns of the table shows that the average forecasting error for more than 70 percent of the companies in this study is lower when we include search terms. However, only for 12 companies[4] (27%) of the sample the forecasting error is lower in models without any search terms. The last column of Table 2 shows the average

[4] These companies are: Campbell Soup, CEC Entertainment, Conagra, Darling, Hershey, Hormel Foods, Industrias Bachoco, Jamba, Kraft Heinz, Pilgrims Pride, Smithfield Foods, and Sun Opta.

forecasting error for the models included in the MCS which is lower than the other two groups for all companies. Therefore, this model selection process is reliable in creating a set that is, on average, superior in terms of forecasting precision.

<< **Table 2 here** >>

To illustrate this graphically, we calculated the percentage change in average *MSFE* of all models with search terms compared to models without search terms to measure the improvement in forecasting for each company. We, then, ranked companies, as Figure 1 shows, based on the improvement in forecasting when search terms are included. The higher negative percentage implies more improvement in forecasting. When adding search terms, trading volume forecasting improves from 2 to 31 percent, depending on the company. Figure 1 also shows that the percentage change in average *MSFE* of models in the MCS compared to all models with search terms ranges from 1 to 20 percent for the companies in our sample.

<< **Figure 1 here** >>

We repeated the same process using closing price as a dependent variable. The average *MSFE* for different forecast groups is reported in Table 3. As shown in this table for 85 percent of the companies including search term improves forecasting power. 15 percent of the companies forecasting error did not improve by including search terms which represents seven out of 46 companies[5]. Comparing trading volume and closing price as a dependent variable we observe that, for the companies included in this study, search terms improves predicting power for closing price slightly more than trading volume. The last column in table 3 indicates the average

[5] These companies are: ADM, Bunge, CEC Entertainment, Darling, Dean Foods, Fogo De Chao, and Smithfield Foods.

MSFE for the models in the MCS set. The average forecasting error for the models in the MCS is lower than the other two groups for all except five companies[6].

<< **Table 3 here** >>

Furthermore, we use Figure 2 to illustrate the improvement in *MSFE* in percentages. Including search terms improves prediction power by 3.5 to 77 percent, depending on the company. Also, the average *MSFE* of models in the MCS is 0.2 to 96 percent lower compared to the average *MSFE* of all models with search terms when forecasting closing price.

<< **Figure 2 here** >>

In general, results indicate that using Google Trends search indexes for the company name, food poisoning, and outbreaks in building forecasting model for closing price and trading volume would improve the prediction power and the MCS procedure identifies the best specifications, effectively. If we sort all estimation from the lowest to the highest *MSFE*, we will find that significant majority of the top models for each company include search terms. The list of most precise specifications for all companies is presented in Appendix tables and discussed further in the next section.

Model Confidence Set

Model confidence set in our study includes specifications that have the lowest *MSFE* and are not, within a certain level of probability, statistically significantly different. To complete the pairwise testing of *MSFEs*, the MCS procedure calculates a *p*-value for each specification. We sort all the estimations for each company from the lowest to the highest *MSFE* and report the top six specifications in the appendix. Table A-1 reports the result for forecasting trading volume and

[6] These companies are: Annies, Campbell Soup, Darling, General Mills, and Kelloggs

Table A-2 for forecasting closing price. The third column on each table shows that only very few specifications have forecasting precision but exclude search terms.[7] In the last column of each table, we report the *p*-value for each specification and identify whether each model could be included in a set with $\alpha = 0.60$ and $\alpha = 0.25$ denoted by $M^{*}_{40\%}$ and $M^{*}_{75\%}$, respectively. The second confidence set, $M^{*}_{75\%}$, is more extensive and therefore includes a higher number of specifications while the first set, $M^{*}_{40\%}$, is more plausible since it is more contained. As the results show, most of the best forecasting models belong to $M^{*}_{40\%}$, some to $M^{*}_{75\%}$, and very few are excluded.

Concluding Remarks

We combined stock market information and *Google Trends* data to test whether we can improve forecasting power of stock market trading volume and closing price, for leading food companies, by using web search query index. We applied the framework to predict trading volume and closing price for 48 companies specialized as Quick Service Restaurants, Food Processing firms, and Animal Slaughtering & Processing firms. We obtained financial market information from *Google Finance*, and online query index from *Google Trends* websites.

Our empirical results show that use of search term information reduces the forecasting error in our sample. Instead of identifying the best forecasting model, we used a procedure to create a model confidence set that satisfies our exclusion condition. This set should only include models that have lowest *MSFE* and are not statistically different from each other. Based on our results, the average *MSFE* for all the models with search terms is lower than the average for models without search terms. The average *MSFE* for models that are selected into the MCS is the

[7] Only one specification (Darling) when forecasting trading volume and seven specifications for six companies (Campbell Soup, CEC Entertainment, Frischs, General Mills, Popeyes Louisiana Kitchen, Red Robin) when forecasting closing price.

lowest. Therefore, the MCS process that we applied in this study can efficiently identify a set of specifications with lowest forecasting error, i.e. best predictive power. Regarding percentage improvement in *MSFE* we find that including search terms in forecasting model for trading volume improves *MSFE* by 2 to 31 percent and improves forecasting power for closing price by 3.5 to 77 percent, depending on the company.

Investors and policymakers are interested in predicting the future movements of the stock market. Financial markets respond to, positive or negative, news in the short run. Predicting near future, nowcasting, with less error requires some information other than the market data. Since information is considerably transmitted online, search queries can be an important indicator of the public response to the news. Accessibility of online search index such as Google Trends provides an excellent opportunity to improve the predictive power of traditional forecasting models. Our empirical results show that including relevant search terms can considerably reduce the forecasting error of models used to predict trading volume and closing price of food companies. We only used two most common search terms related to food safety issues. Further research can focus on developing an algorithm to identify a broader range of search terms relevant to the food industry.

Forecasting literature shows that relying on one particular specification to predict the variable of interest may not be the most efficient strategy. The model confidence set approach that is used in this study creates a set of models that have lowest forecasting error and do not statistically differ from each other. The empirical results show that the average forecasting error of the models in the confidence set is lower than the average of all models with search terms.

References

Afkhami, M., Cormack, L., & Ghoddusi, H. (2017). Google search keywords that best predict energy price volatility. *Energy Economics, 67*, 17-27.

Andrei, D., & Hasler, M. (2014). Investor attention and stock market volatility. *The Review of Financial Studies, 28*(1), 33-72.

Antenucci, D., Cafarella, M., Levenstein, M., Ré, C., & Shapiro, M. D. (2014). *Using social media to measure labor market flows*. Retrieved from

Artola, C., & Martínez-Galán, E. (2012). Tracking the future on the web: construction of leading indicators using internet searches.

Askitas, N., & Zimmermann, K. F. (2009). Google econometrics and unemployment forecasting. *Applied Economics Quarterly, 55*(2), 107-120.

Askitas, N., & Zimmermann, K. F. (2015). The internet as a data source for advancement in social sciences. *International Journal of Manpower, 36*(1), 2-12.

Bordino, I., Battiston, S., Caldarelli, G., Cristelli, M., Ukkonen, A., & Weber, I. (2012). Web search queries can predict stock market volumes. *PloS one, 7*(7), e40014.

Brownstein, J. S., Freifeld, C. C., & Madoff, L. C. (2009). Digital disease detection—harnessing the Web for public health surveillance. *New England Journal of Medicine, 360*(21), 2153-2157.

Carrière-Swallow, Y., & Labbé, F. (2013). Nowcasting with Google Trends in an emerging market. *Journal of Forecasting, 32*(4), 289-298.

Choi, H., & Varian, H. A. L. (2012). Predicting the Present with Google Trends. *Economic Record, 88*, 2-9. doi:10.1111/j.1475-4932.2012.00809.x

Chunara, R., Andrews, J. R., & Brownstein, J. S. (2012). Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak. *The American journal of tropical medicine and hygiene, 86*(1), 39-45.

Cooper, C. P., Mallon, K. P., Leadbetter, S., Pollack, L. A., & Peipins, L. A. (2005). Cancer Internet search activity on a major search engine, United States 2001-2003. *J Med Internet Res, 7*(3), e36. doi:10.2196/jmir.7.3.e36

D'Amuri, F., & Marcucci, J. (2017). The predictive power of Google searches in forecasting US unemployment. *International Journal of Forecasting, 33*(4), 801-816.

Edelman, B. (2012). Using internet data for economic research. *The journal of economic perspectives, 26*(2), 189-206.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature, 457*(7232), 1012-1014.

Goel, S., Hofman, J. M., Lahaie, S., Pennock, D. M., & Watts, D. J. (2010). Predicting consumer behavior with Web search. *Proc Natl Acad Sci U S A, 107*(41), 17486-17490. doi:10.1073/pnas.1005962107

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica, 79*(2), 453-497.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116-1127.

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: traps in big data analysis. *Science, 343*(6176), 1203-1205.

McLaren, N., & Shanbhogue, R. (2011). Using internet search data as economic indicators.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific reports, 3*, srep01684.

Preis, T., Reith, D., & Stanley, H. E. (2010). Complex dynamics of our economic life on different scales: insights from search engine query data. *Philos Trans A Math Phys Eng Sci, 368*(1933), 5707-5719. doi:10.1098/rsta.2010.0284

Rivera, R. (2016). A dynamic linear model to forecast hotel registrations in Puerto Rico using Google Trends data. *Tourism Management, 57*, 12-20.

Scallan, E., Hoekstra, R. M., Angulo, F. J., Tauxe, R. V., Widdowson, M. A., Roy, S. L., . . . Griffin, P. M. (2011). Foodborne illness acquired in the United States--major pathogens. *Emerg Infect Dis, 17*(1), 7-15. doi:10.3201/eid1701.P11101

Smith, D. M., Bansal-Travers, M., Huang, J., Barker, D., Hyland, A. J., & Chaloupka, F. (2016). Association between use of flavoured tobacco products and quit behaviours: findings from a cross-sectional survey of US adult tobacco users. *Tob Control, 25*(Suppl 2), ii73-ii80. doi:10.1136/tobaccocontrol-2016-053313

Vosen, S., & Schmidt, T. (2011). Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting, 30*(6), 565-578.

Vosen, S., & Schmidt, T. (2012). A monthly consumption indicator for Germany based on Internet search query data. *Applied Economics Letters, 19*(7), 683-687.

Wilson, K., & Brownstein, J. S. (2009). Early detection of disease outbreaks using the Internet. *CMAJ, 180*(8), 829-831. doi:10.1503/cmaj.090215

Yao, T., & Zhang, Y.-J. (2017). Forecasting Crude Oil Prices with the Google Index. *Energy Procedia, 105*, 3772-3776.

Tables

Table 1 List of Companies in this Study

Quick Service Restaurants			
McDonald's Corp. (MCD*)	Jack in the Box Inc. (JACK+)	Red Robin Gourmet Burgers, Inc. (RRGB+)	Wendys Co. (WEN+)
Yum! Brands, Inc. (YUM*)	Popeyes Louisiana Kitchen Inc. (PLKI+)	Frisch's Restaurants, Inc. (FRS*)	Sonic Corp. (SONC+)
Jamba, Inc. (JMBA+)	Carrols Restaurant Group, Inc. (TAST+)	Del Taco Restaurants Inc. (TACO+)	Noodles & Co. (NDLS+)
Wingstop Inc. (WING+)	Arcos Dorados Holding Inc. (ARCO*)	CEC Entertainment Inc. (CEC*)	Fogo De Chao Inc. (FOGO+)
Domino's Pizza, Inc. (DPZ*)	Chipotle Mexican Grill, Inc. (CMG*)	†Papa Murphy's Holdings Inc. (FRSH+)	
Food Processing			
Kellogg Co. (K*)	Campbell Soup Co. (CPB*)	Archer Daniels Midland Co. (ADM*)	Conagra Brands Inc. (CAG*)
SunOpta, Inc. (STKL+)	American Lorain Corp. (ALN*)	McCormick & Company, Inc. (MKC*)	Central Garden & Pet Co. (CENT+)
Bunge Ltd. (BG*)	Kraft Foods Group Inc. (KRFT+)	Mondelez International Inc. (MDLZ+)	Annies Inc. (BNNY*)
Hershey Co. (HSY+)	General Mills, Inc. (GIS*)	†AMCON Distributing Co. (DIT*)	Dean Foods Co. (DF*)
Ingredion Inc. (INGR*)	Terravia Holdings Inc. (SZYM+)	Darling Ingredients Inc. (DAR*)	B&G Foods, Inc. (BGS*)
WhiteWave Foods Co. (WWAV*)			
Animal Slaughtering & Processing			
Tyson Foods, Inc. (TSN*)	Hormel Foods Corp. (HRL*)	Industrias Bachoco, S.A.B. de C.V. (IBA*)	Pilgrim's Pride Corp. (PPC+)
BRF SA (BRFS*)	Smithfield Foods, Inc. (SFD*)		

Stock market ticker in parenthesis. * NYSE stock exchange; + NASDAQ stock exchange;
†Trading Volume for this company is not forecasted due to lack of data.
Source: Google finance

Table 2 MSFE for Trading Volume Forecast[a]

Company	models without search terms	models with search terms	MCS models
ADM	0.34115	0.31731	0.30864
American Lorain	1.21143	1.17961	1.09245
Annies	1.07215	0.91837	0.88514
Arcos Dorados	0.47186	0.44977	0.42412
BG Foods	0.52029	0.43834	0.41978
BRFSA	0.45390	0.42137	0.38258
Bunge	0.45565	0.40322	0.38939
Campbell Soup	0.19990	0.21767	0.21756
Carrols Restaurant Group	0.32024	0.29837	0.26403
CEC Entertainment	1.38821	1.40668	1.34097
Central Garden	0.43238	0.40885	0.40045
Chipotle Mexican Grill	0.37532	0.32458	0.32211
Conagra	0.19258	0.21025	0.20435
Darling	0.26400	0.28843	0.27647
Dean Foods	0.33145	0.28935	0.28476
Del Taco	0.75294	0.62949	0.55716
Dominos Pizza	0.44390	0.37198	0.35928
Fogo De Chao	0.66939	0.52944	0.50139
Frischs	0.26443	0.24989	0.24988
General Mills	0.35027	0.34402	0.33899
Hershey	0.15004	0.16218	0.15306
Hormel Foods	0.17243	0.17713	0.17709
Industrias Bachoco	0.44328	0.45821	0.45330
Ingredion	0.15157	0.13810	0.13809
Jack in the Box	0.21163	0.19170	0.15269
Jamba	0.30108	0.33193	0.33187
Kelloggs	0.31702	0.30384	0.30250
Kraft Heinz	0.37844	0.40482	0.38257
McCormick	0.24821	0.23252	0.23009
McDonalds	0.36303	0.34904	0.34576
Mondelez	0.28484	0.28451	0.27861
Noodles Co	0.50350	0.49369	0.48904
Pilgrims Pride	0.37299	0.38739	0.38737
Popeyes Louisiana Kitchen	1.20393	1.14468	1.00424
Red Robin	0.40665	0.35168	0.28394
Smithfield Foods	0.50921	0.64946	0.58418

Company	models without search terms	models with search terms	MCS models
Sonic	0.47704	0.37969	0.37752
Sun Opta	0.67223	0.67435	0.63764
Terravia	0.54036	0.52400	0.52397
Tyson Foods	0.40286	0.31685	0.26712
Wendys	0.54045	0.37409	0.34152
White Wave	0.52334	0.48273	0.41811
Wingstop	0.63663	0.54194	0.47504
YumBrands	0.26762	0.24751	0.24750

[a] Average MSFEs for different forecast groups. The average forecasting error for only 12 companies (Campbell Soup, CEC Entertainment, Conagra, Darling, Hershey, Hormel Foods, Industrias Bachoco, Jamba, Kraft Heinz, Pilgrims Pride, Smithfield Foods, and Sun Opta) or 27% of the sample is lower in models without search terms as variables. The average forecasting error for the models in the MCS is lower than the other two groups for all companies.

Table 3 MSFE for Closing Price Forecast[a]

Company	models without search terms	models with search terms	MCS models
ADM	0.03320	0.03457	0.01532
AMCON	0.06025	0.04925	0.02501
American Lorain	0.21915	0.17061	0.01490
Annies	0.12586	0.11443	0.11583
Arcos Dorados	0.08715	0.08418	0.05696
BG Foods	0.05666	0.03224	0.02882
BRFSA	0.16296	0.10583	0.04236
Bunge	0.05645	0.06385	0.05699
Campbell Soup	0.05087	0.02508	0.02829
Carrols Restaurant Group	0.15150	0.11852	0.04237
CEC Entertainment	0.09934	0.12494	0.06729
Central Garden	0.39180	0.25268	0.03424
Chipotle Mexican Grill	0.05835	0.03744	0.03375
Conagra	0.03588	0.02549	0.02430
Darling	0.02633	0.02833	0.03204
Dean Foods	0.04196	0.04254	0.04254
Del Taco	0.05603	0.04722	0.04699
Dominos Pizza	0.22468	0.14112	0.02700
Fogo De Chao	0.05604	0.05631	0.04635
Frischs	0.12683	0.08086	0.00925
General Mills	0.01875	0.01399	0.02096
Hershey	0.05314	0.04170	0.01005
Hormel Foods	0.06901	0.03241	0.02306
Industrias Bachoco	0.05144	0.04944	0.02148
Ingredion	0.11872	0.08090	0.00752
Jack in the Box	0.14030	0.10229	0.04864
Jamba	0.14966	0.11369	0.03816
Kelloggs	0.02780	0.01566	0.01653
Kraft Heinz	0.04848	0.03268	0.02438
McCormick	0.08612	0.05359	0.01597
McDonalds	0.09096	0.06193	0.02065
Mondelez	0.05742	0.03983	0.01870
Noodles Co	0.38393	0.23756	0.10745
Papa Murphys	0.23670	0.22464	0.09365
Pilgrims Pride	0.07176	0.05934	0.03650
Popeyes Louisiana Kitchen	0.17546	0.11987	0.06226

Company	**models without search terms**	**models with search terms**	**MCS models**
Red Robin	0.05304	0.04464	0.03908
Smithfield Foods	0.08636	0.08690	0.04596
Sonic	0.06048	0.05320	0.04911
Sun Opta	0.08253	0.05086	0.04358
Terravia	0.32372	0.17459	0.16846
Tyson Foods	0.13634	0.05137	0.02199
Wendys	0.15398	0.03556	0.03142
White Wave	0.17163	0.10894	0.00452
Wingstop	0.04801	0.04543	0.04534
YumBrands	0.06923	0.05965	0.02535

[a] Average MSFEs for different forecast groups. The average forecasting error for only seven companies (ADM, Bunge, CEC Entertainment, Darling, Dean Foods, Fogo De Chao, and Smithfield Foods) or 15% of the sample is lower in models without search terms as variables. The average forecasting error for the models in the MCS is lower than the other two groups for all except five companies (Annies, Campbell Soup, Darling, General Mills, and Kelloggs).

Figures

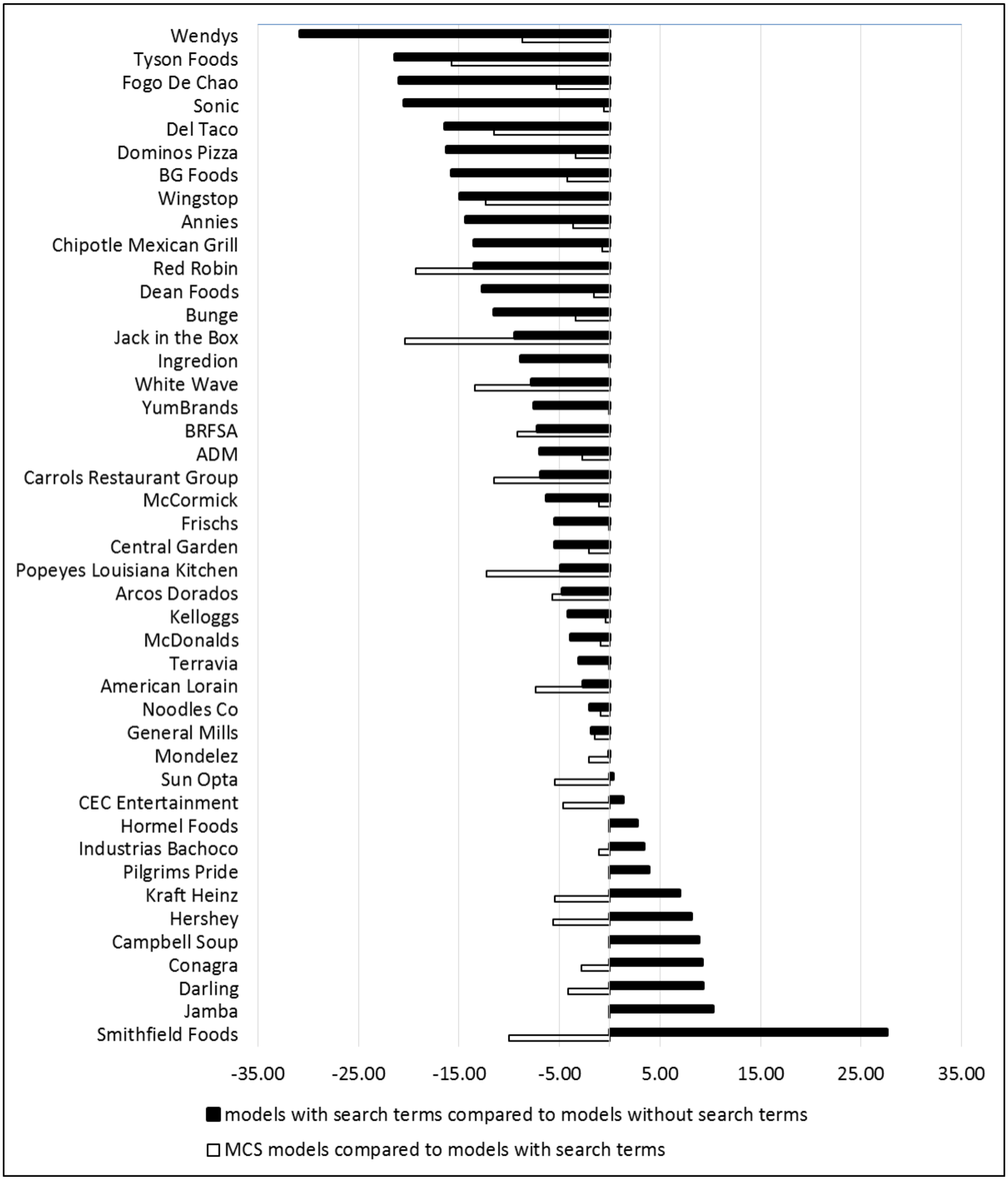

Figure 1 Percentage Change in Average *MSFE* when Forecasting Trading Volume

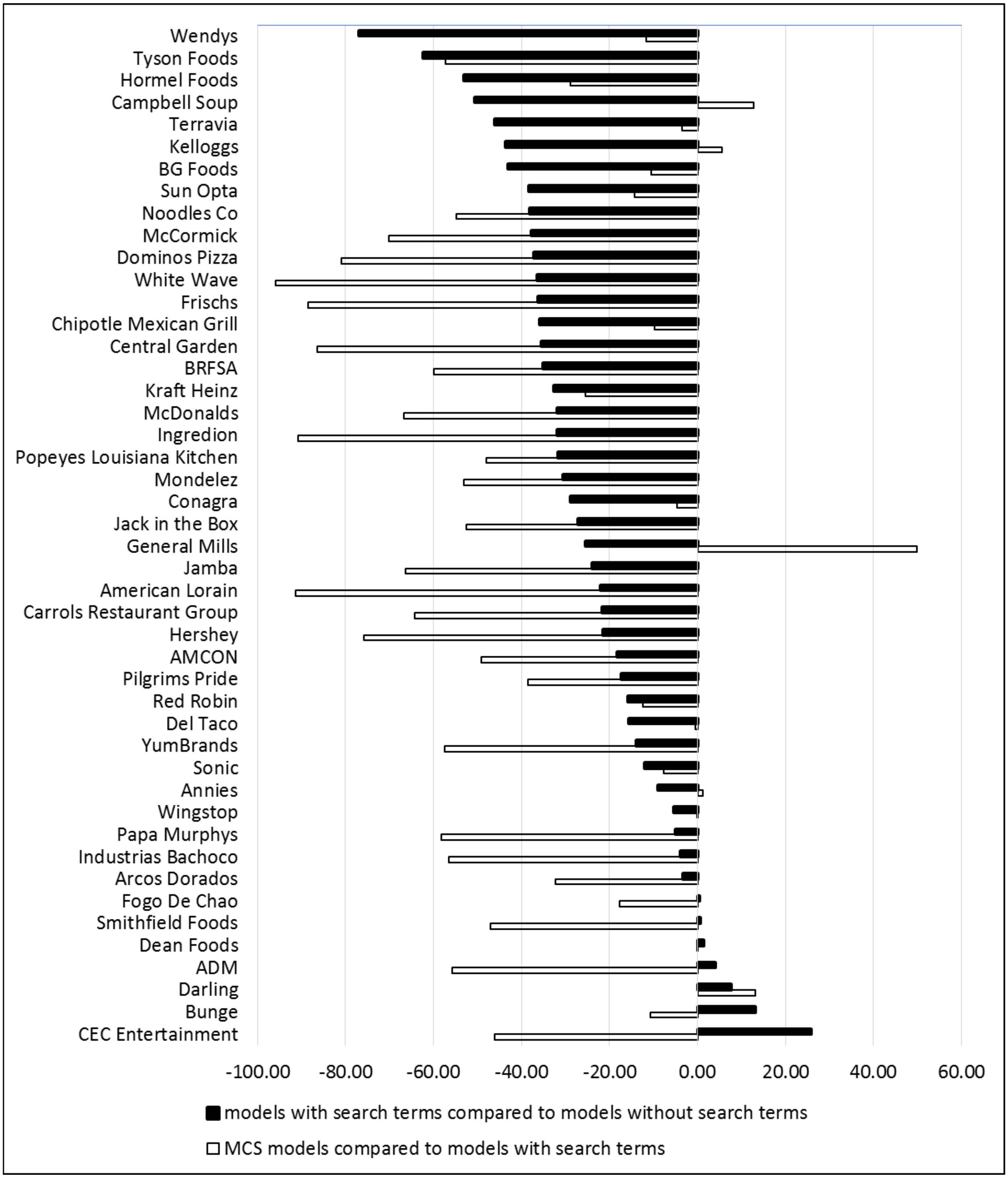

Figure 2 Percentage Change in Average *MSFE* when Forecasting Closing Price

Appendix

Table A-1 Trading Volume Forecasts with Least MSFE[a]

Company	Variables [b]	MSFE	P_{MCS}
	$TV_{-2}+GT_{n}+GT_{out-1}+GT_{out-2}$	0.27413	1.000^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.27421	0.975^{**}
ADM	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{out-1}$	0.27515	0.986^{**}
	$TV_{-2}+GT_{n}+GT_{out-1}$	0.27522	0.986^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.27578	0.976^{**}
	$TV_{-2}+GT_{n}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.27588	0.965^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}$	0.97015	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out}$	0.97018	0.945^{**}
American Lorain	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out-1}$	0.97020	0.945^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.97043	0.940^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out-2}$	0.97051	0.909^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.97057	0.940^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out-1}$	0.66999	1.000^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{out-1}$	0.67723	0.608^{**}
Annies	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out-1}$	0.68424	0.876^{**}
	$TV_{-2}+GT_{n}+GT_{n-2}+GT_{out-1}$	0.68925	0.744^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{out-1}$	0.69162	0.899^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}$	0.69971	0.912^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.36119	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.36130	0.987^{**}
Arcos Dorados	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.36134	0.987^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.36136	0.983^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.36139	0.986^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.36155	0.986^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.37961	1.000^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.38002	0.899^{**}
BG Foods	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.38029	0.957^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.38059	0.974^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.38146	0.974^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.38155	0.958^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.36350	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.36351	0.984^{**}
BRFSA	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.36353	0.984^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.36355	0.989^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.36361	0.989^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.36366	0.984^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Bunge	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.35843	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.35874	0.879^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.35890	0.862^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.35946	0.665^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.35970	0.899^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.36010	0.490^{*}
Campbell Soup	GT_{n}	0.18562	1.000^{**}
	$GT_{n}+GT_{out}$	0.18765	0.855^{**}
	$GT_{n}+GT_{n-1}$	0.18875	0.855^{**}
	GT_{n-1}	0.18936	0.796^{**}
	$GT_{n}+GT_{out-2}$	0.19104	0.662^{**}
	$GT_{n}+GT_{out-1}$	0.19127	0.791^{**}
Carrols Restaurant Group	$TV_{-1}+TV_{-2}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.24821	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.24821	0.830^{**}
	$TV_{-1}+TV_{-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.24835	0.830^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.24837	0.903^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-1}+GT_{out-2}$	0.24888	0.844^{**}
	$TV_{-1}+TV_{-2}+GT_{fp-1}+GT_{out-2}$	0.24892	0.930^{**}
CEC Entertainment	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	1.16436	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	1.16437	0.230
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}$	1.16724	0.230
	$TV_{-1}+GT_{n}+GT_{out}+GT_{out-1}+GT_{out-2}$	1.16761	0.808^{**}
	$TV_{-1}+GT_{n}+GT_{fp}+GT_{out-1}+GT_{out-2}$	1.17355	0.947^{**}
	$TV_{-1}+GT_{n}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	1.17542	0.956^{**}
Central Garden	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.34891	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{out-2}$	0.34901	0.948^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.34906	0.948^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out-2}$	0.34916	0.890^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.34981	0.696^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.35008	0.874^{**}
Chipotle Mexican Grill	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.29418	1.000^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.29422	0.611^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.29594	0.611^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.29597	0.691^{**}
	$TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.29700	0.764^{**}
	$TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.29704	0.970^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Conagra	$TV_{-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.18410	1.000^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.18415	0.936^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.18454	0.940^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.18456	0.963^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.18461	0.968^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.18504	0.971^{**}
Darling	$TV_{-1}+GT_{n}+GT_{out-1}+GT_{out-2}$	0.23442	1.000^{**}
	$TV_{-1}+GT_{out-1}+GT_{out-2}$	0.23455	0.967^{**}
	$TV_{-1}+GT_{n}+GT_{out-1}$	0.23509	0.958^{**}
	$TV_{-1}+GT_{out-1}$	0.23528	0.956^{**}
	$TV_{-1}+GT_{n}$	0.23779	0.929^{**}
	TV_{-1}	0.23820	0.924^{**}
Dean Foods	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.24954	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.24962	0.930^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.24974	0.930^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.24983	0.875^{**}
	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp}+GT_{out-1}+GT_{out-2}$	0.25054	0.846^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out-1}+GT_{out-2}$	0.25055	0.938^{**}
Del Taco	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{out-2}$	0.52681	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{out-2}$	0.52695	0.941^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp-2}+GT_{out-2}$	0.52810	0.868^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out-2}$	0.52811	0.958^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}$	0.52881	0.961^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}$	0.52882	0.961^{**}
Dominos Pizza	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.33061	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.33140	0.895^{**}
	$TV_{-1}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.33154	0.908^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.33235	0.956^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.33247	0.954^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.33278	0.982^{**}
Fogo De Chao	$TV_{-1}+GT_{fp}+GT_{out-1}$	0.46754	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{out-2}$	0.46767	0.988^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{out-2}$	0.46770	0.988^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.46834	0.976^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.46847	0.976^{**}
	$TV_{-1}+TV_{-2}+GT_{fp}+GT_{out-2}$	0.46853	0.973^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Frischs	$TV_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.23559	1.000^{**}
	$TV_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.23568	0.981^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.23586	0.980^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.23655	0.966^{**}
	$TV_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.23723	0.966^{**}
	$TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.23738	0.984^{**}
General Mills	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.31290	1.000^{**}
	$GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.31308	0.966^{**}
	$GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.31372	0.856^{**}
	$GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.31382	0.856^{**}
	$GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.31450	0.811^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.31453	0.878^{**}
Hershey	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{out}$	0.12251	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.12360	0.976^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.12366	0.976^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{out}+$	0.12366	0.961^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.12465	0.911^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.12482	0.938^{**}
Hormel Foods	$GT_{n}+GT_{n-2}+GT_{out-1}$	0.16540	1.000^{**}
	$GT_{n}+GT_{n-2}+GT_{out-1}+GT_{out-2}$	0.16541	0.749^{**}
	$GT_{n}+GT_{n-2}+GT_{out}+$	0.16557	0.778^{**}
	$GT_{n}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.16560	0.784^{**}
	$GT_{n}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.16561	0.912^{**}
	$GT_{n}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.16571	0.912^{**}
Industrias Bachoco	$TV_{-2}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.40445	1.000^{**}
	$TV_{-2}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.40578	0.916^{**}
	$TV_{-2}+GT_{n-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.40631	0.940^{**}
	$TV_{-2}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.40649	0.973^{**}
	$TV_{-2}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.40652	0.973^{**}
	$TV_{-2}+GT_{fp-2}+GT_{out}$	0.40657	0.973^{**}
Ingredion	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.12237	1.000^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.12289	0.964^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.12296	0.987^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.12297	0.987^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.12312	0.987^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.12323	0.987^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Jack in the Box	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.13206	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.13279	0.501^{*}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.13317	0.917^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.13343	0.961^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.13382	0.961^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.13470	0.966^{**}
Jamba	GT_{fp-2}	0.28486	1.000^{**}
	GT_{out-2}	0.28613	0.926^{**}
	$GT_{fp-2}+GT_{out-2}$	0.28731	0.979^{**}
	$GT_{fp-1}+GT_{fp-2}$	0.28893	0.979^{**}
	$GT_{out}+GT_{out-2}$	0.28905	0.985^{**}
	GT_{fp-1}	0.28912	0.985^{**}
Kelloggs	$TV_{-1}+GT_{n}+GT_{n-2}+GT_{fp-2}$	0.28373	1.000^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.28378	0.971^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}$	0.28387	0.978^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-1}$	0.28390	0.984^{**}
	$TV_{-1}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.28393	0.984^{**}
	$TV_{-1}+GT_{n}+GT_{n-2}+GT_{fp-1}$	0.28403	0.973^{**}
Kraft Heinz	$TV_{-1}+GT_{out}+GT_{out-2}$	0.28398	1.000^{**}
	$TV_{-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.28489	0.887^{**}
	$TV_{-1}+GT_{n}+GT_{out}+GT_{out-2}$	0.28515	0.887^{**}
	$TV_{-1}+GT_{n}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.28604	0.871^{**}
	$TV_{-1}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.28984	0.871^{**}
	$TV_{-1}+GT_{n-2}+GT_{out}$	0.28995	0.860^{**}
McCormick	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.21660	1.000^{**}
	$GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out-2}$	0.21748	0.908^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.21784	0.987^{**}
	$GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.21885	0.984^{**}
	$TV_{-1}+GTn+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.21886	0.987^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}$	0.21892	0.987^{**}
McDonalds	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.33124	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}$	0.33153	0.984^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.33159	0.984^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}$	0.33188	0.953^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.33232	0.982^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.33263	0.989^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Mondelez	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.25929	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.25933	0.979^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.25961	0.979^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.25965	0.977^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.25993	0.975^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.26001	0.989^{**}
Noodles Co	$GT_{n-1}+GT_{n-2}+GT_{out-1}$	0.39579	1.000^{**}
	$GT_{n-1}+GT_{n-2}$	0.39673	0.767^{**}
	GT_{n-2}	0.40155	0.786^{**}
	$GT_{n-2}+GT_{out-1}$	0.40216	0.641^{**}
	$GT_{n-1}+GT_{n-2}+GT_{out}$	0.40572	0.786^{**}
	$GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.40727	0.840^{**}
Pilgrims Pride	$TV_{-2}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.35446	1.000^{**}
	$TV_{-2}+GT_{n}+GT_{fp-1}+GT_{out}$	0.35517	0.807^{**}
	$TV_{-2}+GT_{n}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.35560	0.807^{**}
	$TV_{-2}+GT_{n}+GT_{out}+GT_{out-2}$	0.35563	0.923^{**}
	$TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out-2}$	0.35592	0.954^{**}
	$TV_{-2}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.35600	0.987^{**}
Popeyes Louisiana Kitchen	$TV_{-1}+GT_{fp-2}$	0.98474	1.000^{**}
	$TV_{-1}+GT_{fp-2}+GT_{out}$	0.98504	0.904^{**}
	$TV_{-1}+GT_{fp-1}+GT_{fp-2}$	0.98517	0.945^{**}
	$TV_{-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.98519	0.945^{**}
	$TV_{-1}+GT_{fp}+GT_{fp-2}$	0.98538	0.920^{**}
	$TV_{-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.98538	0.948^{**}
Red Robin	$TV_{-1}+TV_{-2}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.25868	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.25889	0.959^{**}
	$TV_{-1}+TV_{-2}+GTn+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.25928	0.959^{**}
	$TV_{-1}+TV_{-2}+GTn+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.26000	0.983^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}$	0.26071	0.983^{**}
	$TV_{-1}+TV_{-2}+GTn+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}$	0.26078	0.961^{**}
Smithfield Foods	$TV_{-1}+GT_{fp}+GT_{fp-2}+GT_{out}$	0.41646	1.000^{**}
	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}$	0.42801	0.963^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.42865	0.963^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.43195	0.980^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.43199	0.954^{**}
	$TV_{-1}+TV_{-2} + GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.43332	0.971^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Sonic	$TV_{-1}+GT_{n-1}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.33100	1.000^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.33149	0.971^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.33215	0.981^{**}
	$TV_{-1}+GT_{n-1}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.33217	0.981^{**}
	$TV_{-1}+GT_{n-1}+GT_{fp-1}+GT_{out-2}$	0.33238	0.984^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.33268	0.965^{**}
Sun Opta	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.61598	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.61603	0.979^{**}
	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.61609	0.982^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.61611	0.982^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}$	0.61626	0.979^{**}
	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}$	0.61646	0.979^{**}
Terravia	$TV_{-1}+GT_{n}+GT_{n-1}$	0.46270	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{out-1}$	0.46306	0.901^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{out-2}$	0.46336	0.901^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.46465	0.916^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{out}$	0.46599	0.955^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}$	0.46632	0.955^{**}
Tyson Foods	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.23215	1.000^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.23370	0.664^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{out}$	0.23403	0.664^{**}
	$TV_{-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.23477	0.761^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}$	0.23539	0.761^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.23607	0.108^{**}
Wendys	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.31929	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.31930	0.911^{**}
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.31968	0.911^{**}
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.31976	0.900^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out-1}+GT_{out-2}$	0.32031	0.900^{**}
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{out}+GT_{out-2}$	0.32051	0.953^{**}
White Wave	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out-2}$	0.36352	1.000^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-2}$	0.36583	0.926^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out-2}$	0.36590	0.777^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{out-1}$	0.36672	0.849^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.36685	0.926^{**}
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{fp-1}$	0.36708	0.876^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
Wingstop	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp}+GT_{out}+GT_{out-1}$	0.42512	1.000**
	$TV_{-1}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.42616	0.725**
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.42652	0.603**
	$TV_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.43003	0.613**
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-1}$	0.43045	0.747**
	$TV_{-1}+TV_{-2}+GT_{n}+GT_{fp}+GT_{out-1}$	0.43480	0.922**
YumBrands	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{out}$	0.25258	1.000**
	$TV_{-1}+GT_{n-1}+GT_{fp}+GT_{out}+GT_{out-2}$	0.25274	0.898**
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{out}+GT_{out-2}$	0.25295	0.898**
	$TV_{-1}+TV_{-2}+GT_{n-1}+GT_{fp}+GT_{out}$	0.25300	0.881**
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}+GT_{out-2}$	0.25318	0.704**
	$TV_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out}$	0.25329	0.924**

[a]MSFEs and MCS p-values for different forecasts with lowest errors.
[b]The complete list of model specifications is available from authors upon request. In this table *TV* stands for trading volume, *GT* for google trends, *n* for company name, *fp* for food poisoning, and *out* for outbreak. First and second lag of each variable is denoted by -1 and -2, respectively.
The forecasts in $M^{*}_{75\%}$ and $M^{*}_{40\%}$ are identified by one and two asterisks, respectively. Only in one company (Darling), one model without search terms appears on the list.

Table A-2 Closing Price Forecasts with Least MSFE[a]

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{MCS}}$
ADM	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.01446	1.000^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01449	0.887^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.01458	0.887^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.01462	0.930^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.01462	0.969^{**}
	$P_{-1}+P_{-2}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01463	0.933^{**}
AMCON	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.02534	1.000^{**}
	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.02536	0.855^{**}
	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.02543	0.789^{**}
	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.02544	0.952^{**}
	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.02553	0.952^{**}
	$P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.02556	0.917^{**}
American Lorain	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01120	1.000^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-2}$	0.01122	0.874^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.01145	0.783^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01148	0.874^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-2}$	0.01149	0.875^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{out}+GT_{out-1}$	0.01158	0.875^{**}
Annies	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.08748	1.000^{**}
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.08775	0.399^{*}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.08935	0.660^{**}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.08936	0.399^{*}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.08962	0.637^{**}
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.08968	0.673^{**}
Arcos Dorados	$P_{-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.05538	1.000^{**}
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.05539	0.989^{**}
	$P_{-1}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.05539	0.896^{**}
	$P_{-1}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.05540	0.989^{**}
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.05540	0.976^{**}
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.05542	0.976^{**}
BG Foods	$P_{-1}+GT_{n-2}+GT_{out-1}+GT_{out-2}$	0.02603	1.000^{**}
	$P_{-1}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.02604	0.915^{**}
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{out-1}+GT_{out-2}$	0.02612	0.915^{**}
	$P_{-1}+GT_{n-2}+GT_{out-2}$	0.02614	0.907^{**}
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.02615	0.907^{**}
	$P_{-1}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.02620	0.835^{**}

Company	Variables [b]	MSFE	P_{MCS}
BRFSA	$P_{-1}+P_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.04101	1.000^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.04102	0.977^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.04105	0.982^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.04106	0.982^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.04109	0.973^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.04109	0.973^{**}
Bunge	$P_{-1}+GT_{n}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.05496	1.000^{**}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.05497	0.838^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.05499	0.907^{**}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{out}$	0.05500	0.927^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.05500	0.947^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-2}+GT_{out}+GT_{out-1}$	0.05500	0.947^{**}
Campbell Soup	$P_{-1}+P_{-2}$	0.02578	1.000^{**}
	$P_{-1}+P_{-2}+GT_{out-1}$	0.02578	0.662^{**}
	$P_{-1}+P_{-2}+GT_{out-2}$	0.02581	0.437^{*}
	$P_{-1}+GT_{out-2}$	0.02581	0.437^{*}
	$P_{-1}+P_{-2}+GT_{out-1}+GT_{out-2}$	0.02582	0.308^{*}
	$P_{-1}+GT_{out-1}+GT_{out-2}$	0.02582	0.469^{*}
Carrols Restaurant Group	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.04144	1.000^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.04145	0.980^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out}$	0.04145	0.980^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{out}$	0.04146	0.898^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.04147	0.936^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}$	0.04147	0.936^{**}
CEC Entertainment	$P_{-1}+P_{-2}+GT_{out-1}+GT_{out-2}$	0.04825	1.000^{**}
	$P_{-1}+P_{-2}+GT_{out-1}$	0.04827	0.780^{**}
	$P_{-1}+P_{-2}+GT_{out-2}$	0.04869	0.535^{*}
	$P_{-1}+P_{-2}$	0.04871	0.588^{*}
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}$	0.05037	0.822^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}$	0.05038	0.909^{**}
Central Garden	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03645	1.000^{**}
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03647	0.985^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03651	0.985^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03652	0.984^{**}
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03654	0.989^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.03655	0.989^{**}

Company	Variables [b]	MSFE	$\boldsymbol{P}_{\mathbf{MCS}}$
Chipotle Mexican Grill	$P_{-1}+GT_{n-2}+GT_{out-1}$	0.03371	1.000^{**}
	$P_{-1}+GT_{out}+GT_{out-2}$	0.03372	0.936^{**}
	$P_{-1}+GT_{out-2}$	0.03373	0.942^{**}
	$P_{-1}+GT_{n-2}+GT_{out}+GT_{out-2}$	0.03373	0.942^{**}
	$P_{-1}+GT_{n-2}+GT_{out-2}$	0.03373	0.925^{**}
	$P_{-1}+GT_{out-1}$	0.03374	0.925^{**}
Conagra	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}$	0.02344	1.000^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}$	0.02345	0.941^{**}
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out}$	0.02345	0.962^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}$	0.02345	0.987^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{out}$	0.02345	0.987^{**}
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-1}$	0.02346	0.986^{**}
Darling	$P_{-1}+ GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out}$	0.03230	1.000^{**}
	$P_{-1}+GT_{n-2}+GT_{fp-1}+GT_{out}$	0.03231	0.974^{**}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.03231	0.974^{**}
	$P_{-1}+GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.03232	0.973^{**}
	$P_{-1}+GT_{n-2}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.03232	0.973^{**}
	$P_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.03234	0.961^{**}
Dean Foods	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.02890	1.000^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.02953	0.846^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.02976	0.887^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.02997	0.915^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.02999	0.915^{**}
	$GT_{n}+GT_{n-2}+GT_{fp}+GT_{fp-1}$	0.03049	0.942^{**}
Del Taco	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.04560	1.000^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.04562	0.915^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.04563	0.979^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.04566	0.979^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.04566	0.979^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.04570	0.964^{**}
Dominos Pizza	$P_{-1}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.02582	1.000^{**}
	$P_{-1}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.02582	0.922^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.02584	0.930^{**}
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.02584	0.946^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.02588	0.952^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.02588	0.976^{**}

Company	Variables [b]	MSFE	P_{MCS}
Fogo De Chao	P_{-1}+P_{-2}+GT_{n-1}+GT_{fp-2}	0.03642	1.000**
	P_{-1}+P_{-2}+GT_{n-1}+GT_{fp-2}+GT_{out-1}	0.03661	0.850**
	P_{-1}+GT_{n-1}+GT_{fp-2}	0.03670	0.850**
	P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp-2}	0.03711	0.815**
	P_{-1}+GT_{n-1}+GT_{fp-2}+GT_{out-1}	0.03712	0.710**
	P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}	0.03739	0.820**
Frischs	P_{-1}+P_{-2}+GT_{out-1}	0.00493	1.000**
	P_{-1}+P_{-2}	0.00509	0.578*
	P_{-1}	0.00518	0.837**
	P_{-1}+GT_{out-1}+GT_{out-2}	0.00519	0.847**
	P_{-1}+P_{-2}+GT_{out-1}+GT_{out-2}	0.00527	0.796**
	P_{-1}+GT_{fp-2} + GT_{out-1}	0.00530	0.833**
General Mills	P_{-1}+P_{-2}+GT_{n-2}+GT_{out-2}	0.01912	1.000**
	P_{-1}+P_{-2}+GT_{n-2}	0.01912	0.933**
	P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{out-2}	0.01915	0.782**
	P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}	0.01916	0.912**
	P_{-1}+P_{-2}+GT_{out-2}	0.01917	0.939**
	P_{-1}+P_{-2}	0.01917	0.912**
Hershey	P_{-1}+GT_{fp}+GT_{out}+GT_{out-2}	0.00886	1.000**
	P_{-1}+GT_{fp}+GT_{out}	0.00887	0.716**
	P_{-1}+P_{-2}+GTfp+GT_{out}	0.00890	0.735**
	P_{-1}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}	0.00890	0.760**
	P_{-1}+GT_{fp}+GT_{out}+GT_{out-1}	0.00900	0.914**
	P_{-1}+GT_{n-2}+GT_{out}	0.00910	0.776**
Hormel Foods	P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out}	0.02376	1.000**
	P_{-1}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out}	0.02384	0.925**
	P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp-1}+GT_{fp-2}+GT_{out}	0.02386	0.925**
	P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}	0.02389	0.910**
	P_{-1}+P_{-2}+GT_{n-1}+GT_{fp-2}+GT_{out}	0.02392	0.910**
	P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out-1}	0.02393	0.979**
Industrias Bachoco	P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}	0.01761	1.000**
	P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-2}	0.01768	0.868**
	P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-1} + GT_{out-2}	0.01772	0.973**
	P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-1}	0.01773	0.975**
	P_{-1}+GT_{n-2}+GT_{fp-2}+GT_{out}	0.01775	0.975**
	P_{-1}+GT_{n-2}+GT_{fp-2}+GT_{out}+GT_{out-2}	0.01781	0.954**

Company	Variables [b]	MSFE	P_{MCS}
Ingredion	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.00601	1.000**
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.00602	0.954**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.00602	0.954**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}$	0.00602	0.875**
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.00606	0.853**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-2}$	0.00606	0.953**
Jack in the Box	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.04787	1.000**
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.04787	0.969**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.04788	0.977**
	$P_{-1}+P_{-2}+GT_{fp-1}+GT_{fp-2}$	0.04788	0.970**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.04789	0.977**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.04792	0.945**
Jamba	$P_{-1}+P_{-2}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.03534	1.000**
	$P_{-1}+P_{-2}+GT_{fp-2}+GT_{out-2}$	0.03534	0.937**
	$P_{-1}+P_{-2}+GT_{fp-2}+GT_{out-1}$	0.03536	0.983**
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out-2}$	0.03536	0.983**
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.03537	0.978**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp-2}+GT_{out-2}$	0.03537	0.975**
Kelloggs	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01601	1.000**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-2}$	0.01602	0.965**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out}+GT_{out-1}$	0.01602	0.933**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-1}$	0.01602	0.982**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.01602	0.982**
	$P_{-1}+P_{-2}+GT_{n-1}$	0.01603	0.982**
Kraft Heinz	$P_{-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02172	1.000**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02175	0.890**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02175	0.912**
	$P_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02186	0.912**
	$P_{-1}+GT_{n}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02190	0.805**
	$P_{-1}+GT_{n-1}+GT_{fp-2}+GT_{out-1}$	0.02206	0.945**
McCormick	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.01472	1.000**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.01472	0.851**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.01472	0.930**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.01473	0.930**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}$	0.01473	0.918**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.01473	0.926**

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P}_{\mathbf{MCS}}$
McDonalds	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{out-2}$	0.01829	1.000^{**}
	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{out-1}+GT_{out-2}$	0.01829	0.817^{**}
	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01832	0.866^{**}
	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.01839	0.886^{**}
	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.01841	0.868^{**}
	$P_{-1}+GT_{n}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.01842	0.859^{**}
Mondelez	$P_{-1}+P_{-2}+GT_{n}+GT_{out-1}$	0.01860	1.000^{**}
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.01861	0.989^{**}
	$P_{-1}+P_{-2}+GT_{n}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.01862	0.989^{**}
	$P_{-1}+P_{-2}+GT_{out-1}$	0.01864	0.987^{**}
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.01864	0.989^{**}
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}$	0.01865	0.989^{**}
Noodles Co	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.10131	1.000^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.10144	0.513^{*}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}$	0.10147	0.725^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.10172	0.725^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-2}$	0.10176	0.828^{**}
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.10185	0.811^{**}
Papa Murphys	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.08688	1.000^{**}
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-2}$	0.08704	0.950^{**}
	$P_{-1}+P_{-2}+GT_{out-1}+GT_{out-2}$	0.08709	0.978^{**}
	$P_{-1}+P_{-2}+GT_{out-2}$	0.08725	0.981^{**}
	$P_{-1}+GT_{n-1}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.08728	0.978^{**}
	$P_{-1}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.08729	0.983^{**}
Pilgrims Pride	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.03335	1.000^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{out-1}$	0.03347	0.615^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.03350	0.694^{**}
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{out-1}$	0.03363	0.676^{**}
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GTout+GT_{out-1}$	0.03371	0.694^{**}
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.03373	0.825^{**}
Popeyes Louisiana Kitchen	$P_{-1}+GT_{out}+GT_{out-1}$	0.05701	1.000^{**}
	$P_{-1}+P_{-2}+GT_{out}+GT_{out-1}$	0.05725	0.238
	$P_{-1}+GT_{out}$	0.05748	0.426^{*}
	$P_{-1}+GT_{fp}+GT_{out}+GT_{out-1}$	0.05766	0.802^{**}
	$P_{-1}+GT_{out-1}$	0.05787	0.829^{**}
	P_{-1}	0.05788	0.819^{**}

Company	**Variables** [b]	**MSFE**	$\boldsymbol{P_{\mathrm{MCS}}}$
Red Robin	$P_{-1}+P_{-2}+GT_{out-1}$	0.03593	1.000**
	$P_{-1}+GT_{out-1}$	0.03609	0.948**
	$P_{-1}+ P_{-2}+GT_{n}+GT_{out-1}$	0.03612	0.948**
	$P_{-1}+ P_{-2}+GT_{out}+GT_{out-1}$	0.03621	0.906**
	$P_{-1}+GT_{n}+GT_{out-1}$	0.03623	0.901**
	$P_{-1}+ P_{-2}$	0.03624	0.906**
Smithfield Foods	$P_{-1}+P_{-2}+GT_{fp-2}$	0.00838	1.000**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-2}$	0.00869	0.862**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{fp-2}$	0.00879	0.862**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{fp-2}$	0.00901	0.672**
	$P_{-1}+GT_{fp-2}$	0.00906	0.776**
	$P_{-1}+GT_{n-2}+GT_{fp-2}$	0.00975	0.717**
Sonic	$GT_{fp-1}+GT_{fp-2}+GT_{out-1}+GT_{out-2}$	0.03957	1.000**
	$GT_{fp-1}+GT_{fp-2}+GT_{out-1}$	0.03958	0.970**
	$GT_{fp-1}+GT_{fp-2}+GTout+GT_{out-1}$	0.03991	0.988**
	$GT_{fp-1}+GT_{fp-2}+GTout+GT_{out-1}+GT_{out-2}$	0.04019	0.989**
	$GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.04026	0.988**
	$GT_{fp-2}+GT_{out}+GT_{out-1}$	0.04041	0.989**
Sun Opta	$P_{-1}+P_{-2}+GT_{n}+GT_{fp}+GT_{out-2}$	0.04231	1.000**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-1}$	0.04236	0.861**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GTfp+GT_{fp-1}+GT_{out}+GT_{out-1}$	0.04238	0.968**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{fp}+GTout+GT_{out-1}$	0.04241	0.861**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-1}+GTout+GT_{out-1}$	0.04242	0.967**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-1}+GT_{out-2}$	0.04244	0.968**
Terravia	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.16256	1.000**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.16265	0.600*
	$P_{-1}+P_{-2}+GT_{n-2}+GTfp+GT_{fp-1}+GT_{fp-2}+GTout+GT_{out-2}$	0.16280	0.803**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.16283	0.882**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.16295	0.882**
	$P_{-1}+P_{-2}+GT_{n-2}+GT_{fp-1}+GT_{out}+GT_{out-2}$	0.16299	0.803**
Tyson Foods	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{fp}$	0.02136	1.000**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}$	0.02136	0.989**
	$P_{-1}+GT_{n-1}$	0.02137	0.989**
	$P_{-1}+GT_{n-1}+GT_{out-1}$	0.02137	0.989**
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}+GT_{out-1}$	0.02139	0.973**
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{fp}+GT_{fp-2}$	0.02141	0.954**

Company	Variables [b]	MSFE	P_{MCS}
Wendys	$P_{-1}+GT_{n}+GT_{n-1}+GTfp+GT_{out-1}+GT_{out-2}$	0.02454	1.000**
	$P_{-1}+GT_{n}+GT_{n-1}+GTfp+GT_{out-1}$	0.02457	0.939**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp-2}+GT_{out-1}$	0.02464	0.939**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{out}+GT_{out-1}+GT_{out-2}$	0.02464	0.964**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{out-1}+GT_{out-2}$	0.02466	0.964**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{out-1}$	0.02467	0.976**
White Wave	$P_{-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.00474	1.000**
	$P_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.00480	0.767**
	$P_{-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.00493	0.767**
	$P_{-1}+GT_{n-2}+GT_{fp}+GT_{fp-1}+GT_{fp-2}+GT_{out}$	0.00494	0.965**
	$P_{-1}+GT_{n-2}+GT_{fp-1}+GT_{fp-2}$	0.00504	0.983**
	$P_{-1}+GT_{fp-1}+GT_{fp-2}+GT_{out}+GT_{out-1}$	0.00504	0.962**
Wingstop	$P_{-1}+P_{-2}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GTout+GT_{out-2}$	0.03714	1.000**
	$P_{-1}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GTout+GT_{out-2}$	0.03753	0.851**
	$P_{-1}+P_{-2}+GT_{fp}+GT_{fp-2}+GTout+GT_{out-2}$	0.03755	0.851**
	$P_{-1}+P_{-2}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.03795	0.910**
	$P_{-1}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.03815	0.910**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{fp}+GT_{fp-2}+GT_{out}+GT_{out-2}$	0.03839	0.895**
YumBrands	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{out-2}$	0.02109	1.000**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out-2}$	0.02123	0.864**
	$P_{-1}+GT_{n-1}+GT_{n-2}+GT_{out-1}+GT_{out-2}$	0.02127	0.847**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{n-2}+GT_{out-2}$	0.02141	0.934**
	$P_{-1}+GT_{n}+GT_{n-1}+GT_{n-2}+GT_{out-1}+GT_{out-2}$	0.02142	0.909**
	$P_{-1}+P_{-2}+GT_{n-1}+GT_{out-2}$	0.02144	0.934**

[a] MSFEs and MCS p-values for different forecasts.
[b] The complete list of model specifications is available from authors upon request. In this table *P* stands for closing price, *GT* for google trends, *n* for company name, *fp* for food poisoning, and *out* for outbreak. First and second lag of each variable is denoted by -1 and -2, respectively.
The forecasts in $M^*_{75\%}$ and $M^*_{40\%}$ are identified by one and two asterisks, respectively. In six companies (Campbell Soup, CEC Entertainment, Frischs, General Mills, Popeyes Louisiana Kitchen, and Red Robin), models without search terms appears on the list.