Project Report

Impact of Rising Diesel Prices and Truck-Driver Availability on Food Transportation and Distribution

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USDA Report

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Abstract: The food transportation and distribution industry was profoundly disrupted over the last few years, especially amid the COVID-19 pandemic. Two main driving factors in the context of food transportation, (1) the rising diesel prices and (2) the lack of available truck drivers have posed challenges, leading to a substantial surge in transportation costs, subsequently contributing to higher market prices. We curated a panel dataset encompassing key variables such as diesel prices, truck-driver availability, and prices for the most consumed food commodities (i.e., apples, potatoes, onions, and tomatoes) pre-, amid-, and post- the COVID-19 pandemic, covering the period from January 2017 to December 2022. Using a fixed-effects regression, this study investigates the impact of fuel prices and truck-driver availability on the marginal price of food associated with transportation in the U.S. fresh-food market. Our results indicate that, *ceteris paribus,* the rising diesel prices and truck-driver availability pose a significant positive impact on transportation marginal price.

Keywords: *food price, diesel price, truck driver availability, econometrics, regression.*

1. Introduction

The trucking industry plays a critical role in food transportation. Statistically, 83% of agricultural products are shipped by trucks, with an even higher percentage for dairy, fruit, vegetables, and nuts at 92%.[1] As the backbone of food transportation, many factors can impact the trucking industry directly or indirectly. In particular, surging fuel prices and the lack of available drivers have altered trucking distribution patterns, especially amid the COVID-19 pandemic, resulting in some operational changes. For example, it was reported that trucks had shortened traveling distances, lowered food delivery frequencies, and tried to maximize multiple deliveries on each trip (Kwangwari, 2022). This ultimately impacts the prices end-consumers pay at grocery and food stores. According to the ATRI Operational Cost of Trucking Report, 2022 was the costliest year to operate in the trucking industry (breaking the prior record) –with or without fuel costs included. The average operational cost of trucking surpassed $2.25 per mile in 2022 (Campbell, 2023). Furthermore, increasing food prices significantly reduces consumers' ability to afford food, particularly for those living in low-income regions, where food spending (proportional to income) is considerably higher. For example, the USDA Economic Research Service (ERS) reports that low-income households on average spent 31.2% of their income on food while wealthier counterparts spent only 8% in 2022.[2]

The objective of this study is to analyze the impact of surging fuel prices and truck-driver availability on food transportation costs and in turn on the retail price of most popularly consumed foods. Using a panel dataset from 2017 to 2022, a Fixed Effects Regression model is developed to examine the transportation impacts on food prices. Our results indicate that food prices are significantly and positively affected by the aforementioned transportation factors. Further, we find that food prices are more susceptive to diesel inflation than to truck-driver shortage. Specifically, we find that the presence of truck-driver shortage increases food prices ranging from 0.68% to 3.06%, while doubling the diesel price results in a food price increase ranging from 3.76% to 23.27%.

The remainder of the report is organized as follows. Section 2 discusses the background and the relevant literature. The dataset and methodology are discussed in Section 3. The model

[1] https://wsfb.com/zero-emission-transportation-industry
[2] www.ers.usda.gov.

and the variables for our analysis are explained in Section 4. Section 5 provides a discussion and comparison of regression results across food commodities and transportation factors. Finally, the main findings are summarized, and research limitations are discussed in Section 6.

2. Background and Literature

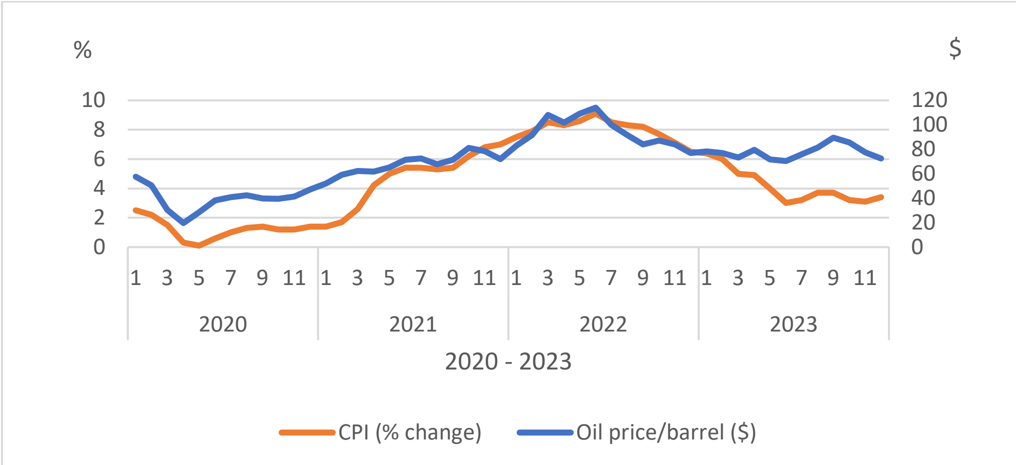
2.1 Food Inflation

The average annual food-at-home prices increased 11.4% from 2021 to 2022, the largest increase since 1979. From 2022 to 2023 the food-at-home price increased by 5.0%, still above the 20-year historical level of retail food price inflation of 2.5 % per year (USDA-ERS, 2024). Prices for several categories grew more slowly than their historical averages, including beef and veal (3.6%), eggs (1.4%), fresh vegetables (0.9%), fresh fruits (0.7%), and fish and seafood (0.3%).

There are a variety of factors contributing to inflation during the study period, including the COVID-19 pandemic and the Russia-Ukraine conflict. COVID-19 severely disrupted the food supply chain, from production, transportation, logistics, and distribution to retail. Severe labor shortages due to illness, quarantine practices, social distancing policy, and travel restrictions, caused disruptions in farms and food-processing facilities. Transportation, both global and domestic, also faced challenges due to lockdowns, quarantines, and restrictions on movement. Border closures and reduced air, sea, and land transport capacity delayed deliveries, thus increasing costs. As restaurants closed and people stayed home, there was a shift from eating out to home cooking. At-home food demand surged, and supply disruptions pushed up food prices.

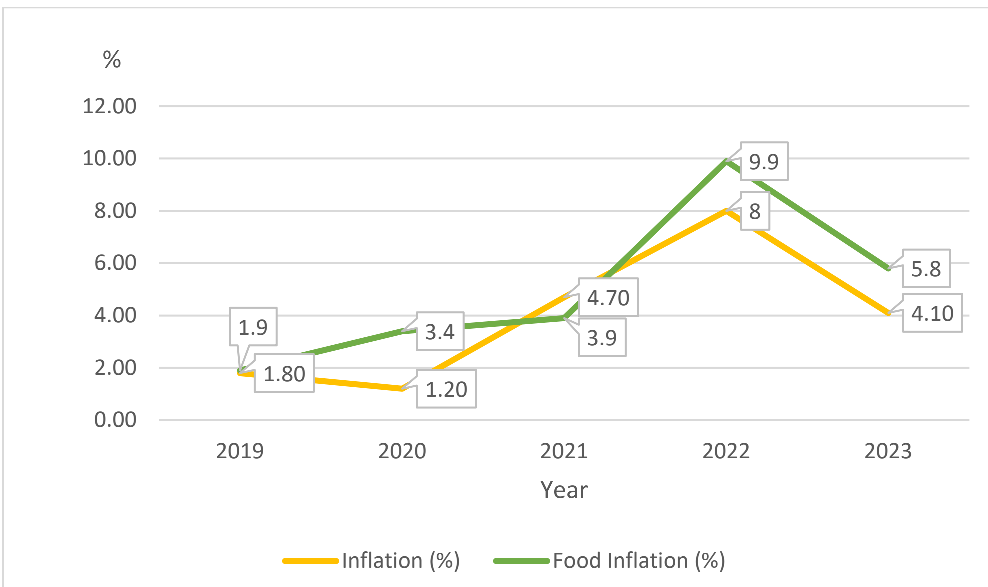
Geopolitical tensions, such as the outbreak of the Russia-Ukraine war in February 2022, also contributed to inflation. Before the conflict, 40% of European gas was imported from Russia, and as the war broke out, gas prices spiked dramatically in response to fears of supply shortages. Oil prices peaked in 2022 with the inflation rate following suit (Fig. 1). Food inflation was more volatile than overall inflation (Fig. 2), particularly in view of soaring gas prices after 2022.

Figure 1. Consumer Price Index vs. Oil Price (Years 2020-2023)



(Source: Bureau of Labor Statistics and Macrotrends)

Figure 2. Annual Inflation: All vs. Food (Years 2019 – 2023)



(Source: Bureau of Labor Statistics)

2.2 Diesel Price, Driver, and other Factors

2.2.1 Diesel Price

Diesel, as the main fuel source for trucking, accounts for 28.5% of marginal costs – the second-largest expense in the operational costs of trucking (ATRI 2023), and hence diesel-price fluctuations inevitably affect transportation costs. Several studies have analyzed the impact of fuel prices on food prices. For example, Baffes (2007) examined 35 commodities for the 1960–2005 period and found that agricultural products were significantly affected by high oil prices (ranked second among 35 commodities); a 10% increase in oil prices boosted food prices by 1.8%. Kuhns & Volpe (2014) found that energy and transportation accounted for 9% of retail food costs.

In recent years, oil prices have fluctuated due to COVID-19 and the Russia-Ukraine War. Initially, the COVID-19 outbreak reduced petroleum demand, and oil prices dropped from $54.53/barrel in January 2020 to $19.67/barrel in April 2020. With COVID vaccinations, loosening restrictions, and market recovery, oil prices started to rebound in May 2020, climbed up to $82.87/barrel in January 2022, and peaked at $114.03/barrel in June 2022 following the Russia-Ukraine War (Fig. 1).

2.2.2 Truck-Driver Availability

Truck-driver shortages are often manifest in rising prices (Richards et al., 2024), and truck driver availability has been an ongoing challenge in the past few decades.[3] Driver wages account for more than 40% of the marginal expense – the single largest trucking operation cost (ATRI, 2023). Although the trucker wage is relatively high,[4] driver availability and retention have been a persistent issue, especially in the for-hire long-distance truckload sector (BLS Monthly Labor Review, 2019).[5]

The pandemic worsened labor shortages due to health concerns, quarantine mandates, and restrictions on movement, causing a decrease in available drivers. Many older drivers chose early retirement due to health risks, while others were unable to work due to COVID-19 infections or caregiving responsibilities. It is reported that the average turnover rate of long-haul truckers was 94% before the pandemic; this number was estimated to reach 150% after the pandemic.[6]

According to Aday and Aday (2020), the food system was highly vulnerable to disruptions due to its reliance on labor-intensive agricultural production and transportation systems. With

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[3] https://www.prepassalliance.org/the-ongoing-truck-driver-shortage-causes-effects-and-solutions/

[4] The average annual wage in 2023 for heavy- and tractor-trailer truck drivers was $46,370, while for light- or delivery-service truck drivers was $41,960. The median annual wage for heavy and tractor-trailer truck drivers was $54,320 in May 2023 (US Bureau of Labor Statistics, 2023)

[5] https://www.bls.gov/opub/mlr/2019/

[6] "There Is a Massive Trucker Shortage Causing Supply Chain Disruptions and High Inflation," *Forbes*, January 12, 2022.

fewer drivers available to transport goods and disruptions in food production, the price of food in the U.S. rose sharply. The combined effects of the pandemic and reduced driver availability significantly increased truck rates. According to Cass Information Systems, trucking costs rose 6.5% from February to March 2022, almost double the increase in freight demand (3.4%). The rising truck rates trickled down to restaurants, grocery stores, and ultimately consumers. However, there are scarce studies investigating the impact of trucker availability on food prices in the literature.

In addition to transportation, many other factors contribute to price fluctuations of food, such as weather and climate conditions, global demand shifts, production costs, trade and government policies, etc. In contrast to those factors, which have been intensively studied in the extant literature, the transportation impacts on food inflation have not drawn decent attention. Therefore, the objective of this study is to unfold the transportation factors to conduct a more in-depth analysis.

2.3 Literature Review

There has been little empirical research to examine the influence of fuel prices in conjunction with driver availability on food transportation and distribution costs. The most relevant study is Volpe et al. (2013), which studies the relationship between fuel prices and wholesale-produce prices using the data for 2000-2009. This study provided empirical insights into the ways fuel prices are transmitted to wholesale-produce prices through transportation costs. The study which selected six types of California grown fruits and vegetables found that rising fuel prices increase the wholesale-produce price, especially when the transportation distance is long. Their study concluded that a 100% increase in diesel prices would result in a 12% to 21% increase in short-term wholesale-produce prices, varying by shipping routes and commodities.

One of the most relevant studies is by Richards, et al. (2024) which examined the impact of labor shortages on agricultural trucking rates. Richards et al. developed an empirical examination based on an equilibrium job search, matching, and bargaining framework in which they estimated the role of labor shortages in accelerating driver-wage growth, and truck rates for agricultural products. It is reported that the COVID-19 pandemic was responsible for a rise in for-hire trucker wages of some 38% and an average increase of nearly 50% in truck rates and that the gap between trucker job openings and successful matches explains a significant, but small, rise in truck rates. In contrast, our study aims to make a more comprehensive and deeper exploration of the joint effect of diesel prices and truck driver availability on the transportation marginal food price associated with different agricultural products, instead of truck rate.

2.4 Data Source

Our analysis covers the period from January 2017 through December 2022 - three years before and three years after the outbreak of COVID-19 in January 2020. Based on data availability and the most purchased fresh food commodities, we selected four food items as the focal commodities in our study – apple, onion, tomato, and potato. Potatoes, onions, and tomatoes are ranked as the three most purchased vegetables in the US markets in 2022.[7] In addition, apples are the most consumed fruit in the U.S., followed closely by oranges.[8] We compile a dataset on key variables such as diesel prices, truck-driver availability, and food prices for the selected commodities (i.e., apples, potatoes, onions, and tomatoes) for the period from January 2017 to December 2022, and the data are collected from multiple sources as illustrated in Table 1. First, the fresh food prices at free-on-board shipping points and destination, terminal markets are collected from *USDA's Agricultural Marketing Service* (AMS). Data on the truck-driver availability for the selected commodities between shipping points and terminal markets are sourced from the USDA's *Specialty Crops National Truck Rate Report*. Weekly on-highway diesel prices are collected from *Energy Information Administration* (EIA). Finally, data on the gross domestic product (GDP) and consumer price index (CPI), are obtained from the *Federal Reserve Economic Data* (FRED).

The panel data is compiled as follows: First, data on shipping points are mapped with terminal markets by considering the actual traveling distance. Second, to handle the mismatch of data frequency, linear interpolation is adopted to convert weekly (i.e., diesel price and truck-driver availability), monthly (i.e., CPI), and quarterly (i.e., GDP) data to daily to match the frequency of the marginal price. Inevitably, some data that cannot be properly matched in the data cleaning

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[7] In 2022, the percentage of households purchasing potatoes, onions, and tomatoes were 85%, 84%, and 81%, respectively (https://www.freshproduce.com/resources/consumer-trends/top-20/).

[8] https://www.agmrc.org/commodities-products/fruits/apples

process is removed in the third step. Fourth, the records with negative marginal prices[9] (i.e., the price at the terminal market is cheaper than that at the shipping point) are also removed. The reason for the negative marginal price might be threefold: 1) data entry problem, 2) mismatch bias in the data cleaning process, and 3) food pricing strategy (e.g., food price drops while being delivered to the terminal market). Because the records with negative marginal prices are minor and most likely to be either errors or only temporary, we have removed them from the panel data. After processing the raw data, the final four panels contained 176,090 complete observations for apples, 20,720 for onions, 177,319 for potatoes, and 56,334 for tomatoes, covering the period from January 2017 to December 2022.

2.5 Econometrics Methodology

Panel data are compiled and analyzed using the *Fixed Effects Regression* approach by fixing attributes of food type, origin, and destination (Wooldridge, 2019). Theoretically, the Fixed Effects Regression can be adopted to control omitted variables that are time-invariant and to mitigate endogeneity, an issue that arises when independent variables correlate with the error term. In this study, food types are controlled to account for the price differences between qualities and varieties (e.g., gala, fuji, golden crispy apples, etc.). Food sources and shipping destinations are further fixed to account for the cost differences among states (e.g., labor, diesel, shipping distance, etc.). The Fixed Effects Regression allows us to control those inherent differences across entities and accordingly isolate the transportation effect on food prices.

Additionally, to minimize the omitted-variable bias and investigate the causal inference between the transportation factors and the transportation price spread, five models have been tested sequentially (see Appendix A) which considers macroeconomic impacts (e.g., CPI), the onset of COVID, seasonality, and entity features (e.g., food types, shipping origins, and destinations) to control for time-variant and -invariant variables. The multicollinearity issue is investigated with the *variance inflation factor* (VIF) test (see Appendix B), and the models are refined by fixing more variables while dropping those variables that will cause multicollinearity issues. The refined models for each food item are summarized and discussed in Section 5.

[9] The marginal prices for the four food items exhibit normal distributions with 2% to 10% of negative values, and those negative values are removed from the datasets.

It is worth noting that the data used in this study are not only large-scale, but also reliable as sourced from multiple authorities, including USDA, EIA, and FRED. The large and high-quality data satisfy the theoretical requirements for causal inference and help mitigate the endogeneity concern, which is typically caused by biased sampling and measurement errors.

3. Models and Analysis

3.1 Variables

Dependent variables

The dependent variable selected in the model is the price spread from shipping - which is calculated as the incremental price from the shipping point to the terminal market. The shipping price spread is used instead of the terminal market price to focus on transportation effects. Food pricing (at either origin or destination) is complex and impacted by a variety of factors such as own-price and cross-price elasticities, shelf life, seasonality, weather, planting area, etc. The price spread, however, is less impacted by these overall changes in demand and can better isolate transportation impacts.

Another advantage of using the shipping price increment as the dependent variable is to mitigate endogeneity or reverse causality with GDP and/or CPI (the control variables selected in the study). The endogeneity issue might impair the model performance if the food price at the terminal market is employed as the dependent variable because of its potential correlation with those macroeconomic indexes (i.e., GDP and CPI). As explained above, the food shipping contributes to the transportation segment, which only accounts for 2.9% of GDP (2021 Bureau of Transportation Statistics).[10] Therefore, adopting the shipping price spread in the model can avoid the endogeneity issue.

To focus on the food transportation segment, this study followed the conventional treatment in the literature, e.g., Volpe et al. (2013), to consider the price increment pertaining to transportation, which is referred to as the *transportation price spread* (TPS) throughout this study. The TPS is calculated as the difference between the terminal market price ($MP_{i,t+\Delta t}$) and the shipping point price ($SP_{i,t}$),

[10] https://www.bts.gov/

$$TPS_{i,t} = MP_{i,t+\Delta t} - SP_{i,t}.$$

In the above formula, the index i denotes the four food commodities selected in our study, namely, $i \in \{$apple, orange, onion, tomato$\}$; the index t denotes time period, and Δt denotes the transportation time needed to transport commodity i from the shipping point to the terminal market. To track the transportation time (Δt), we use the transportation distance (between the shipping point and the terminal market) divided by the average truck speed[11] to match the price data in two separate datasets of the shipping point and terminal market. For example, to track the red delicious apple packed in a carton tray with the grade of 88 that left Washington (i.e., shipping point) on January 3 with the destination of Los Angeles, its terminal market price is retrieved as the exact apple carton tray in the dataset of Los Angeles on January 5, considering that the estimated transportation time from Washington to Los Angeles is two days.

Independent variables

To study the transportation impact on food prices, we focus on the following two independent variables throughout our analysis.

(1) Truck-Driver Availability Index ($Avail_t$):

The Availability Index ($Avail_t$) is an index ranging from 1.0 to 5.0, where 1.0 means (surplus) very easy to hire a truck compared with the same quarter in the previous year; and 5.0 means (shortage) very difficult to hire a truck compared with the same quarter the previous year. Two sets of regression analyses were performed with different measures of the Availability Index. In the first analysis, we assume the truck-driver availability index is treated as a continuous variable.[12] Such a model examines how food price is impacted when the shortage level intensifies gradually. However, considering the model interpretability and rating bias, an additional regression model is developed with the Availability Index set as a binary variable, with 0 for surplus and 1 for shortage. In particular, the ratings of 4.0 (slight shortage) and 5.0 (shortage) are defined as shortage and denoted as 1, and the rest ratings (i.e., 1.0-3.0) are defined as no shortage and denoted as 0. This model, therefore, investigates how food price is affected when the truck driver is in short supply. The results of the two models are both provided in the report; the former with a 5-scale index is

[11] https://www.energy.gov/eere/vehicles/fact-671-april-18-2011-average-truck-speeds
[12] The assumption of equal intervals between index levels is required to ensure the rigor and robustness of the model.

given in the appendix (see Table 7 Appendix C), and the latter with a binary index is discussed in the main text (see Table 3).

(2) Diesel Price ($Diesel_t$):

Trucks moved nearly 83% of agricultural freight in 2018 (USDA, 2020) and are primarily fueled with diesel. Therefore, we use this variable in the regression model to examine how the food price reacts to a percent change in diesel price. The diesel price data is sourced from EIA, and its natural log value is taken as an independent variable. Restrained from data availability, the national diesel prices (rather than the regional prices) are considered in the model to generalize the diesel price fluctuations and to effectively examine their impact on food transportation.

Due to the differences between the two selected independent variables, the truck-driver availability with bounded values (i.e., 1-5 or 0-1) and the diesel price with unbounded values, we develop two additional sets of regression analyses to minimize the impact on analytical results stemming from the variable differences. One keeps the original, unbounded diesel price as the independent variable while the other standardizes the diesel price to range from 0 to 1 in the study period (i.e., January 2017 to December 2022). The results of both models are provided in the report; the former with the original data is discussed in the main text, and the latter is relegated to Appendix D. Both models show that the impact of truck-driver availability is consistently significant and positive across the commodities on their price.

Control variables

To investigate the impact of economic factors such as inflation and consumer demand, CPI and GDP are used as control variables (X_t) in the model, and their data are obtained from FRED. We also control the impact of COVID-19 pandemic by using a binary variable with January 2020 as the tipping time point. In particular, we set the factor as $COVID_{t<Jan2020} = 0$, $COVID_{t \geq Jan2020} = 1$. Seasonality has also been controlled to account for seasonal harvest. Four quarters are considered in a year, denoted as $Season_t$ with $t = 1, 2, 3, 4$.

Table 1. Variables and Data Sources

Variables	Notation	Type / Frequency	Data Source	Note
Transportation Marginal Price (TPS)	$MP_{i,t+\Delta t} - SP_{i,t}$	Dependent Var./ Daily	USDA	Marginal food price to consider the price increment from the shipping point to the terminal market.
CPI	An element of $X_{i,t}$	Control Var./ Monthly	FRED	CPI is included to control the price effect from inflation. The natural log value is taken to present proportional change.
GDP	An element of $X_{i,t}$	Control Var./ Quarterly	FRED	GDP is included to control the price effect from demand. The natural log is taken to present proportional change.
Seasonality	Q_i	Binary		Q_1, Q_2, Q_3, Q_4 are included to track the impact of seasonality in term of each quarter season.,
COVID	An element of $X_{i,t}$	Control/Binary Var.		COVID-19 (January 2020) is included to control the demand shock from the pandemic.
Truck-Driver Availability	$Avail_{i,t}$	Independent Var. (Index: 1-5)/ Weekly	USDA	Availability index: 1-Surplus; 2-Slight Surplus; 3-Adequate 4-Slight Shortage; 5-Shortage
Diesel Price	$\ln(Diesel_{i,t})$	Independent Var./ Weekly	EIA	Diesel price is included to investigate the impact of food prices on transportation. Its natural log value is taken to present proportional change.

Final Model

After resolving the omitted-variable bias and multicollinearity issues as discussed in Section 3.2, the model performance (R^2) is significantly improved from 0.07 to 0.89 (see Appendix A), and the final model is presented as follows:

$$TPS_{i,t} = \beta_1 Avail_t + \beta_2 \ln(Diesel_t) + \delta X_t + \gamma_i + \varepsilon_{i,t},$$

where X_t encapsulates a set of control variables[13] (i.e., CPI, quarter season, and COVID), γ_i denotes the food attribute fixed effect (e.g., food types, shipping origins, and destinations), and $\varepsilon_{i,t}$ presents an error term that follows a typical normal distribution with zero mean.

Unlike Volpe et al. (2013), who used a fixed estimate of shipping duration,[14] we estimated the duration by considering the actual transportation distance, which can significantly reduce measurement errors. In addition, rather than adopting a market-specific regression model, we employed fixed-effect regression by controlling the product features, shipping points, and destinations, which allowed us to focus on transportation and derive its general and nationwide effects on food prices (not limited to California-sourced products). Finally, departing from Volpe et al. (2013), we do not consider the control variable of food supply (i.e., the estimated overall monthly U.S. supply of fresh produce), because the dependent variable, the transportation price spread ($TPS_{i,t}$) between shipping points and terminal markets, selected in our model can effectively rule out the noises from demand and supply and isolate the transportation effect.

3.2 Descriptive Statistics

Table *2* shows the descriptive statistics of the variables for the four selected food commodities (i.e., apple, onion, potato, and tomato). The mean availability index ranges from 3.18 (for tomato) to 3.58 (for potato), indicating that the average truck-driver availability ranges between "*Adequate*" and "*Slight Shortage.*" The mean diesel price ($Diesel_t$) ranges from \$3.12/gal to \$3.76/gal. Among the four commodities, apple is the most expensive commodity, with the largest price volatility at both the shipping point ($SP_{i,t}$) and the terminal market ($MP_{i.t+\Delta t}$), followed by potato, tomato, and onion. When looking at the transportation price spread, $TPS_{i,t} = MP_{i,t+\Delta t} - SP_{i,t}$, apple has the largest average transportation price spread, followed by potato, onion, and tomato.

[13] The assumption of equal intervals between index levels is required to ensure the rigor and robustness of the model. CPI were kept for only apples and onions. More details about the VIF tests can be found in Appendix B.

[14] Volpe et al. (2013) generally assumed a fixed, 7-day shipping duration for all the products shipped from California to all the destinations.

Table 2. Descriptive Statistics of Variables for Selected Commodities

Variables	Availability (Index: 1.0-5.0)	Diesel Price ($ per Gallon)	Food Price ($ Per LB at Shipping Point)	Food Price ($ Per LB at Terminal Market)	Price Spread ($ Per LB)
Apple					
Mean	3.31	3.19	0.61	0.88	0.28
Std	0.75	0.77	0.20	0.26	0.16
Max	5.00	5.81	2.07	6.51	5.78
Min	2.00	2.36	0.25	0.34	0.00
C.V.	0.23	0.24	0.33	0.30	0.57
Onion					
Mean	3.50	3.12	0.30	0.47	0.17
Std	1.00	0.66	0.14	0.18	0.09
Max	5.00	5.81	0.98	1.50	0.78
Min	1.00	2.36	0.08	0.14	0.00
C.V.	0.29	0.21	0.47	0.38	0.53
Potato					
Mean	3.58	3.50	0.31	0.49	0.18
Std	0.92	1.01	0.15	0.21	0.10
Max	5.00	5.81	1.07	1.44	0.84
Min	1.00	2.36	0.06	0.15	0.00
C.V.	0.26	0.29	0.48	0.43	0.56
Tomato					
Mean	3.18	3.76	0.65	0.93	0.28
Std	1.14	1.01	0.35	0.47	0.24
Max	5.00	5.81	3.33	5.28	3.42
Min	1.00	2.36	0.22	0.24	0.00
C.V.	0.36	0.27	0.54	0.51	0.86

*Abbreviations: Std (*Standard Deviation*); C.V. (*Coefficient of Variation*)

4. Analytical Results and Discussions

After addressing the issues of endogeneity, multicollinearity, and discrepancy in variable types discussed in Sections 3 and 4, the model is refined, and the results are reported in Table 3. For each food commodity, the first column in Table 3 reports the coefficients, followed by their relative effect in relation to the item's unit price in the second column. Our models statistically interpret an average of 88.73% of variations in food price (i.e., R^2 values), and the analytical results reveal that there exists a significant and positive correlation between the price spread and the transportation factors. The results also show that due to the impact of COVID-19, food prices experienced a significant increase.

Across all the four selected commodities, we find that a truck-driver shortage increases food prices by 0.6¢ to 1.5¢. This is equivalent to 0.68% to 3.06% increase in relation to the respective unit price[15]. When the diesel price doubles, the food price increase ranges from 3.5¢ to 11.5¢, equivalent to 3.76% to 23.27% of increase in relative terms. We also find that in the study years following the onset of COVID (2020 – 2022), the food price increase ranged from 1.8¢ to 4.3¢, equivalent to 2.05% to 8.78% relatively.

We discuss the analytical results in detail for each item, followed by a discussion to compare across four items (i.e., apple, onion, potato, and tomato) and two transportation factors (i.e., diesel price and truck-driver availability).

[15] The onion's result for truck-driver availability is insignificant and thus excluded from this statement.

Table 3. Impacts on Transportation Price Spread

	Apple		Onion		Potato		Tomato	
	(Ave. \$0.88/lb)		(Ave. \$0.47/lb)		(Ave. \$0.49/lb)		(Ave. \$0.93/lb)	
	Coeff.	Relative%	Coeff.	Relative%	Coeff.	Relative%	Coeff.	Relative%
Availability_binary	0.006***	0.68%	0.001	0.23%	0.015***	3.06%	0.013***	1.40%
ln(Diesel)	0.078***	8.86%	0.081***	17.23%	0.115***	23.47%	0.035***	3.76%
COVID	0.018***	2.05%	0.001	0.21%	0.043***	8.78%	0.033***	3.55%
Q1	-0.910***	-103.41%	-0.886***	-188.51%	0.270***	55.10%	0.354***	38.06%
Q2	-0.908***	-103.18%	-0.897***	-190.85%	0.248***	50.61%	0.350***	37.63%
Q3	-0.899***	-102.16%	-0.899***	-191.28%	0.302***	61.63%	0.329***	35.38%
Q4	-0.902***	-102.50%	-0.887***	-188.72%	0.287***	58.57%	0.403***	43.33%
Type	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Origin	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Destination	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.912		0.891		0.905		0.841	
Observation	N= 176090		N= 20729		N=177319		N= 56334	

Statistical Significance Levels: *p < 0.1; **p < 0.05; ***p < 0.01.

4.1 Regression Results

From Table 3, we can see that the coefficients of both the independent variables –truck-driver availability and diesel price –are significant and positive for apples implying that the apple price is positively affected by transportation costs. Specifically, *ceteris paribus*, when there is a truck-driver shortage, apple price increases by 0.6¢ (0.68% relatively). Similarly, when the diesel price doubles, the price of apples increases by 7.8¢ (8.86% relatively) (equivalent to an additional 0.078¢ for every percent increase in diesel price). Furthermore, the positive coefficient of COVID for apples indicates that apple's price increased after COVID.

The onion price is positively correlated with both diesel price and truck-driver availability, though not statistically significant for truck-driver availability. Holding other variables constant, the price of the onion increases by 8.1¢ when the diesel price increases by 100%. This is equivalent to a 17.23% increase related to its unit price. The model performance for apples and onions is satisfactory with 0.912 and 0.891 of the R^2 values, respectively.

For potatoes and tomatoes, their prices are both significantly and positively correlated with transportation factors. Holding other variables fixed, potato and tomato prices increase by 1.5¢ (3.06% relatively) and 1.3¢ (1.40% relatively), respectively, when truck-drivers are in short supply. For 100% increase in diesel price, the prices of potato and tomato increase by 11.5¢ and 3.5¢, respectively, equivalent to 23.47% and 3.76%, respectively, in relation to their unit prices. Finally, the positive coefficients of the COVID variable indicate that prices of potato and tomato increased after COVID. The performances of both models are also statistically satisfactory, with 0.905 and 0.841 of R^2 values, respectively.

In terms of the truck-driver availability, we have performed the analysis based on two different settings: binary values and 5-scale index. In both analyses, the impact of truck-driver availability is shown consistently significant and positive on food prices. In particular, in the binary setting, as shown in Table 3, the coefficient of availability ranges from 0.23% (onions) to 3.06% (potatoes) in relation to their respective price. In the 5-scale index setting as shown in Table 7 (Appendix C), the coefficient of the availability ranges from 0.11% (onions) to 1.43% (potatoes) in relation to their respective price.

In terms of seasonality, each of the four focal commodities shows a significant impact from seasonality, in terms of Q1, Q2, Q3 and Q4. In particular, with a significance level $p=0.01$, apples have the largest impact in Q1 with a coefficient of -0.91; both onions and potatoes have the largest impact in Q3 with the coefficients 0.899 and 0.302, respectively; while tomatoes have the largest impact in Q4 with the coefficient 0.403.

4.2 Discussion

In general, the coefficients of both the independent variables for all four commodities (except the truck-river availability for onion) confirm the positive relationships of transportation costs with the food price. That is, the food price increases when the truck driver is in short supply and/or the diesel price rises, but the magnitude of the impact varies by food type. The results also indicate that the prices of three out of four items (i.e., apple, potato, and tomato) increased during the study period after COVID, with the magnitude ranging from 1.8¢ (apple) to 4.3¢ (potato).

Among our four selected commodities, potato is the most sensitive, when considering both diesel price and truck-driver availability. As potato is mostly planted in Idaho, remote and far from major hubs like California, New York, and Texas, its supply chain is heavily reliant on truck transportation. Thus, the fluctuations in truck-driver availability and diesel prices are transmitted to potato prices. Similarly, distanced from the major markets, apples and onions are mainly planted in Washington, and exhibit a similar sensitivity level as potatoes. However, compared with onions and potatoes, apples have more stringent storage requirements. For example, apples in Washington are harvested from August to early November and later placed in cold storage to supply the national market year-round. Compared with onions and potatoes, the shorter shelf life and higher storage costs make apples less sensitive to transportation, but more to other factors.

Among the four selected commodities, tomatoes are the least sensitive to transportation. This is because tomatoes are mainly imported from Mexico through Texas and Arizona, while onions, potatoes, and apples are mostly produced domestically. Compared to the other commodities, the shelf life of tomatoes is relatively short, just five days in cold storage. Due to the reliance on importation and the extremely short shelf life, tomato prices are more sensitive to other marketing factors (e.g., demand and supply) besides transportation.

When comparing the effects of diesel price and truck-driver availability, we find that the diesel price has more impact on commodity prices than the truck-driver availability index. Recall that two variations of the variable $Avail_t$ are studied, a binary variable (Table 3) and a 5-level index (Table 7); regardless of the type, the variable $Avail_t$ is an index with a narrowly bounded scale, while the variable $\ln(Diesel_t)$ describes percentage change in diesel price and can be unbounded. Also, the average standard deviation of the 5-scale truck-driver availability index is 0.95 - 0.75, 1.00, 0.92, and 1.14 for apple, onion, potato, and tomato, respectively, while that of the percentage change in diesel price was 25.25% - 24.13%, 21.15%, 28.86%, and 26.86%, respectively. That is, the average effect of truck-driver availability from 2017 to 2022 for the four items is 0.6¢/lb, and that of diesel is 1.8¢/lb - three times the truck-driver availability. During the study period, there was a notable fluctuation in diesel prices. Between October 2020 and June 2022, diesel prices increased from a low of $2.36 to a high of $5.81 (i.e., 146% increase). During the period under this study, the estimated food price increases resulting from diesel price increase were 7.2¢/lb for apples, 7.3¢/lb for onions, 10.3¢/lb for potatoes, and 3.3¢/lb for tomatoes (see Appendix D).

Our study also found that prices (significantly for apples, potatoes, and tomatoes, but insignificantly for onions) have been increasing since the COVID-19 pandemic, and the overall price increase for the four commodities in our study ranged from 2.05% to 8.78%. In particular, potatoes and tomatoes exhibited a stronger reaction to COVID-19 than apples, possibly attributable to the different production modes between vegetables and fruits. For example, vegetable production often requires more intensive labor for planting, harvesting, and processing. During the COVID-19 lockdown, disruptions in labor availability led to reduced production, higher production costs, and, subsequently, increased food prices.

Compared with Volpe et al. (2013), which used fuel price to represent transportation costs, our study deconstructed transportation into two major components: fuel price and truck-driver availability,[16] which account for almost 70% of marginal shipping costs. In contrast to the Volpe study, we also extended the study from only California-sourced produce to food sourced from 16 states and shipped to 9 terminal markets from 2017 to 2022. Our study concurs with Volpe et al. (2013) that transportation plays a critical role in food pricing. We also find that food prices are more susceptible to changes in fuel prices than in truck-driver availability. Our analysis shows that, when diesel prices double, food prices increase from 3.76% (for example- tomato – most reliant on import) to 23.47% (for example, potato – most reliant on trucking), in contrast to the result by Volpe et al. (2013) that the impact of diesel price on commodity prices ranged from 12% to 21%

[16] Fuel price and truck-driver cost account for 28.5% and 40.3% of marginal cost per mile, respectively, in 2022 (Leslie and Murray, 2023).

increase. When there is a truck-drive shortage, food prices increase between 0.68% (apple) to 3.06% (potato). Thus, the average effect of an increase in diesel price was 1.8¢/lb. across the selected commodities, while that for truck-driver availability was 0.6¢/lb. during the study period (2017-2022). Finally, we found that prices have been increasing after the COVID-19 pandemic, and inflation for the selected commodities ranged from 2.05% (apple) to 8.78% (potato).

5. Conclusions

This study performed a regression analysis to explore the impact of transportation factors (i.e., diesel price and truck-driver availability) on food prices. First, our findings indicate that the upsurge in diesel prices, coupled with increasing truck-driver availability issues, exerted a higher pressure on food prices. Second, we find that food prices increased in the study period after COVID-19. Finally, our study finds that fluctuations in diesel prices wield a stronger impact compared with the availability of truck drivers. Notably, potatoes display the highest sensitivity to transportation costs due to their relatively distant location from markets and concentrated farming; tomatoes exhibit comparatively lower sensitivity due to their heavy reliance on importation.

This study has several limitations. First, the study's exclusive emphasis on diesel prices and truck-driver availability as primary determinants may overlook the potential influence of other contextual and market-specific factors on food prices. Future research may consider potential factors like population growth, planted areas, and impacts of extreme weather and wars. Second, due to the lack of routing information, this study fails to capture the actual diesel costs associated with each route but mainly relies on estimation in the model. Third, given a relatively short study time frame (i.e., six years) and the relatively fixed characteristics of the food market (i.e., food supply and demand are relatively fixed in the short term), we used a fixed-effect model without considering the time influence on food price. Future research should analyze a dataset with an extended time frame and adopt dynamic models to investigate the evolving relationships between the variables under study. Finally, though there may exist inherent differences among different food markets, our model could be tested in other countries or regions with similar transportation ecosystems (i.e., rising diesel and labor costs).

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Appendix

Appendix A: Models & Results - TPS Impacted by Diesel Price and Truck-Driver Availability

Five models have been built and tested to iteratively improve the model performance. The performance and results of the five models are reported in Table 5. Model 1 is the original model which includes all the variables, the independent and control variables, but with no fixed effects. To address the multicollinearity issue, the control variables are further adjusted, and the model results are reported as Model 2. To further improve the model performance (i.e., R^2), we fixed food types, shipping origins, and destinations, and the resulting models are reported as Models 3, 4, and 5, respectively.

Table 5. Five models to improve the model performance

	Model 1 (Initial Model)	**Model 2** (No Multicollinearity)	**Model 3** (Fix Food Type)	**Model 4** (Fix Origins)	**Model 5** (Fix Destinations)
Apple **N= 176090**					
Avail_binary	0.025***	0.030***	0.008***	0.007***	0.006***
ln(Diesel)	0.039***	0.078***	0.085***	0.086***	0.078***
ln(GDP)	0.259***				
ln(CPI)	0.004	0.183***	0.073***	0.075***	0.153***
COVID	0.010***	0.020***	0.028***	0.027***	0.018***
Constant	-2.408***	-0.876***			
Q1			-0.464***	-0.353***	-0.910***
Q2	0.027***	0.027***	-0.458***	-0.346***	-0.908***
Q3	0.048***	0.052***	-0.448***	-0.337***	-0.899***
Q4	0.006***	0.010***	-0.450***	-0.338***	-0.902***
R^2	0.069	0.068	0.843	0.844	0.912
Onion **N= 20729**					
Avail_binary	0.002*	0.001	0.000	-0.003**	0.001
ln(Diesel)	0.071***	0.055***	0.065***	0.063***	0.081***
ln(GDP)	-0.097***				
ln(CPI)	0.266***	0.200***	0.201***	0.194***	0.196***

COVID	0.003	-0.001	0.000	-0.005***	0.001
Constant	-0.421*	-0.999***			
Q1			-0.987***	-0.945***	-0.886***
Q2	-0.014	-0.015***	-0.999***	-0.962***	-0.897***
Q3	-0.011	-0.013***	-0.992***	-0.961***	-0.899***
Q4	-0.001	-0.002***	-0.990***	-0.950***	-0.887***
R^2	0.063	0.062	0.833	0.844	0.891
Potato					
N=177319					
Avail_binary	0.003***	0.012***	0.016***	0.012***	0.015***
ln(Diesel)	-0.042***	0.104***	0.111***	0.106***	0.115***
ln(GDP)	0.065***				
ln(CPI)	0.580***				
COVID	-0.009***	0.035***	0.047***	0.048***	0.043***
Constant	-3.664***	0.019***			
Q1			0.151***	0.217***	0.270***
Q2	-0.012***	-0.012***	0.131***	0.193***	0.248***
Q3	0.020***	0.030***	0.185***	0.255***	0.302***
Q4	0.009***	0.017***	0.175***	0.241***	0.287***
R^2	0.181	0.150	0.832	0.849	0.905
Tomato					
N= 56334					
Avail_binary	0.020***	0.022***	0.008***	0.011***	0.013***
ln(Diesel)	-0.086***	0.007*	0.037***	0.038***	0.035***
ln(GDP)	-0.058				
ln(CPI)	0.536***				
COVID	-0.015***	0.017***	0.036***	0.036***	0.033***
Constant	-2.052***	0.237***			
Q1			0.134***	0.045**	0.354***
Q2	-0.003	-0.003	0.134***	0.045**	0.350***
Q3	-0.014***	-0.007**	0.116***	0.027	0.329***
Q4	-0.052***	0.062***	0.193***	0.105***	0.403***
R^2	0.018	0.015	0.818	0.821	0.841
Type			Fixed	Fixed	Fixed
Origin				Fixed	Fixed
Destination					Fixed

Statistical Significance Levels: *p < 0.1; **p < 0.05; ***p < 0.01.

Note: Models 1 and 2 use multivariable regression with three seasonality dummy variables to avoid the dummy variable trap. Models 3 to 5 apply a fixed effects model, incorporating seasonality as four fixed terms alongside fixed effects for food type, origin, and destination.

Appendix B: VIF Test for Multicollinearity

To address the multicollinearity issue, we have tested the *variance inflation factor* (VIF), and the results are reported in Table 6. Typically, if a VIF value exceeds the threshold of 5.0, then there exists multicollinearity in the model. In view of the table, GDP ($X_{GDP,t}$) needs to be removed for apples and onions (Test 3), and GDP ($X_{GDP,t}$) and CPI ($X_{CPI,t}$) need to be removed for potatoes and tomatoes (Test 4). To further address multicollinearity as suggested above, the regression analysis is executed in Model 2 in Table 5. We find that all coefficients are significant, but R^2 values remain relatively low.

Table 6. VIF Test Results

Variables	**Collinearity Statistics-Variance Inflation Factor**													
	Apple			**Onion**			**Potato**				**Tomato**			
Test	1	2	**3***	1	2	**3***	1	2	3	**4***	1	2	3	**4***
Avail_binary	1.33	1.30	1.12	1.29	1.19	1.11	1.46	1.43	1.21	**1.16**	1.37	1.34	1.16	**1.15**
$ln^{(\mathbf{Diesel})}$	5.05	5.05	2.89	4.96	4.87	2.45	8.69	8.58	5.56	**1.29**	7.97	6.85	6.17	**1.20**
$ln^{(\mathbf{GDP})}$	16.37	8.88	**N/A**	17.93	8.84	**N/A**	23.17	12.65	**N/A**	**N/A**	14.95	10.01	**N/A**	**N/A**
$ln^{(\mathbf{CPI})}$	8.75	N/A	**4.75**	8.90	N/A	**4.39**	14.31	**N/A**	7.81	**N/A**	12.94	**N/A**	8.66	**N/A**
COVID	2.96	2.94	**2.14**	3.79	3.79	**2.43**	3.18	**3.16**	2.26	**1.17**	2.69	**2.55**	2.11	**1.13**
Q2	1.40	1.39	**1.40**	1.86	1.85	**1.83**	1.35	**1.35**	1.35	**1.35**	1.48	**1.48**	1.46	**1.46**
Q3	1.46	1.46	**1.38**	2.00	1.95	**1.81**	1.32	**1.32**	1.32	**1.27**	1.46	**1.45**	1.39	**1.32**
Q4	1.53	1.51	**1.43**	1.69	1.69	**1.65**	1.39	1.37	1.39	**1.35**	1.55	1.51	1.52	**1.38**

Note: VIF values are computed for multiple regressions for each selected commodity. A value for a variable indicates its inclusion in the current round of regression, while N/A signifies its exclusion from the regression.

Appendix C: Analytical Results with the 5-scale Truck-Driver Availability Index

By comparing the results of Table 3 (with the binary Truck-Driver Availability Index) and Table 7 (with the 5-level index), we can see that the differences in the coefficients are minor. Considering the result interpretability and the potential rating bias, the results of the binary index (i.e., shortage and surplus) are kept in the main text for discussion.

Table 7. Analytical Results with the 5-level Truck-Driver Availability Index

	c (Ave. \$0.88/lb)		**Onion** (Ave. \$0.47/lb)		**Potato** (Ave. \$0.49/lb)		**Tomato** (Ave. \$0.93/lb)	
	Coeff.[17]	Relative%[18]	Coeff.	Relative%	Coeff.	Relative%	Coeff.	Relative%
Availability	0.007***	0.80%	0.0005	0.11%	0.007***	1.43%	0.005***	0.54%
ln(Diesel)	0.080***	9.09%	0.081***	17.23%	0.114***	23.27%	0.037***	3.98%
ln(CPI)	0.137***	15.57%	0.194***	41.28%				
COVID	0.018***	2.05%	0.001	0.21%	0.042***	8.57%	0.034***	3.66%
Q1	-0.846***	-96.14%	-0.881***	-187.45%	0.253***	51.63%	0.334***	35.91%
Q2	-0.842***	-95.68%	-0.891***	-189.57%	0.232***	47.35%	0.331***	35.59%
Q3	-0.834***	-94.77%	-0.894***	-190.21%	0.286***	58.37%	0.312***	33.55%
Q4	-0.840***	-95.45%	-0.882***	-187.66%	0.270***	55.10%	0.385***	41.40%
Type/ Orig./ Destination	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.912		0.891		0.905		0.841	
Observation	N= 176607		N= 20720		N=177319		N= 56334	

[17] Coefficients are reported as dollar (e.g., \$0.007 = 0.7¢).

[18] The relative % is calculated by dividing the coefficient by its unit price, which allows us to compare the relative impact of transportation. For example, the apple's coefficient of availability is 0.7¢, divided by its unit price, \$0.88/lb, and the relative effect of driver availability is 0.80%. When the driver availability intensifies by one level, the apple price increases by 0.80%.

Appendix D: Analytical Results with Bounded Variables for Apple

To align with the truck-driver availability index, which is a bounded value ranging from 1 (surplus) to 5 (shortage), the diesel price and the CPI are also bounded from 0 to 1, and the analytical results are presented in the table below. The original model shows the results without bounding the diesel price and the CPI, followed by the models with bounded prices. We find that bounding the diesel price and CPI does not affect the coefficients significantly. Additionally, given that there were no outliers for the data (the requirement of the Ordinary Least Squares (OLS) assumptions), allowing a larger variance in the independent variables (i.e., unbounded diesel price and CPI) renders a smaller variance of their corresponding coefficients, hence improving the accuracy of the estimated slopes. Therefore, we decided to keep the diesel price and the CPI unbounded using their original scale in the final model.

Table 8. Analytical Result Comparison with Unified Diesel Price and CPI for Apple

VAR	Orig. Model with ln(diesel)	VAR	Model with std(diesel)	VAR	Model with std(diesel) & std(CPI)
Availability	0.007***	Availability	0.008***	Availability	0.009***
ln(Diesel)	0.076***	norm(Diesel)	0.071***	norm(Diesel)	0.074***
ln(CPI)	0.164***	ln(CPI)	0.154***	norm(CPI)	0.034***
COVID	0.016***	COVID	0.016***	COVID	0.018***
R^2	0.912	R^2	0.912	R^2	0.912

Apple: N= 176090. Min-Max Standardization: (X – min(X)) / (max(X) – min(X))

Appendix E: Comparison between the Average Effects of Diesel and Truck-Driver Availability

To compare the effects of diesel and truck-driver availability, we revisit Table 7, which reports the analysis in terms of the 5-scale availability index (a detailed measure of the index compared to its binary setting). In view of Table 7, for truck-driver availability:

- The average coefficients: ($0.007+$0.007+$0.005)/3 = $0.0063;
- The standard deviation 2017-2022 = 0.95;
- The average effect of truck-driver availability is: $0.0063*0.95 = $0.006.

As for the diesel price:

- The average impact of the ln(diesel) is: ($0.080+$0.081+$0.114+$0.037)/4 = $0.078;
- The standard deviation 2017-2022 = 25.25%;
- The average effect of the diesel price is: $0.078*[ln(1+25.25%)-ln(1)] = $0.018.

Between October 2020 and June 2022, the diesel price sharply increased from $2.36 to $5.81, equivalent to a 146% increase. Accordingly, its average effect on food prices is estimated as:

- Apple: $0.080*[ln(5.81)-ln(2.36)] = $0.072;
- Onion: $0.081*[ln(5.81)-ln(2.36)] = $0.073;
- Potato: $0.114*[ln(5.81)-ln(2.36)] = $0.103;
- Tomato: $0.037*[ln(5.81)-ln(2.36)] = $0.033.