Banco de México

Working Papers

N° 2023-18

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December 2023

Documento de Investigación
2023-18

Working Paper
2023-18

Grab a Bite? Prices in the food away from home industry during the COVID-19 pandemic*

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Abstract: The pandemic generated heterogeneous demand shocks in the food away from home industry's consumption channels: on-site and deliveries/takeaways. Hence, price adjustments by consumption channel could have also been different. This study examines dishes' prices intended to be consumed as deliveries, which come from an online food ordering and delivery platform in Mexico City (CDMX); as well as those aimed at on-site consumption, which are considered in CDMX's CPI. I document that during part of the period between April 2020 and March 2022 delivery prices grew at a faster rate than those for on-site consumption. This is consistent with the idea of positive demand shocks for delivery prices and negative for on-site prices. By March 2022, their cumulative price growth across both consumption channels was similar.

Keywords: Inflation; Nominal rigidities; Restaurants; Machine Learning

JEL Classification: C5; E30; E60

Resumen: La pandemia generó choques de demanda heterogéneos en los canales de consumo de la industria de alimentos fuera del hogar: presencial y entregas a domicilio. Así, los ajustes de precios por canal de consumo también podrían haber sido diferenciados. Este estudio examina los precios tanto de platillos destinados a ser consumidos a domicilio, provenientes de una plataforma de pedidos y entrega de alimentos en la CDMX; como de aquellos orientados al consumo presencial, considerados en el índice de precios al consumidor de la CDMX. Se documenta que durante parte del periodo de abril de 2020 a marzo de 2022 los precios de los platillos a domicilio crecieron más aceleradamente que aquellos para consumo presencial. Ello es consistente con la idea de choques positivos de demanda sobre los precios de los platillos a domicilio y negativos en los presenciales. Hacia marzo de 2022, el incremento acumulado de precios en ambos canales de consumo fue similar.

Palabras Clave: Inflación; Rigideces nominales; Restaurantes; Aprendizaje de Máquina

*I would like to thank Alejandrina Salcedo, Josué Cortés and comments from participants in the 2021 Nontraditional Data, Machine Learning and Natural Language Processing in Macroeconomics Conference organized by Bank of Canada, Banca d'Italia and the Federal Reserve Board; as well as seminars at Banxico and CEMLA. Denisse Dueñas and Briseida Galván contributed with outstanding research assistance. All errors are mine.

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1 Introduction

As most firms in the service sector, price-setters in the Food Away From Home (FAFH) industry were affected by the COVID-19 pandemic.[1] On the one hand, rising input costs, temporal closures, restricted capacity, as well as suppressed demand are among the shocks firms in this industry faced through their traditional consumption channel: on-site dining. On the other hand, there was a sudden and rapid adoption of online food ordering and delivery platforms by eateries in order to provide an additional consumption channel: deliveries and/or takeaways.

This paper studies price adjustments in the FAFH industry during the COVID-19 pandemic in Mexico City. As the pandemic generated heterogeneous demand shocks across both on-site and deliveries/takeaways consumption channels, price responses in each of these channels might have also been different. Hence, I analyze prices from dishes intended to be consumed as deliveries/takeaways in Mexico City, as well as the FAFH component of Mexico City's CPI, which is calculated with prices intended for on-site consumption. Deliveries/takeaways prices come from an Online Food Ordering and Delivery (OFOD) platform gathered via web scraping from April 2020 to March 2022.

As the web scraped data from the OFOD platform has not been studied before, I first document a number of stylised facts from this data source. For instance, I show that dish categories like Beverages with and without Alcohol, Eggs, Pizza and Desserts exhibited less cumulative inflation over the time of study than other dish categories.[2] In contrast, prices of Mains, Chicken, Barbacoa, as well as Group Combos reported greater cumulative inflation between April 2020 and March 2022. I reach these conclu-

[1]Examples of price-setters in this industry are restaurants, cafeterias, canteens, bars, fast-food establishments, pizza places, taco shops, among others establishments that provide ready-to-eat meals. These meals can be either consumed on firms' premises (on-site dining) or elsewhere (takeaways/deliveries). According to the 2018 Classification of Individual Consumption According to Purpose (COICOP) by UN (2018), Group 11.1 "Food and Beverage Serving Service" covers food and beverage services provided by restaurants, cafés and similar eating facilities. Moreover, Group 11.1 encompasses different features like with or without waiter; with or without seating; with or without entertainment; at schools, work premises, hospitals or military wardrooms. Importantly, Group 11.1 does not specify the consumption channel: on-site, takeaways or deliveries.

[2]The analysis by dish categories arises as some dishes on restaurants' menus are more likely to be substituted by home-production when ordering food delivery (this substitution is not possible when dining on-site). One might think of soups, beverages or salads in this situation, while mains, desserts and alcoholic beverages (cocktails) could be more difficult to substitute by home-production. Although in a different context, Cortes and Pan (2013) show that outsourcing home-production increased female labor participation in Hong Kong. In the light of their findings, my research highlights that, as cooking time might make some dish categories more prone to substitution, there might be some strategic response from multi-product price-setters, such as restaurants.

sions by computing price indices by dish categories: *Online Average Variation Indices*, or Online AVIs, as they are calculated using the average of individual online price variations, which is then imputed to an index base April 2020 = 100. Furthermore, when decomposing individual price changes into their frequency and size of adjustments, the former seems to be more important explaining price dynamics in the aforementioned dish categories. Also, multi-outlet restaurants tend to change their prices less frequently and, given a price change, the size of price changes is on average larger than at independent restaurants.[3] Finally, the evidence suggests that episodes with greater number of COVID-19 cases were associated with periods of more frequent online price changes, whereas the size of online price variations remained fairly constant throughout the first two years of the pandemic.

I then provide the comparison between deliveries/takeaways price dynamics and those observed for on-site consumption. Specifically, I compute an aggregate version of Online AVI by pooling all products (regardless of dish category or restaurant type) and compare its behavior to the FAFH component of Mexico City's CPI.[4] As mentioned before, although both Online AVI and Mexico City's FAFH CPI use restaurants as price-informants, they do not stem from the same consumption channel: Online AVI encompasses prices intended for deliveries and Mexico City's FAFH CPI considers on-site dining prices.[5] Thus, it is not obvious a priori whether the dynamics of these two

[3]The analysis by type of restaurant (independent or multi-outlet) comes from the literature on how firm characteristics matter on firms' heterogeneous responses to shocks. For instance, in the context of price-setting behavior, Gilchrist et al. (2017) find that liquidity constrained firms in the US increased prices in 2008, while their unconstrained competitors cut prices. While not validated by merging prices with balance sheets information at restaurant level, independent and multi-outlet restaurants might or might not exhibit similar price trends.

[4]Categories in Mexico's CPI part of the FAFH industry: (i) Restaurants and others; (ii) Cooked food (others); (iii) Grilled chicken; (iv) Barbacoa or Birria; (v) Pizzas; (vi) Carnitas; (vii) Nightclub; (viii) Cafeterias, canteens, torta and taco shops (in Spanish, *Loncherías, fondas, torterías y taquerías*).

[5]Another difference is the price gathering technique. On the one hand, Online AVI uses data collected via web scraping only. On the other hand, between April 2020 and March 2022, some prices in the FAFH component of Mexico City's CPI might have been manually collected from some of the many OFOD platforms operating in Mexico City, while some others collected through various communication channels. As stated by INEGI's CPI press releases starting April 2020, price collectors may contact price-setters for this (and other) categories in the CPI via *internet, e-mail, phone and other information technologies*. Whilst INEGI's CPI press releases outline the overall share of missing prices in the CPI, they do not specify (i) share of missing prices in the FAFH industry, (ii) distribution of the communication channels used by price collectors to reach out price-setters in this industry, (iii) how this distribution has changed over time, nor (iv) any geographical dimension on how these communication channels are used, especially in Mexico City. Thus, it might be the case that some price collectors used data from OFOD platforms. Nonetheless, they only collected prices for the items in the sample (while web scraping collects all prices displayed on the website). It is worth

price indices would exhibit the same patterns or not.

Indeed, Online AVI and Mexico City's FAFH CPI differ for most part of the 24 months under study. Online AVI exhibited a steady increase from April to November 2020, period characterized by the first and toughest lockdown in Mexico City, negatively affecting on-site dining and boosting online food ordering and deliveries. In this period, as Online AVI's monthly variations were greater than Mexico City's FAFH CPI monthly variations, Online AVI accumulated a positive difference with respect to Mexico City's FAFH CPI. From December 2020 to March 2021, the gap between Online AVI and Mexico City's FAFH CPI stabilized. These months encompassed the second infection wave over the winter holidays in Mexico and with limited effects of the COVID-19 vaccines as their rollout gained momentum in February 2021. One year into the pandemic, in April 2021, Online AVI reported a 6% y-o-y inflation rate, while Mexico City's FAFH CPI exhibited an annual growth rate of 4%. As the COVID-19 vaccination rollout progressed in Spring 2021, in turn lowering contagion risks of face-to-face interactions for on-site dining, the gap between these two FAFH price indices started diminishing from April 2021 to July 2021. From December 2021 to March 2022, the difference between indices further decreased. At the end of the second year of the pandemic, the cumulative inflation rate from April 2020 to March 2022 was 12% for the two FAFH price indices.

In the context of the pandemic, these patterns can be rationalized as follows. On the one hand, restaurants faced raising costs regardless their consumption channel. On the other hand, their demand might have been affected differently depending their consumption channel. Specifically, for most part of the pandemic, ready-to-eat meals intended to be consumed at home (Online AVI) might have seen a surge in demand, while ready-to-eat meals intended to be consumed at restaurants' premises (Mexico City's FAFH CPI) might have experienced a fall in demand. Possibly, for prices encompassed in Online AVI, it was easier to pass-through rising costs while facing a positive demand shock. For on-site prices in Mexico City's FAFH CPI, it would have been more challenging passing-through rising costs as they suffered a negative demand shock. Hence, Online AVI might serve as evidence that part of FAFH demand was channeled through online food ordering and delivery platforms. Further research is required for advancing our understanding on price setting dynamics distinguishing between consumption channels.

This paper is related to three strands in the literature. First, although web scraped

noticing that prior to April 2020 the Mexican CPI survey would normally gather prices for the FAFH component of Mexico City's CPI (i.e. those in Footnote 4) via direct visits to brick-and-mortar stores.

data is increasingly used for analyzing inflation and its macroeconomic implications, to the author's knowledge this is the first paper studying inflation from the FAFH industry through the lens of web scraped data. The literature has mainly focused on goods' prices observed at supermarkets or departmental stores. See, among others, Cavallo (2018), Peña and Prades (2021), and Solórzano (2023). In contrast, this research focuses on prices from an industry in the service sector.

Second, analyzing risks of infection in restaurant settings, Fetzer (2022) reports that an intervention designed to actively increase demand for on-site dining contributed to subsequent clusters of new infections in the UK.[6] These infection risks, on the one hand affecting on-site dining negatively, and on the other hand boosting deliveries/and takeaways, are the leading explanation I propose in understanding why AVI and observed Mexico City's FAFH CPI exhibit heterogeneous dynamics. Based on cost-related price determinants, Mexico City's FAFH CPI counterfactuals suggests that AVI might have been able to reflect the increasing costs in the industry as demand for takeaways and deliveries soared. In contrast, observed Mexico City's FAFH CPI might have been prevented from doing so due to infection in restaurant settings and, thus, a demand fall.

Third, the use of highly disaggregated data for studying price-setting in the FAFH industry. For instance, using micro-data from the underlying FAFH component in the European CPI, Hobijn et al. (2006) report that restaurant prices in the euro area increased dramatically after the introduction of the Euro, while EU countries that did not adopt the Euro did not observe such increase. While the COVID-19 pandemic does not provide a clear focal period for resetting prices as the Euro changeover, I do find firms concentrate otherwise staggered price increases around periods with a downward trend of COVID-19 infection rates. Furthermore, Fougère et al. (2010) study the impact of minimum wage increases in France on price quotes from restaurants encompassed in the French CPI. Consistent with the literature, my findings suggest that, among numerous inflation drivers in different factor markets, labor costs remain a key determinant for Mexico City's FAFH CPI.[7,8]

[6] The policy, "Eat out to help out" (EOHO), subsidized the cost of meals and non-alcoholic drinks by up to 50% across participating restaurants across the UK for meals served on Mondays-Wednesdays (capped to £10 per person). González-Pampillón et al. (2021) look at the EOHO scheme and find that it induced higher footfall and increased recruitment in the industry. Neither, Fetzer (2022) nor González-Pampillón et al. (2021) address price-setting dynamics.

[7] However, I do not distinguish between the role of minimum wage or not workers.

[8] Bils and Klenow (2004), Nakamura and Steinsson (2008), Klenow and Malin (2010) and Dhyne et al. (2009) remain influential work documenting the stylized facts of price setting. My analysis departs from this literature as I do not leverage CPI micro-data (i.e. price surveys mostly gathering

This paper is organized as follows. Section 2 describes the web scraped dataset and the machine learning classifiers dealing with the unstructured data. Section 3 presents some price-setting's stylized facts from the online dataset. Section 4 compares Online AVI and Mexico City's FAFH CPI. Section 5 concludes.

2 Data

In this section, I first provide an overview on the web scraping compilation and a few descriptive statistics from the OFOD dataset under study in this paper. Secondary data sources, like Mexico City's CPI or input-costs series, are discussed in Section 4 and in the Appendix for brevity. Machine learning algorithms used to classify products into dish categories are then described, followed by the classification of restaurants.

2.1 Data Description

The main dataset used in this research comes from daily observations of dishes advertised by restaurants in an Online Food Ordering and Delivery (OFOD) platform in Mexico City.[9] The price revision, carried out by Banco de México, is executed by parsing out the platform's website. In broad terms, the price revision consists in gathering data from each and every dish or item displayed on the platform. That is, the enquiry considers the product's identifier, description and price for each dish, as well as the restaurant offering the dish.

The dataset at hand starts in April 1st, 2020 and ends in March 31st, 2022.[10] Figure 1 provides some descriptive statistics on the price enquiry. Panel 1a depicts the number of observations revised throughout the day. Notably, prior to April 2021, it took around 17 hours for parsing all items in the platform. The collection time decreased to 12 hours on average between April 2021 and September 2021. Since then price gathering takes about five hours. The shorter length in the price collection task is compensated by the greater number of items revised by the minute as highlighted by the red and orange col-

data via direct-visit and encompassing data from several industries). Subsection 4.1 outlines why comparisons with the FAFH subcomponent of the CPI should be taken with caution.

[9]For confidentiality reasons, the name of the platform cannot be disclosed. Nonetheless, the dataset is available for research purposes through a non-disclosure agreement with Banco de México's EconLab.

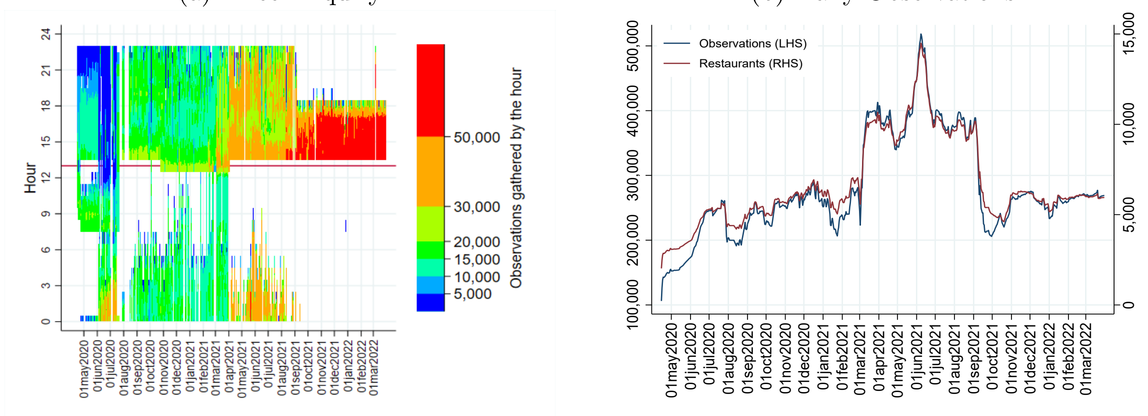
[10]As the "Stay-at-Home" state commenced in Mexico City in March 2020, there is no pre-pandemic benchmark available. See Subsection A.8 or Appendix A.7 for a brief recount of the COVID-19 pandemic in Mexico City.

ors in Panel 1a. Modifications on the platform's operation, coupled with adjustments in the enquiry explain these patterns in the data revision process. Panel 1b illustrates the 14-days moving averages on the number observations (items/dishes) and restaurants. All in all, the median number of observations and restaurants per day are 273,346 and 6,217, respectively.

Figure 1: Data Collection

Hourly and Daily Observations

(a) Price Enquiry (b) Daily Observations



Note: Panel 1a depicts the number of observations scraped by the hour on a daily basis. The red horizontal line indicates 13:00 hrs. The maximum number of observations ever scraped in one hour is 83,298. Panel 1b shows the number observations (items/dishes) and restaurants reported on a daily basis. Series are smoothed as 14-days moving averages for illustration purposes. Days with less than 100,000 observations are considered as outliers and neglected from the analysis (the 5th percentile is about 106,000). Figures depicting atypical days and without smoothing are reported in the Appendix. Data from April 1st, 2020 to March 31st, 2022. Source: Author's own work based on OFOD platform's data.

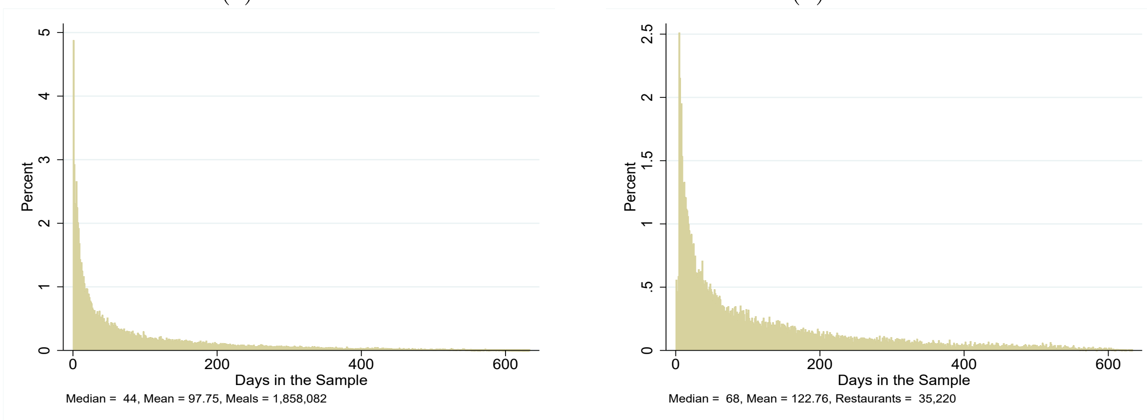
Figure 2 shows the distribution of dishes and restaurants by the number of days in the sample. For instance, Panel 2a reports that over 1.8 million different meals have appeared in the sample. On average, a meal is observed for 97.75 days in the sample; while its median is 44 days. Moreover, Panel 2b summarizes the distribution of the panel of restaurants by the number of days in the dataset. There have been over 33,000 firms in the sample, each of them appearing, on average, about 120 days in the sample.

2.2 Data Classification

One of the most cited drawbacks in the use of big data sources is their unstructured nature. This data feature is overcome with the deployment of machine learning techniques. Hence, in this section I provide details on the classification of the

Figure 2: Histogram on the Panel of Dishes and Restaurants

(a) Dishes (b) Restaurants



Note: Data from April 1st, 2020 to March 31st, 2022. Days with less than 100,000 observations are considered as atypical and neglected from the analysis (the 5th percentile from the raw dataset is about 106,000). Furthermore, restaurants with less than five days of history and/or offering less than five items per day on average are also neglected from the analysis. The figure shows the distribution of dishes and restaurants, Panel 2a and Panel 2b respectively, by the number of days in the sample. Source: Own calculations based on OFOD platform's data.

dataset in two dimensions. The first classification divides dishes (observations) into 18 categories. These categories come from common headers in restaurants' menus (e.g. starters, desserts), as well as few subcategories contained in the Mexican CPI (e.g. pizza or grilled chicken). The second classification opens up firms into independent and multi-outlet restaurants.

2.2.1 Supervised Machine Learning For Dish Classification

Dishes (the cross-sectional dimension of the panel) are classified using machine learning techniques. I outline the steps undertaken for this task here and leave in Appendix A.2 the detailed classification description and some forensic statistics on performance.

First, this approach requieres the construction of a manually produced training set, under which a number of algorithms are trained. To that end, out of the around 616,000 unique descriptions in the dataset, I manually classify more than 13,000 random dishes based on the descriptions provided by the restaurants. Thus, the manual classification considers a little more than 2% of the dishes in question.

The dishes are classified into 19 categories. The categories are: (1) Starters, (2) Salads, (3) Soups, (4) Eggs, (5) Mains, (6) Pizzas, (7) Tacos, (8) BBC, (9) Grilled and Roasted Chicken, (10) Desserts, (11) Beverages with Alcohol, (12) Beverages without

Alcohol, (13) Meals with Beverages, (14) Meals without Beverages, (15) Group Combos, (16) Dessert Combos, (17) Extras, (18) Others (Non-Food) and (19) Ambiguous.[11] These categories are chosen on the basis of (i) well-recognized headers in many restaurants' menus, (ii) categories with direct mapping to Mexico's CPI categories and (iii) the research question at hand.

Second, after applying text cleaning procedures, I convert the collection of dish descriptions into a matrix of token (words) counts.[12] The matrix contains unigrams (single words) and bigrams (pair of consecutive words) in the descriptions.[13] Over 32,000 unigrams and bigrams are then used as explanatory variables by the classifiers.

Third, the classifiers used for this analysis are (i) decision tree, (ii) random forest, (iii) multinomial naive Bayes and (iv) multinominal logistic regression. All classifiers require some form of hyper-parameter selection prior to estimation. To that end, I use k-fold cross validation procedures, which are exposed in great detail in Appendix A.2.[14]

Fourth, after training the classifiers using 80% of the training set, algorithms are deployed over the remaining (unseen) 20% of the manually constructed training set.[15]

As shown in great detail in Appendix A.2, the *multinomial logistic regression* is selected as the winner across models. It is the one with greatest accuracy (average point estimate), as well with the lowest computational time. Figure 3 depicts the confusion matrix on the prediction of dish labels using the multinomial logistic regression fitted under the complete training set. It provides a graphical representation on whether predictions are accurate relative to the true values. Each cell reports the share of each instance such that every row (true labels) adds up to one. Correct predictions lay in the

[11]BBC stands for Barbacoa, Birria and Carnitas, which are common taco fillings. BBC is considered in the Mexican CPI as a specific product category. Meals with/without Beverages consider two- or three-course meals. E.g. a Meal with Beverage could be a bundle of starter, salad, main and a beverage.

[12]The matrix's columns represent each and every single word appearing at least once in the collection of descriptions, the matrix's rows are the dishes/products in the dataset, and each matrix cell counts the number of times a word (column) appears in the description (row). See Appendix A.2 for more.

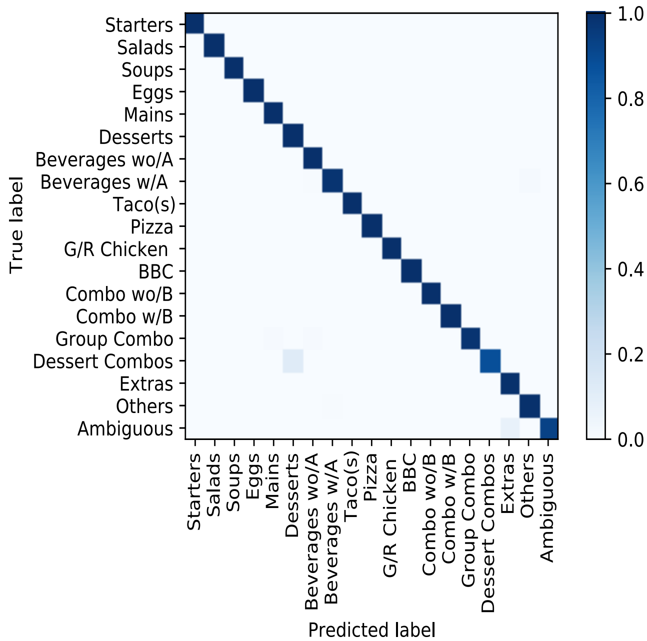
[13]For instance, the unigram representation of "Today is Monday" is ["Today", "is", "Monday"], while the bigram representation is ["Today is", "is Monday"]. Unigrams and bigrams with a frequency less or equal than three in the overall word count of the dataset are neglected. In Appendix A.2, I show there are minor differences in the classifiers' performance when using (i) unigrams only with the same cut-off threshold (frequency less or equal than three) and (ii) unigrams only with no cut-off threshold (universe of words in the dataset).

[14]The grid of parameters used for this search is detailed in Table 2 and the optimal set of parameters are reported in Table 3. Also, as category sizes are highly unbalanced in the training set, I outline in Appendix A.2 the steps taken to overcome the over specialisation of classifiers.

[15]Forensic statistics on the performance of the various classifiers over the different matrices of token (words) counts are depicted in Figure 15 of Appendix A.2.

diagonal, values outside the diagonal highlight prediction errors. As shown in Figure 3, most cells on the diagonal report values close to one.

Figure 3: Multinomial Logistic Regression Confusion Matrix
Predictions Over the Entire Training Set



Note: This figure depicts the confusion matrix on the prediction of dish labels using the multinomial logistic regression fitted under the complete training set. It provides a graphical representation on whether predictions are accurate relative to the true values. Each cell reports the share of each instance such that every row (true labels) adds up to one. Correct predictions lay in the diagonal, values outside the diagonal highlight prediction errors. Statistics on the performance of various classifiers are reported in the Appendix A.2. Source: Author's own work based on OFOD platform's data.

Finally, Table 1 adds on the impact of the machine learning techniques used in this research. The first bloc of columns reports the composition of the manually classified dataset. The second bloc of columns summarizes the outcome labels generated through the logistic regression. Thus, the classification burden of large and fast arriving data is alleviated, while minimizing the classification errors, through the use of machine learning techniques. This allows to shed further insights on the highly detailed data at hand.

2.2.2 Manual Restaurant Classification

As described above, price-setting dynamics might differ by type of restaurant. One might think their resource constraints are different and, therefore, so are their responses to accommodate adverse shocks (low demand for on-site dining) and/or positive shocks

Table 1: Dishes' Labels

By Classification Approach

	Course Type	Manual Count	Manual Share (%)	Supervised ML Count	Supervised ML Share (%)
1	Starters	640	5.24	16,625	3.27
2	Salads	996	8.15	15,049	2.96
3	Soups	64	0.52	5,604	1.10
4	Eggs	447	3.66	8,819	1.73
5	Mains	3,948	32.31	251,969	49.54
6	Desserts	1,063	8.70	55,010	10.81
7	Beverages wo/Alcohol	2,639	21.60	89,490	17.59
8	Beverages w/Alcohol	208	1.70	9,539	1.88
9	Tacos	429	3.51	23,256	4.57
10	Pizzas	1,444	11.82	20,819	4.09
11	Grilled/Roasted Chicken	15	0.12	345	0.07
12	BBQ, Birria, Carnitas (BBC)	23	0.19	788	0.15
13	Combo wo/Beverage	55	0.45	355	0.07
14	Combo w/Beverage	100	0.82	7,647	1.50
15	Group Combo	124	1.01	3,171	0.62
16	Dessert Combo	25	0.20	175	0.05
	Total	12,220	100.00	508,661	100.00

Note: *Extras, Others* and *Ambiguous* are also considered in the classification exercise but not reported for brevity as they are not used in the analysis (all in all there are the around 616,000 unique descriptions in the dataset). *Manual* stands for the classification made by hand and used for training the different classifiers. This training set is available upon request. *Supervised ML* summarizes the results on deploying the machine learning classifier on unseen data (i.e. observations not encompassed in the training set). For more on the classification task, see Appendix A.2. Source: Own calculations based on data from an OFOD platform.

(high demand for online ordering and delivery products). For instance, Gilchrist et al. (2017) show that financially constrained price-setters increased prices in the 2008 Great Financial Crisis, while their unconstrained counterparts cut prices.

Thus, the dataset is also classified with respect to the restaurants' nature, either multi-outlet or independent. Multi-outlet restaurants are those belonging to a franchise chain or with multiple branches.[16] The remaining restaurants, primarily those with not repeated names in the dataset, are considered as independent. This classification is carried out manually as there is little uncertainty on the classification rules in place.

In Appendix A.3, Figure 17 summarizes the composition of restaurants in the sample. It seems that, although restaurant chains have multiple outlets across Mexico City,

[16]Franchise chain are well-known restaurants brands often found on high streets and shopping centers. These restaurants normally has sister-brands and belong to a corporates reporting their balance sheets as they participate in financial markets. Restaurants with branches are those sharing the exact same name (or in some cases the neighbourhood is added to the name e.g. "Taco Shop ABC Reforma" and "Taco Shop ABC Insurgentes"). These groups of restaurants typically operate only in Mexico and are often family-run. They may or may not participate in financial markets. In the Appendix, Figure 18 shows that (i) the share of multi-outlet eateries is evenly split between chained and franchised restaurants and (ii) they offer about the same number of products/meals, which is greater than those offered in independent restaurants.

they constitute a small fraction of restaurants in the sample (about 10%). In fact, the relative size of independent restaurants grew since the start of the pandemic. Also in Appendix A.3, I show that (i) multi-outlet restaurants offer in general more dishes than independent restaurants; and (ii) there is a small negative trend on the median number of dishes offered by restaurants (regardless its type). Finally, Figure 19 in Appendix A.3 highlights that price-resetting is not fully synchronized within restaurants, i.e. when a restaurant decides to reset one price, it might not reset all its prices.

3 FAFH Prices During the COVID-19 Pandemic

3.1 Experimental FAFH Price Indices

This section provides evidence on the evolution of prices using web scraped prices from an OFOD platform in the FAFH industry operating in Mexico City between April 2020 and March 2022. Price indices are reported by dish category and restaurant type.[17]

3.1.1 Price Index Definition

Let the *"Average Variation Index"* or *AVI* be defined as:

$$y_t = \Pi_{i \in \Theta} \left(\frac{p_{i,t}}{p_{i,t-1}} \right)^{\frac{1}{N_t}} \tag{1}$$

$$AVI_t = y_t AVI_{t-1} \text{ for } t \geq 1 \tag{2}$$

where $p_{i,t}$ is the fortnightly price, calculated as the geometric average of daily data over two weeks, for product i at fortnight t.[18] The term y_t computes the geometric average of price changes in fortnight t relative to *t-1* using products observed in at least 75% of fortnights, $i \in \Theta$.[19] The average variation y_t is then chain linked to a Jevons index

[17]As INEGI does not publish any price subindex neither at the dish category nor at the type of restaurant level, this section does not provide any comparison between price indices using web scraped data and INEGI's FAFH CPI in Mexico City. In the next section, I provide a Mexico City aggregate using web scraped data (pooling all type of dishes and restaurants), list their similarities and differences with Mexico City's FAFH CPI, and compare their dynamics.

[18]The fortnightly frequency of calculation is for comparison purposes with the Mexican CPI, which is published at such frequency and is used later in the paper.

[19]The restriction on the number of fortnights in the sample limits the effect of seasonal or special edition products, as well as short-lived restaurants in the OFOD dataset. As there are 42 fortnights in the sample, I opted for this strategy as a benchmark. In the Appendix, I compute AVI without

April 2020 = 100. Note, if a dish is observed in *t-1* but not *t*, it is not considered in the geometric average at time *t*.[20] Hence, as it compares a fixed basket of goods between *t* and *t-1*, this index is somewhat similar to the methodology followed by most CPIs.[21] Moreover, *AVI* employs individual price changes (the average of), which in turn can be further decomposed into extensive and intensive margins, as I report in the next section.

In Appendix A.4, I compute a second price index named *"Average Price Index"* or *API*. In broad terms, *API* is a Unit Value Index as it originates from the geometric average price in fortnight *t* relative to *t-1*, which in turn is chain linked to a Jevons index *April* 2020 = 100. For recent studies using Unit Value Indices in the context of price data, see Diewert (2020), Diewert and Fox (2020) and Flower and Karachalias (2019). As *API* considers greater flexibility in terms of allowing entry/exit of goods from one period to the next one relative to *AVI*, I leave the discussion of *API* dynamics and its comparison to *AVI* to the Appendix.

3.1.2 AVI Evolution By Dish Category

Figure 4 summarizes the evolution of prices according to the dish classification proposed in Section 2.2. Panel 4a suggests that Beverages with Alcohol have systematically reported the lowest average price increase among dishes since the start of the pandemic. Also, Eggs, Beverages without Alcohol and Pizzas are among the dish categories exhibiting slower price increases than most categories. In contrast, Mains prices grew at a faster pace since the start of the pandemic. Panel 4b depicts dish categories generally consumed by groups. It seems that Combos with Beverages also exhibits slower price growth relative to other Combos. Surprisingly, after being the only category reporting a decrease in its price level early in the pandemic, Dessert Combos is the dish category that ended with the greatest cumulative inflation in March 2022 (see Figure 5).

The slower increase of beverage prices relative to prices from other categories in Figure 4 might suggest that, as customers consumed their food orders at home, they might have opted to save money by not ordering beverages through the OFOD platform. Po-

this restriction and show that the qualitative results do not change.

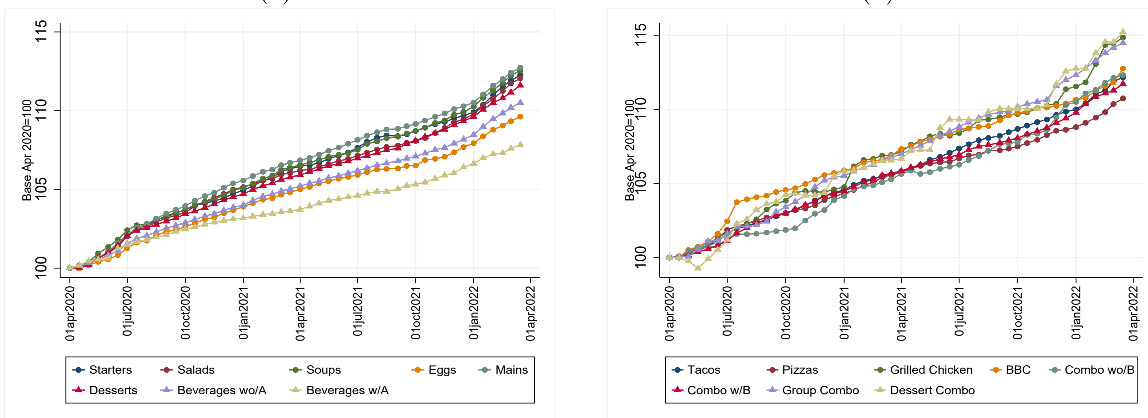
[20] By not considering the item in the average nor imputing a zero variation, this approach is equivalent as if the average variation was imputed to dishes not observed in fortnight t. In fact, imputing the average variation of observed goods on missing goods is a common approach used in price surveys by National Statistical Offices.

[21] AVI does not follow a fixed basket of goods in all periods as the CPI. It encompasses limited entries and exits of products according to the definition of set Θ.

Figure 4: Average Variation Index

By Dish Type

(a) (b)



Note: Price indices computed using Equation 1 and Equation 2. Indices are calculated and illustrated in a fortnightly basis. Data from April 2020 to March 2022. Observations are classified into dish categories using a multinomial logistic regression, which reported the greatest accuracy with respect to other supervised machine learning classifiers. For more on the data and classification techniques, see Section 2. Source: Author's own elaboration with data gathered through web scraping from an OFOD platform operating in Mexico City.

tentially, customers substituted beverages with home production as restaurants might add little value to some beverages (e.g. soft drinks or beers). This consumption strategy is less appealing (or not allowed) for customers when consuming their meals on restaurants' premises. On the other hand, hungry customers might have centered their orders on dish categories with greater value added from restaurants, like mains or desserts, when consuming at home.

3.1.3 AVI Evolution By Type of Restaurant

Figure 6 illustrates AVI by type of restaurant. According to AVI, both independent and multi-outlet restaurants follow a very similar price trends. However, it seems that multi-outlet eateries move before independent restaurants as the dashed line tends to be above the pale solid line most of the time in Figure 6.[22]

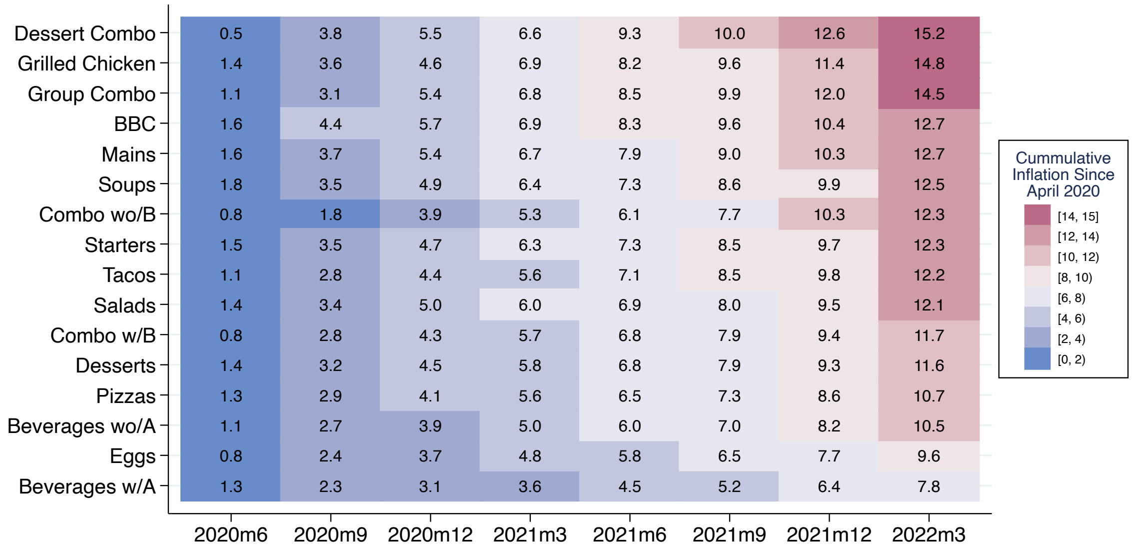
However, Figure 6 also shows that there are some breaks in the multi-outlet series, which are not present in the independent series.[23] As Hobijn et al. (2006) document for

[22]It is not surprising that AVI encompassing both type of restaurants (bold solid line) is similar to AVI independent restaurants (pale solid line) as there are more independent eateries than multi-outlet restaurants in the sample. See Figure 17a for more on the restaurant composition in the sample.

[23]Though small, these breaks (humps) can be seen in May 2020, January 2021, and March 2021.

Figure 5: Cumulative Inflation by Dish Category According to AVI

Dish categories sorted vertically by their March 2022 values



Note: Each entry is the cumulative inflation rate since the start of the pandemic for a given dish category (row) and point in time (column). Indices are calculated in a fortnightly basis but the first fortnight of every quarter is reported for illustration purposes. As the base period is April 2020 = 100, they are computed as AVI at a given time minus 100. Data from April 2020 to March 2022. Observations are classified into dish categories using a multinomial logistic regression. For more on the data and classification techniques, see Section 2. Source: Author's own work based on web scraped data from an OFOD platform operating in Mexico City.

restaurants in the euro area during the currency exchange over, the apparent bumpy price adjustment stemming from multi-outlet restaurants could be explained by their synchronization on price-resetting. In contrast, the smoother series for independent eateries could be a reflection of staggered price-resetting across these restaurants.

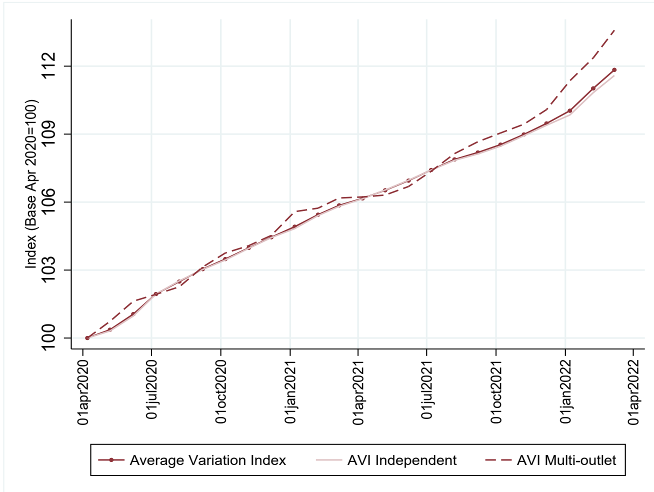
3.2 Stylized Facts from FAFH Prices in the Pandemic

This section presents quantitative evidence on the frequency and size of price adjustments as observed from the OFOD platform.[24] The results are presented in three steps. First, I present price moments using the complete time window in the dataset in order to formulate an overview for the different dish categories and type of restaurants under study. Second, I take a closer look at the difference in price adjustments across types

[24] As they are informative in the calibration of New Keynesian models, these price statistics have been studied using survey data in the past. As mentioned in the Introduction, the use of web scraped prices is ever more prevalent in studying price-setting dynamics.

Figure 6: Average Variation Index

By Type of Restaurant



Note: Price index computed using Equation 1 and Equation 2. Datas from April 2020 to December 2021. Observations are manually classified according to its type of restaurant. For more on the data and classification techniques, see Section 2. Source: Own calculations with data gathered through web scraping from and online food ordering and delivery platform operating in Mexico City.

of restaurants. Finally, I study whether there is evidence of heterogeneous price-setting throughout the different stages of the pandemic from April 2020 to March 2022.

3.2.1 Price-setting Across Dish Categories

The frequency and size of price adjustments are analyzed through the lens of linear models. The econometric frameworks allow controlling for seasonal patterns that might affect all prices (e.g. weekend or payday effects) and/or restaurant-specific characteristics. Due to the high frequency of the dataset, as well as the features therein, the linear framework provides greater interpretability to the results.[25]

In order to study whether there are heterogeneous frequencies of price adjustments across dish categories, I fit a linear probability model using daily data of the form:

$$P\left(y_{i,j,n} = 1|x\right) = DishType_i' \, \beta_1 + \theta_{j(i)} + \theta_n + \varepsilon_{i,j,n} \tag{3}$$

where $y_{i,j,n} = 1$ is a dummy variable if the price of product i in restaurant j on day n

[25] An alternative option would have been to report unconditional price moments on the proportion of price adjustments and the size of price changes, as in Bils and Klenow (2004) or Dhyne et al. (2009). An empirical framework that controls for factors such as unobserved heterogeneity or seasonal patterns provides further insights, specially in the presence of demand and supply shocks stemming from the COVID-19 pandemic, than reporting unconditional moments of price adjustments.

changed with respect to day $n-1$, $\Delta p_{i,j,n} \neq 0$, or zero otherwise. $DishType_i$ is the categorical variable of product i's dish category as proposed in Section 2.2. $\theta_{j(i)}$ and θ_n represent the products' restaurant and time fixed effects, respectively. Additionally, I decompose price hikes and price drops by running the same model using $y^{Hikes}_{i,j,n} = 1$ if $\Delta p_{i,j,n} > 0$ and zero otherwise; as well as $y^{Drops}_{i,j,n} = 1$ if $\Delta p_{i,j,n} < 0$ and zero otherwise. Standard errors $\varepsilon_{i,j,n}$ are clustered at the restaurant level. Moreover, for consistency with the price indices presented in Subsection 3.1, I use products observed in at least one day in 75% of fortnights in the sample i.e. $\forall\, i \in \Theta$ as defined in Equation 1. Note, however, I use products' daily price observations $p_{i,j,n}$; which contrasts with the fortnightly average prices $p_{i,t}$ employed in Subsection 3.1.2. As documented by Eichenbaum et al. (2014) and Cavallo (2017), the use of average prices when studying the frequency and size of price adjustments result in smaller and more frequent price changes than they actually are.

A second equation analyzes the heterogeneous size of price adjustments, given a price change, across dish categories:

$$\mid \Delta p_{i,j,n} \mid = DishType_i' \; \beta_1 + \theta_{j(i)} + \theta_n + \varepsilon_{i,k,n} \tag{4}$$

where $\mid \Delta p_{i,j,n} \mid$ is the absolute value of (log) price changes.[26] Similarly to the linear probability model in Equation 3, (i) two further models are estimated for price hikes ($\Delta p_{i,j,n} > 0$) and price drops ($\Delta p_{i,j,n} < 0$); (ii) the sample considers products observed in at least one day in 75% of fortnights in the sample ($i \in \Theta$ as defined in Equation 1); (iii) I use daily price observations $p_{i,j,n}$; and (iv) standard errors are clustered at restaurant level. In what follows, results from the coefficients of interests, β_1, are reported in a graphical representation in Figure 7 and Figure 8. Regression estimates of β_1 are left in the Appendix in Table 4 for brevity.

Figure 7 depicts estimates from the fixed effects associated to dish categories, β_1, in Equation 3 (frequency of price changes) and Equation 4 (size of price adjustments). Without loss of generality, Starters is the base category. Hence, β_1 should be interpreted as deviations from the base category in percentage points.[27] Whiskers in both panels

[26] The log price change is defined as $\Delta p_{i,j,n} = ln(P_{i,j,n}) - ln(P_{i,j,n-1})$, where $P_{i,j,n}$ is the nominal price of product i in restaurant j on day n as observed in the OFOD platform. One way to avoid price hikes and price drops cancelling out in the regression coefficient is taking the absolute value of prices changes. This is a common practice in studies analyzing nominal rigidities, like Bils and Klenow (2004), Nakamura and Steinsson (2008), Dhyne et al. (2009), among others.

[27] For instance, negative values in Figure 7 represent, say, less frequent price changes than Starters, whilst positive values mean more frequent price changes than Starters.

illustrate 95% confidence intervals. First, Panel 7a highlights that Mains, Tacos, Pizzas, BBC, Combo with Beverages and Group Combos adjust their prices more frequently relative to the base category, Starters. The categories with less frequent price changes than Starters are Desserts, Beverages without and with Alcohol. The remaining categories do not exhibit statistically significant differences (5%) in terms of how often they change prices relative to Starters. Second, Panel 7b reports that Beverages without and with Alcohol exhibit greater price changes, given a price change, relative to the base category, Starters. In contrast, those with smaller price changes than Starters are Mains, Pizza, BBC and Group Combo. The remaining categories do not exhibit statistically significant differences (5%) with respect to Starters in terms of the size of price adjustments.

Figure 8 shows estimates from regressions distinguishing price hikes and price drops. Panel 8a shows that Mains, Tacos, Pizzas and Group Combos change their prices more frequently than Starters due to more frequent price hikes; while Combos with Beverages adjust their prices more often as a result of more frequent price drops. Moreover, categories changing their prices less frequently than Starters, like Desserts, Beverages without and with Alcohol, report less frequent price hikes. Also, Beverages without and with Alcohol change less frequently prices due to less frequent price drops than the base category. The remaining categories do not exhibit any statistically significant difference in terms of the frequency of price hikes or price drops relative to Starters. Panel 8b highlights that, relative to Starters and given a price change, Beverages without and with Alcohol exhibit greater price changes due to larger price hikes and not because of the size of price drops. Also, smaller price hikes are behind the categories exhibiting smaller price adjustments in general, like Mains, Pizza and Group Combo. It is worth noticing that there is greater dispersion in the size of price drops than in the size of price hikes, as shown by the wider confidence intervals in Panel 8b.

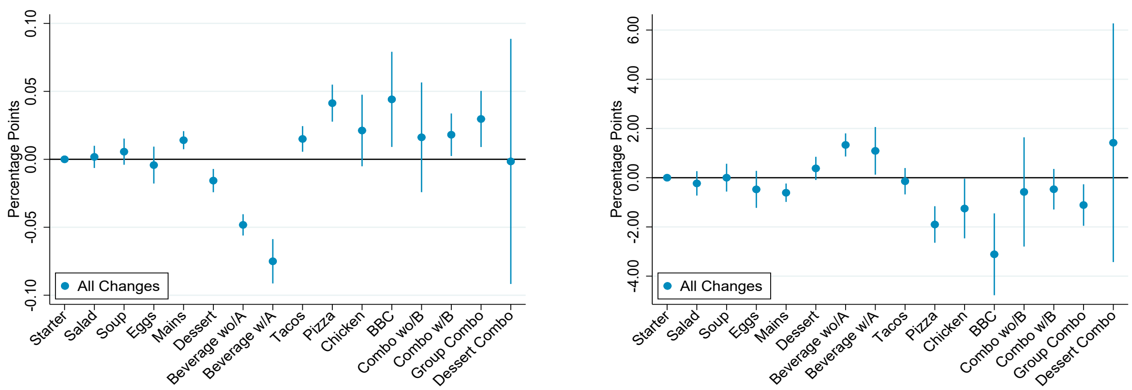
Thus, in general, it seems categories adjusting their prices more often tend to do so by smaller margins than other categories. In contrast, dish categories adjusting less frequently prices are more likely to exhibit larger price changes relative to other categories. Furthermore, the price-setting heterogeneity along both extensive and intensive margins across dish categories is mainly driven by the behavior of price hikes rather than price drops. That is, categories resetting their prices more (less) often are those exhibiting more (less) frequent price hikes; and categories adjusting prices by greater (smaller) magnitudes tend to be the ones with greater (smaller) price hikes.

Figure 7 and Figure 8 provide evidence that among the extensive and intensive margins of price adjustments, the former seems to be more relevant for the cumulative inflation rates by dish categories described in Subsection 3.1.2. For instance, four out of the top five dish categories with the greatest cumulative inflation between April 2020 and March 2022 (Chicken, Group Combos, BBC and Mains) report more frequent but smaller price adjustments.[28] In contrast, three out of the bottom five categories in terms of cumulative inflation (Combos with and without Beverages and Desserts) change less often but by greater margin.[29]

Figure 7: Stylized Facts of Price Changes Regardless Sign of Adjustment

Coefficients as Deviations From Base Category

(a) Frequency (b) Size



Note: Scatters in Panel 7a represent point estimates from the linear probability model in Equation 3, while Panel 7b shows point estimates from Equation 4. Regression results are reported in Table 4. Whiskers in both panels illustrate the 95% confidence intervals of point estimates. Estimates obtained using products observed in at least 75% of fortnights between April 2020 and March 2022. *Starters* is the base category. Observations classified into dish categories using a multinomial logistic regression. For more on the data and classification techniques, see Section 2. Source: Author's own estimates using data from web scraped prices as displayed on an OFOD platform operating in Mexico City.

In the Appendix, I provide further robustness checks on the heterogeneity of price adjustments. While, the above regressions control for time fixed effects, one could think that seasonal patterns might better fit this type of data (e.g. pay-day effect around the start/end of the month and/or weekend effects). The results suggest that using seasonal fixed effects instead of time fixed effects change very little the results for both the frequency and size of price-resetting.[30] Also, when I relax the constraint of using

[28] Just one out of the top five (Combo Desserts) changes less frequently but by greater amounts.

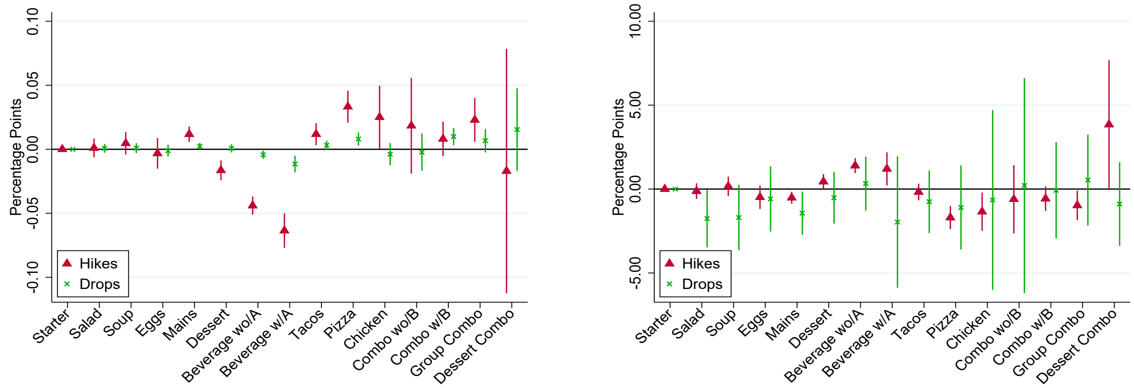
[29] One out of the bottom five (Eggs) does not show a statistically significant difference with the base category; and another (Pizzas) reports more frequent but smaller price adjustments.

[30] Figure 26 and Table 4 in the Appendix. They are day of the week, calendar day, month and year.

Figure 8: Stylized Facts of Price Changes by Sign of Adjustment

Coefficients as Deviations From Base Category

(a) Frequency (b) Size



Note: Scatters in Panel 8a represent point estimates from the linear probability model in Equation 3, while Panel 8b represent point estimates from Equation 4. Regression results are reported in Table 4. Whiskers in both panels illustrate the 95% confidence intervals of point estimates. Estimates obtained using products observed in at least 75% of fortnights between April 2020 and March 2022. *Starters* is the base category. BBC is omitted for illustration purposes. Data comes from web scraped prices as displayed on an OFOD platform operating in Mexico City. Observations classified into dish categories using a multinomial logistic regression. For more on the data and classification techniques, see Section 2. Source: Author's own estimates based on OFOD platform's data.

representative products (defined by the Θ set in Subsection 3.1.1) and instead I use all products in the above regressions, the qualitative conclusions hold.[31]

3.2.2 Stylized Facts by Type of Restaurant

I can also look at the differences between restaurant types. As detailed above, an eatery can be considered as independent or multi-outlet. I fit the following model:

$$z_{i,j,t} = RestaurantType_j \times DishType_i' \, \beta_1 + \theta_{j(i)} + \theta_n + \varepsilon_{i,j,t} \tag{5}$$

where $z_{i,j,t}$ can take the form of either $P\left(y_{i,j,t} = 1|x\right)$, like in Equation 3; or $\mid \Delta y_{i,j,t} \mid$, as in Equation 4. $RestaurantType_j$ is a dummy variable equal to one if restaurant j is a multi-outlet restaurant and zero if it is an independent eatery. The remaining setup stays the same as in Subsection 3.2.1.[32]

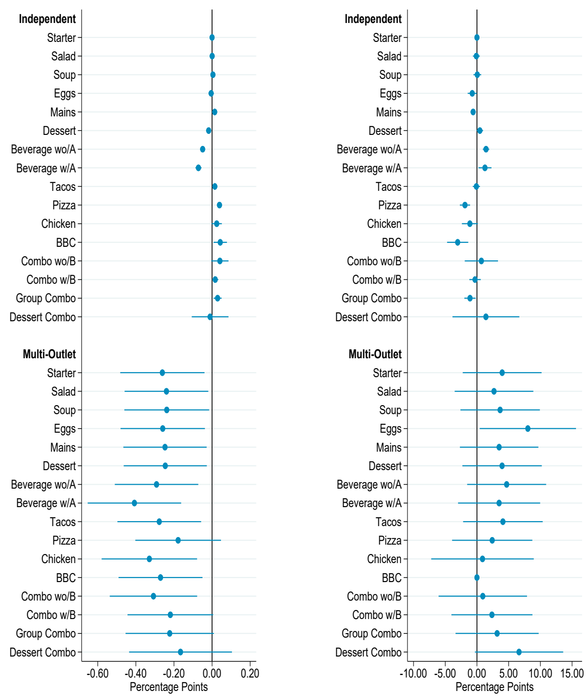
[31] In the Appendix, Figure 27 compares estimates using observations in Θ to those computed employing all observations in the dataset. Regression results are reported in Table 5.

[32] Specifically, $\theta_{j(i)}$ and θ_n represent the products' restaurant and time fixed effects, respectively. Standard errors $\varepsilon_{i,j,t}$ are clustered at restaurant level. I use products observed in at least one day in

Figure 9 summarizes the estimates from Equation 5, while Table 6 and Table 7 in Appendix A.6 report the full set of results. Panel 9a shows that multi-outlet restaurants tend to change their prices less frequently than independent restaurants. In the Appendix, I show that this result is mainly driven by less frequent price drops at multi-outlet restaurants than at independent restaurants. Then, given a price change, Panel 9b highlights that point estimates on the size of price changes is, on average, larger at multi-outlet restaurants than at independent restaurants. However, the difference on the size of price adjustments across type of restaurants within dish categories is generally not statistically significant.

Figure 9: Stylized Facts of Price Adjustments by Restaurant Type

(a) Frequency of Changes (b) Size of Adjustments



Note: Scatters represent point estimates from Equation 5. Whiskers illustrate point estimates' 95% confidence intervals. Results based on dishes (and therefore restaurants) appearing in at least 75% of fortnights in the sample. Regression results are reported in Table 6 and Table 7. Estimates computed using web scraped prices from an OFOD platform in Mexico City from April 2020 to March 2022. Source: Author's own elaboration.

75% of fortnights in the sample i.e. $\forall\ i \in \Theta$ as defined in Equation 1. Daily price observations for $z_{i,j,t}$ are used in the regression.

3.2.3 Price-setting Across Pandemic Stages

Price-setting decisions are also studied in the context of the COVID-19 pandemic. In particular, whether prices in the OFOD platform exhibited heterogeneous patterns during the first two years of the pandemic. Hence, I estimate the following model:

$$z_{i,j,t} = Pandemic_k + DishType_i' \, \beta_1 + \theta_{j(i)} + \theta_N + \varepsilon_{i,j,t} \tag{6}$$

where $z_{i,j,t}$ can take the form of either $P\left(y_{i,j,t} = 1|x\right)$, like in Equation 3; or $\mid \Delta y_{i,j,t} \mid$, as in Equation 4. $Pandemic_k$ is a categorical variable signaling five stages of the pandemic $k = 1, ..., 5$ defined for the purpose of this study (see definition below). θ_N encompasses seasonal fixed effects and the remaining setup stays the same as in Subsection 3.2.1.[33] For a general overview of the COVID-19 pandemic in Mexico City, health-related restrictions affecting FAFH services, as well as relief programs that, to the author's knowledge, were implemented and could have benefited restaurants, see Appendix A.7.[34]

The different stages in the categorial variable $Pandemic_k$ in Equation 6 are:[35]

- $Pandemic_1$ or *1st wave (1/2)*: The first and toughest lockdown measures in Mexico City. Through the lens of the official risk-tier system in Mexico City, this stage was characterized by the "Stay-at-home" and first "Red" state from April 2020 (start of the dataset) until June 2020, inclusive (see Figure 10). Among other health-related restrictions, "Stay-at-home" posed the temporal suspension of restaurants' on-site dining services.[36] Thus, there was a rapid adoption of OFOD platforms by customers and restaurants as deliveries and takeaways were the only

[33]Seasonal effects consider month, calendar day and day of the week fixed effects. Moreover, $\theta_{j(i)}$ represents the products' restaurant fixed effects. Standard errors $\varepsilon_{i,j,t}$ are clustered at restaurant level. I use daily price observations for $z_{i,j,t}$ and products $i \in \Theta$ as defined in Equation 1 (at least one day in 75% of fortnights).

[34]I provide an overview on how the FAFH industry was affected by social distancing and other health-related measures implemented to contain the virus. Furthermore, I list the relief programs that, to the author's knowledge, could have benefited restaurants in Mexico City. Though, due to the variables in the OFOD dataset, as well as public data on relief program recipients, it is not possible to have an idea on the share (or number) of restaurants (owners and/or staff) under study benefited by any of the programs. Hence, this research does not leverage any relief program data, specially in terms of recipients (restaurant owners or staff). See more details in Appendix A.7.

[35]Results using as a categorical variable the actual colors in the risk-tier system in Mexico City are reported in Appendix A.9. I opt not to use those results as benchmark since their interpretation is less straight forward e.g. the "Orange" state encompasses periods without and with vaccine rollout and, thus, different perceived risks by customers. In contrast, $Pandemic_k$ poses a parsimonious chronological approach.

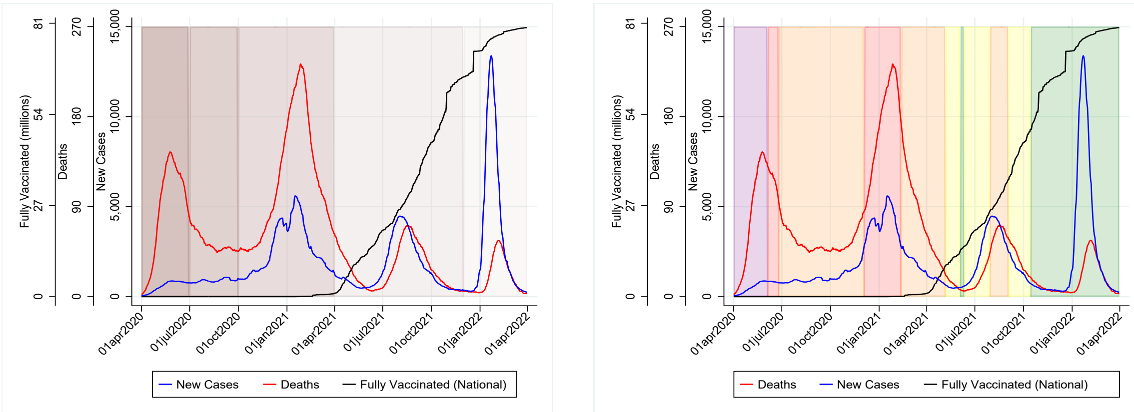
[36]See Appendix A.7 for the complete timeline of health-related restrictions suffered by the FAFH industry. Although these restrictions did not affect restaurants' meals preparations for takeaway or deliveries services, their price-setting might have been affected as they could not offer on-site dining.

channels to access FAFH services. In the "Red" state eateries could offer their services outdoors only (e.g. parking lots, streets or sidewalks) and until 6pm only. Takeaways and deliveries were allowed before and after 6pm.

- *Pandemic*$_2$ or *1st wave (2/2)*: After the first peak on the number of deaths, this stage was marked by some relaxation on social distancing measures, including indoors services by restaurants but up to 30% capacity. It encompasses part of the first "Orange" state and runs from July 2020 to September 2020, inclusive.
- *Pandemic*$_3$ or *2nd wave*: This period was characterized by a new spike in cases and deaths, partially driven by the Day of the Death and Christmas gatherings. Regarding the official risk tier system in Mexico City, the variable encompasses part of the first "Orange" state, followed by a new "Red" and subsequent "Orange" states. It considers two quarters, from October 2020 to March 2021, inclusive. Although for most of this period vaccines were unavailable, it is worth noticing that vaccination in Mexico started in December 24th, 2021 for health-workers, teachers and+65 years old, mainly in rural areas. According to WHO statistics, by late March 2021, 0.7% of Mexico population was fully vaccinated.
- *Pandemic*$_4$ or *3rd wave*: This period saw the vaccination rollout, as well as the summer "Delta Wave". In terms of the official risk tier system in Mexico City, this stage includes part of the second "Orange" state, as well as the first "Yellow" and "Green" states. During the "Yellow" state, restaurants were allowed for indoor dining with up to 50% seating capacity. For the "Green" state all on-site dining restrictions were lifted. This stage covers eight months, from April 2021 to November 2021, inclusive. By late November 2021, about 50% of Mexico population was fully vaccinated according to WHO statistics.
- *Pandemic*$_5$ or *4th wave*: In the last period under study, the number of new cases increased again as the "Omicron Wave" gained momentum. Despite the great number of new cases, the official risk-tier system in Mexico City stayed in "Green" over this period. It considers four months, from December 2021 until March 2022 (end of the dataset), inclusive. According to WHO statistics, 62% of Mexico population was fully vaccinated by April 2022.

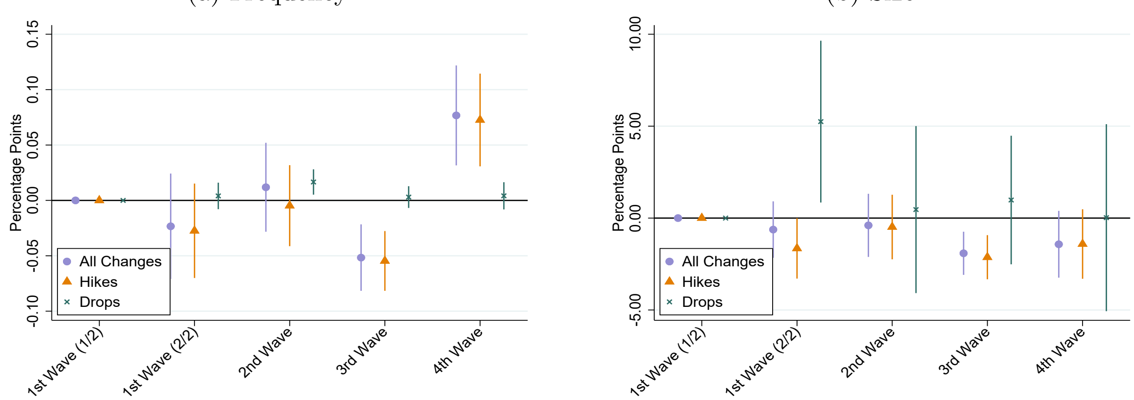
Figure 11 summarizes the results from Equation 6, while in Appendix A.8 Table 8 reports the full set of results. Panel 11a shows that point estimates from the *1st wave's second half* and the *3rd wave* are negative, implying less frequent price changes relative to the base category (*1st wave's first half*). Specifically, less frequent price hikes. Though, only the *3rd wave* is statistically significant different (5%) with respect to the base category. Intuitively, as the *1st wave's second half* saw the relaxation of some social distancing measures (e.g. indoors restaurant services but up to 30% capacity) and the 3rd wave saw the vaccination rollout (and the Delta Wave summer), the OFOD platform was no longer the only consumption channel, perhaps less bargaining power and, thus,

Figure 10: $Pandemic_k$ Five Stages
New Cases and Deaths in Mexico City and Fully Vaccinated People in Mexico
(a) $Pandemic_k$ (shades) (b) From highest (purple) to lowest (green) risk



Note: Panel 10a highlights the categorical variable $Pandemic_k$ defined by the author. Each color represents one of the five stages in $Pandemic_k$. Panel 10b illustrates Mexico City's risk-tier color system as announced by Mexico City's local authorities (*Gobierno de la Ciudad de México*, in Spanish). Announcements, and actions to be taken (e.g. maximum seating capacity in restaurants), were made official by their publication on Mexico City's local authorities gazette. Colors in the graph reflect the actual publication date on the gazette, and not when actions took place (normally 3 working days after). Both Panel 10a and Panel 10b plot the (i) number of new cases, (ii) deaths and (iii) number of fully vaccinated people (complete 1- or 2-shot schemes not Mexico City specific but nation wide). Source: (i) and (ii) come from the Health Secretariat's General Directorate of Epidemiology, an agency part of Mexico's Federal Government; while (iii) comes from Mathieu et al. (2021).

Figure 11: Stylized Facts of Price Changes at Different Stages in the Pandemic
Coefficients as Deviations From Base Category
(a) Frequency (b) Size



Note: Scatters in Panel 11a and in Panel 11b represent point estimates from Equation 6. Regression results are reported in Table 8 in the Appendix. Whiskers in both panels illustrate the 95% confidence intervals of point estimates. Estimates obtained using products observed in at least 75% of fortnights between April 2020 and March 2022. *1st Wave (1/2)* is the base category. See Section 2 for more on the data. Source: Author's own work with data from web scraped prices as displayed on an OFOD platform operating in Mexico City.

less often price changes. In contrast, the 2nd and *4th waves* exhibit greater frequency of price changes when looking at their point estimates. Notably, the *4th waves* is the period with the greatest frequency of price changes in the sample, which in turn is statistically different with respect to the base category (5%). While in the *4th wave* all restaurants' on-site dining restrictions were totally lifted, on-site dining and deliveries/takeaways became (as close as they can be) substitutes for the first time since the start of the pandemic, the number of new cases went up again due to the "Omicron Wave" and households opted to OFOD services once again.[37] With respect to the size of price adjustments, as illustrated in Panel 11b, there is less heterogeneity across waves. The base category (*1st wave's first half*), *1st wave's second half* and *2nd wave* have very similar point estimates. Then, the *3rd* and *4th waves* show smaller price changes on average but only the *3rd wave* is statistically significant different to the base category (5%).

All in all, the extensive margin of price adjustments exhibits greater heterogeneity across pandemic stages than the intensive margin. Point estimates suggest that acute periods of infections (see Figure 10a) were perceived by restaurants as opportunities to reset their prices more frequently on the OFOD platform, but these estimates are not always statistically different to less acute periods. In contrast, the size of price adjustments stayed relatively constant throughout the two years. Finally, it is not clear that less frequent price changes are accompanied by larger price adjustments, as it was in the case of the type of dish analysis above.

The stylized facts reported in this section provide novel evidence that can be used in future work to further evaluate menu-cost models for multi-product firms as those proposed by Alvarez and Lippi (2014), Nakamura and Steinsson (2010), Hobijn et al. (2006), among others. Specifically, big data sources stemming from web scraping, coupled with machine learning techniques for their processing and classification, allow us to shed further light on the price-setting decisions followed by multi-product agents, such as restaurants.

4 FAFH Prices Across Consumption Channels

In this section, I benchmark an overall version of Online AVI, developed by pooling all products regardless their type of dish and restaurant, to the FAFH component of

[37] Although in its early stages, by this time the Russia-Ukraine conflict had also already affected food commodity prices.

Mexico City's CPI. That is, having used only web scraped prices from the OFOD platform so far in the paper, I introduce an additional price series stemming from a subset of concepts in the Mexican CPI. This latter price series, defined as Mexico City's FAFH CPI, aggregates Mexico City's elemental price indices listed in footnote 4.

Despite both Online AVI and Mexico City's FAFH CPI share the same objective in measuring the rising costs for consumers on ready-to-eat meals (i.e. FAFH industry), it is unclear a priori whether Online AVI and Mexico City's FAFH CPI might (or not) exhibit similar patterns. For instance, Online AVI comes from a novel data source and it is calculated with numerous sampling and methodological differences with respect to the Mexican CPI survey. Moreover, in the context of the COVID-19 pandemic, price-setting dynamics of ready-to-eat meals might reflect health risks perceived across consumption channels in these two FAFH price indices: deliveries/takeaways as Online AVI comprises; and on-site dining as Mexico City's FAFH CPI reports.

In this section, first, I present a brief discussion on differences and similarities across price indices in terms of consumption channels, price collection techniques, sample sizes, methodologies, among other features. The curious reader may be referred to Appendix A.7 for a recount in general grounds on how the COVID-19 pandemic affected the FAFH industry in Mexico City (e.g. restrictions, relief programs, vaccination rollout).

Second, I highlight that both Online AVI and Mexico City's FAFH CPI (i) exhibited different trends in their cumulative inflation rate since the start of the pandemic in April 2020; (ii) one year into the pandemic, their annual inflation rates showed a negative correlation; and (iii) the cumulative inflation rate from April 2020 to March 2022 was 12% for the two FAFH price indices.

While the levels of these two FAFH price indices seem to be at odds for most parts of the period under study, in the light of the pandemic Online AVI might have reflected the industry's raising input costs at the time. In contrast, these increasing costs might have been more difficult to pass-through for the on-site consumption channel, as observed in Mexico City's FAFH CPI, due its face-to-face nature and perceived health risks.

4.1 AVI and CPI Data and Methodologies: Brief Comparison

Despite both Online AVI and (a subset of) the CPI report price dynamics from ready-to-eat meals served by restaurants, one needs to put into perspective their consumption channels, data gathering methods, methodological differences, as well as the pandemic context and how it interacts with such data and methodological differences. Only then it is possible to understand whether prices set by restaurants encompassed in Online AVI and Mexico City's FAFH CPI might or not exhibit similar patterns.[38,39]

First, Online AVI and (a subset of categories in) the CPI are considered fair measures on the evolution of prices in the Food Away From Home Industry (FAFH). According to the 2018 Classification of Individual Consumption According to Purpose (COICOP) by UN (2018), Group 11.1 "Food and Beverage Serving Service" covers food and beverage services provided by restaurants, coffee shops and similar eating facilities.[40] Thus, as long as food and beverages are provided by eateries, prices from these products are considered as part of Group 11.1. Both datasets report prices of products served by eateries i.e. price informants are restaurants and the like. Hence, it seems that prices included in Online AVI and part of the CPI can be considered as proxies for the evolution of consumer prices in the FAFH.

Second, another potential difference are the price gathering techniques. On the one hand, Online AVI uses data collected via web scraping only. On the other hand, between April 2020 and March 2022, some prices in the FAFH component of Mexico City's CPI might have been manually collected from some of the many OFOD platforms operating in Mexico City, while some others collected through various communication channels.[41] While some price collectors might have used OFOD platforms as their data source, they only collected prices for the items in the sample (while web scraping collects all prices displayed on the website). It is worth noticing that prior April 2020 the Mexican CPI survey would normally gather prices for the FAFH component of Mexico City's CPI via direct visits to brick-and-mortar stores.

[38] As Debreu (1959) puts it "(...) a good at a certain location and the same good at another location are *different* economic objects, and the specification of the location at which it will be available is essential. (...) a commodity is therefore defined by a specification of all its physical characteristics, of its availability date and its availability location. As soon as one of these three factors changes, a *different* commodity results." In the context of this paper, although the producer's location is the same (restaurant), the consumer's location is different (sales channel). Hence, they are different services/objects.

[39] See Cavallo (2018) and Solórzano (2023) for a general overview on sample or substitution bias when comparing price moments computed with data gathered through direct visit or via web scraping.

[40] Group 11.1 is further decomposed by facilities' characteristics: with/without waiter; with/without seating; with/without entertainment; at schools, work premises, hospitals or military wardrooms.

[41] As stated by INEGI's CPI press releases starting April 2020, price collectors may contact price-setters for this (and other) categories in the CPI via *internet, e-mail, phone and other information technologies*. INEGI's CPI press releases outline the overall share of missing prices in the CPI, they do not specify (i) share of missing prices in the FAFH industry, (ii) distribution of the communication channels used by price collectors to reach out price-setters in this industry, (iii) how this distribution has changed over time, nor (iv) any geographical dimension, especially in Mexico City.

Regardless of how their prices are gathered, third, FAFH products considered in Online AVI and CPI are intended to be consumed in different places. That is, their consumption channels are different. Prices employed for computing Online AVI come from ready-to-eat meals to be consumed mainly at home through deliveries or take-aways. FAFH prices used for the CPI come from ready-to-eat meals intended to be consumed at restaurants' premises. By limiting face-to-face interactions, consumption on products included in Online AVI might represent lower infection risks to customers than consumption on products considered in the CPI survey. As a result, each of these consumption channels might have experienced demand shocks in opposite directions.[42]

Fourth, regarding methodological differences, CPI's price collectors select a subset of products in restaurants' menu such that these products can form a set menu (e.g. starter, main, dessert and beverage). Then, price collectors add up prices from these products, known as a composite price, which is then chain linked to an index. The evolution of composite prices is what matters for computing the FAFH categories in the CPI. It is worth noticing that, as it is the sum of prices, products with the highest price carry greater weight in affecting the composite price, generally mains. In contrast, Online AVI considers the average variation of individual prices pooling all products from all restaurants altogether. The average variation is then imputed to an index. Thus, there are neither composite prices nor restaurant level measures in Online AVI.[43]

Fifth, in terms of sample size, on the one hand, the CPI survey considers 237 different restaurants in Mexico City. On the other hand, as presented in Section 2, Online AVI is computed using data from over 5,000 different eateries in Mexico City.

Sixth, Online AVI is computed using data from an OFOD platform operating in Mexico City. Although, INEGI publishes price indices for 55 regions, I narrow down the CPI series under study and use those from the Mexico City area only.

Seventh, prices in both data sources include taxes and non-conditional sales (e.g. 2x1 or 50% off), while they exclude tips. Web scraped prices do not include delivery fees nor conditional discounts (e.g. upon minimum order value).

[42]According to Banco de México's System of Economic Information, there was a fall in the number of transactions and amount spent on restaurants' Point of Sale (PoS) terminals in April 2020. However, these statistics do not grasp by how much demand for OFOD services increased since April 2020 as OFOD platforms are regarded as e-commerce and not as restaurants' PoS. Statistics on e-commerce normally pool transactions from passenger-ride platforms, online goods ordering platforms, etc.

[43]Motivated by concerns that restaurants with more items would implicitly carry greater weight in AVI, an earlier version of this work reported an exercise where restaurant-specific AVIs were computed and then averaged out. The results are nearly identical, omitted for brevity and available upon request.

4.2 Contrasting Online AVI and Mexico City's FAFH CPI Dynamics

The main purpose of this subsection is to describe the dynamics both FAFH price indices exhibited during the period under study. Short comments regarding the state of the pandemic in Mexico City are included in this subsection. The full description of events on how the pandemic unfolded in Mexico City are presented in Subsection A.7 and omitted here for brevity.

Figure 12 compares Online AVI and Mexico City's FAFH CPI as published by INEGI from April 2020 to March 2022. Panel 12a illustrates both price indices in levels with base April 2020 = 100. Panel 12b depicts monthly changes from these two indices. Panel 12c shows the difference between Online AVI and Mexico City's FAFH CPI (base April 2020 = 100) at any given point in time. Panel 12d reports the year-on-year inflation rates reported by these indices.

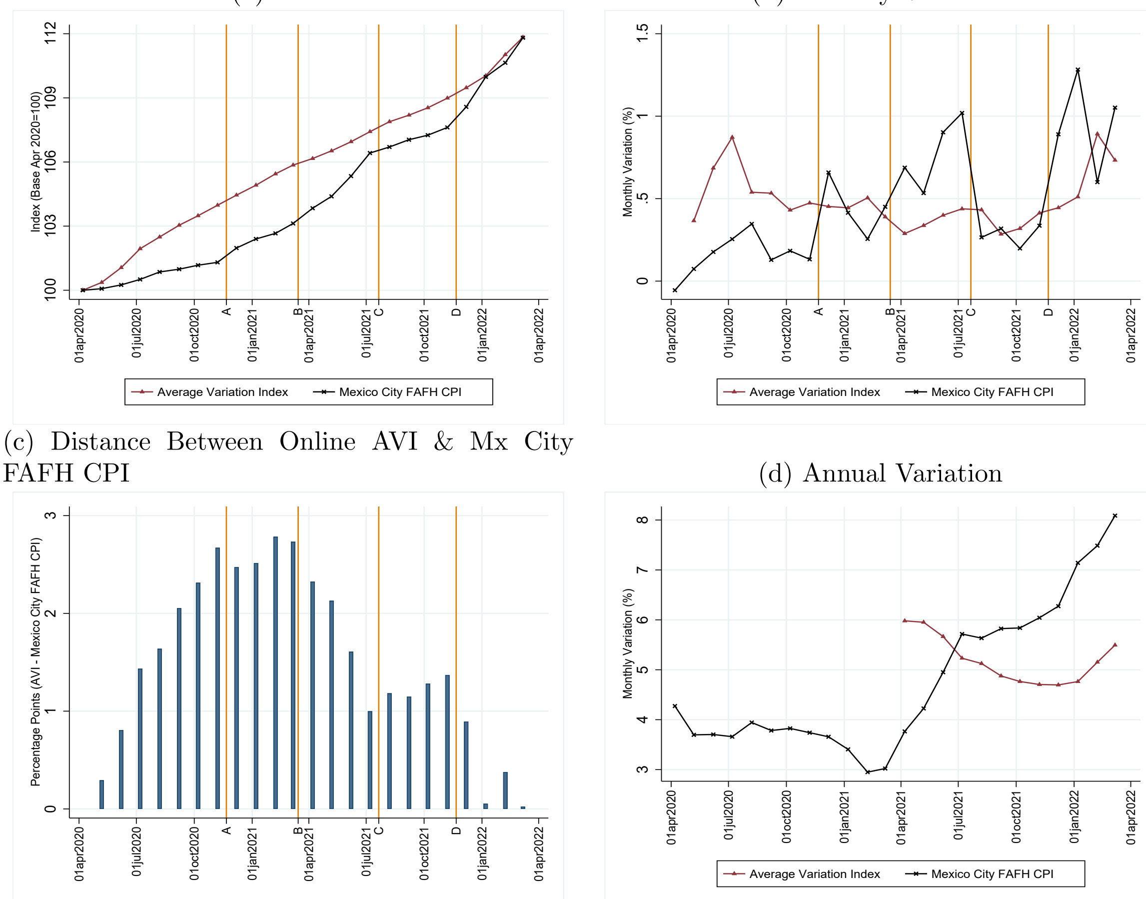
Panel 12a illustrates that Online AVI exhibited a steady increase from April to November 2020 (origin to reference point A). This period was characterized by the first and toughest lockdown in Mexico City, affecting on-site dining and boosting to online food ordering and deliveries, as well as the first loosening restriction. In this period, as AVI's monthly variations were greater than Mexico City's FAFH CPI monthly variations. See Panel 12b. Thus, Online AVI accumulated a positive difference with respect to Mexico City's FAFH CPI, as shown in Panel 12c.

Then, from December 2020 to March 2021, the gap between Online AVI and Mexico City's FAFH CPI stabilized (points A to B in Figure 12). See Panel 12c. During this time, monthly variations of Online AVI and Mexico City's FAFH CPI greatly overlapped. See Panel 12b. These months encompassed the second infection wave over the winter holidays in Mexico and with limited effect of COVID-19 vaccines as their rollout started in February 2021.

One year into the pandemic, April 2021, Panel 12d highlights that Online AVI reported a 6% y-o-y inflation rate. In contrast, Mexico City's FAFH CPI exhibited an annual growth rate of 4%.

As the COVID-19 vaccination rollout progressed in Spring 2021, in turn lowering contagion risks of face-to-face interactions for on-site dining, the gap between these two FAFH price indices started diminishing from April 2021 to July 2021 (points B to C). See Panel 12c. This was mainly driven by greater month-to-month Mexico City's

Figure 12: Online Average Variation Index (AVI) and Mexico City's FAFH CPI



(a) Levels

(b) Monthly Variation

(c) Distance Between Online AVI & Mx City FAFH CPI

(d) Annual Variation

Note: The first fortnight of every month is depicted for illustration purposes (both price indices are originally available at fortnightly frequencies). OFOD data available from April 2020 to March 2022. Online AVI is computed as defined in subsection 3.1.1 by pooling all products regardless type of product or restaurant. Mexico City's FAFH CPI is the weighted average of price indices as published by INEGI from Mexico City's (i) Restaurants and others; (ii) Cooked food (others); (iii) Grilled chicken; (iv) Barbacoa or Birria; (v) Pizzas; (vi) Carnitas; (vii) Nightclub; (viii) Cafeterias, canteens, torta and taco shops. Source: Author's own calculations based on data from an OFOD platform and INEGI.

FAFH CPI variations than those reported by Online AVI, as highlighted in Panel 12b.

Between August and November 2021 (C to D) the monthly variations were very similar for the two price indices. See Panel 12b. The Delta wave peaked in these months.

Then, from December 2021 to March 2022 (to the right of D), the difference between indices greatly diminished. See Panel 12c. These winter months saw the arrival of the Omicron variant and a sharp increase in the number of COVID-19 cases. According to official figures about 60% of Mexicans had had at least one COVID-19 shot by December 2021 (see Appendix A.7 for more on the vaccination rollout).

Strikingly, the cumulative inflation rate from April 2020 to March 2022 was 12% for the two FAFH price indices. See Panel 12a. Note, however, the annual inflation rates depicted in Panel 12d show a negative correlation in 2021, followed by a similar trend in 2022. Though, the levels of annual inflation rates are different.

5 Conclusions

The Food Away From Home (FAFH) industry was one of the most affected by the COVID-19 pandemic. Among other factors, heterogeneous demand shocks faced by restaurants across both on-site and deliveries/takeaways consumption channels might have lead to different price responses in each of these channels. This paper studies the FAFH inflation in Mexico City analysing prices from dishes intended to be consumed as deliveries/takeaways in Mexico City, as well as the FAFH component of Mexico City's CPI calculated with prices intended for on-site consumption.

As prices from dishes intended to be consumed as deliveries/takeaways come from a novel web scraped dataset from an OFOD platform, I first document that (i) Beverages with and without Alcohol, Eggs, Pizza and Desserts exhibited less cumulative inflation than other dish categories over the first two years of the COVID-19 pandemic; (ii) Mains, Chicken, Barbacoa, as well as Group Combos reported the greatest cumulative inflation rates; (iii) the frequency of price changes seems to be more important than the size of price adjustments in explaining price dynamics in the aforementioned dish categories; and (iv) multi-outlet restaurants tend to change their prices less frequently and, given a price change, the size of price changes is on average larger than at independent restaurants. I also show that episodes with greater number of COVID-19 cases were associated with periods of more frequent price changes, whereas the size of price variations remained fairly constant throughout the first two years of the pandemic.

I then compute an aggregate price index using web scraped data, named Online AVI, and benchmark it to the FAFH component of Mexico City's CPI. Although both AVI and Mexico City's FAFH CPI use restaurants as price-informants, Online AVI comes from a novel dataset that make it unclear a priori whether it might (or not) exhibit similar patterns to the Mexico City's FAFH CPI. Importantly, these two FAFH price indices have different consumption channels (deliveries for AVI and on-site dining for Mexico City's FAFH CPI).

Indeed, empirical results suggest that Online AVI and Mexico City's FAFH CPI exhibit heterogeneous trends for most part of the pandemic's first year: Mexico City's FAFH CPI stayed close to 4%, while Online AVI reported a 6% annual inflation rate. By the end of the second year of the pandemic in March 2022, both price indices suggest a cumulative 12% inflation rate.

Although web scraped data is increasingly used for analyzing inflation, to the author's knowledge the literature has mainly focused on goods' prices observed at supermarkets or departmental stores. In contrast, this research contributes to the literature by focusing on analyzing web scraped prices in an industry at the service sector.

The rapid adoption of online ordering and delivery platforms while on-site dinning was depressed, as well as demand shocks affecting in opposite directions consumption channels, leave this industry as a prosperous area of research. Among some of the venues to be explored in the FAFH industry are the study of multi-product pricing models, the analysis of price dispersion as online platforms allow greater number of alternatives and easier price comparisons, as well as the assessment of pass-through determinants.

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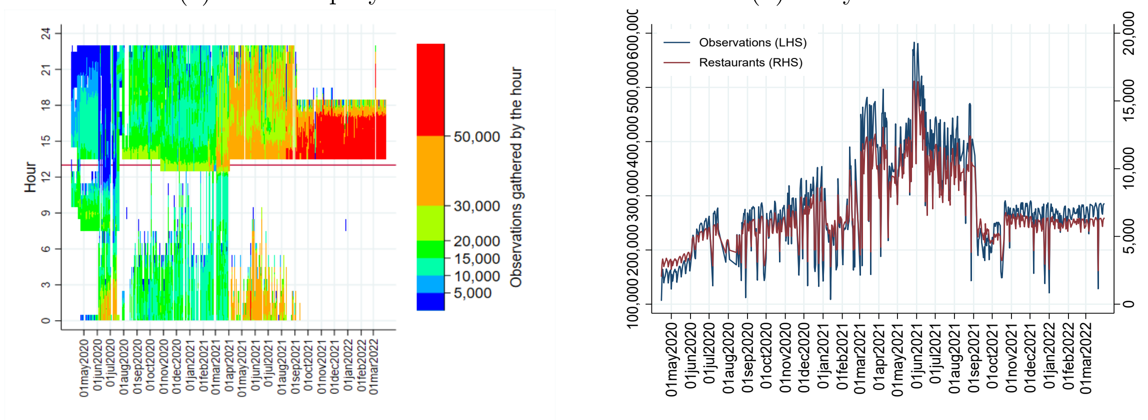
A Appendix

A.1 Data

Figure 13: Data Collection

Hourly and Daily Observations

(a) Price Enquiry (b) Daily Observations

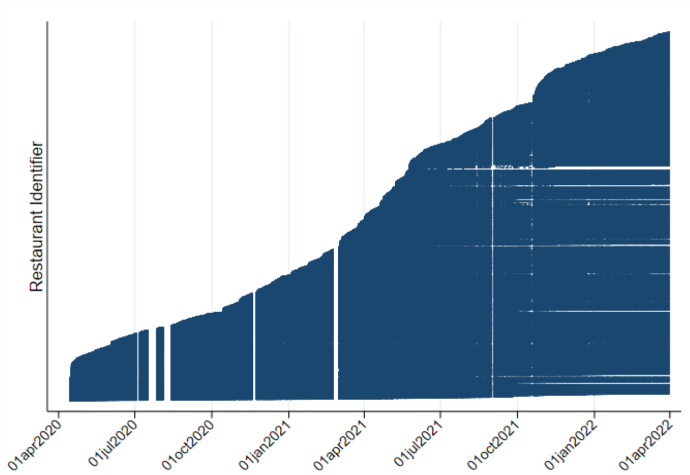


Note: Data from April 1st 2020 and ends in March 31th 2022. Panel 13a depicts the number of observations scraped by the hour on a daily basis. The red horizontal line indicates 13:00 hrs. The maximum number of observations ever scraped in one hour is 83,298. Panel 13b shows the number observations (items/dishes) and restaurants reported on a daily basis. Source: Author's own elaboration based on data from an OFOD platform.

Figure 14 depicts if a given restaurant identifier (y-axis) is effectively observed on a given day (x-axis). While the number of scatters makes it difficult to observe when a single scatter disappears, when few eateries stop appearing in the sample they are displayed as a horizontal white line/bar. One of these horizontal bars can be observed starting in August/September 2021 and dragged until the end of the sample, for instance.

Figure 14, on top of some investigative work on the dataset, provides mild evidence of obfuscation strategies. That is, restaurants stop using their identifier and get a new one. This is less of a concern for the classification of observations. However, for the computation of experimental prices indices might be a problem as I impose a threshold on the number of fortnights a dish (hence, a restaurant) must appear in the dataset in order to be included in a given price index. Though, (i) Figure 14 shows the minority of restaurants are in this situation and (ii) as shown in Appendix A.4.3, when I remove the threshold on the number of fortnights in the sample the qualitative results stemming from price indices hold. Furthermore, obfuscation might widens standard errors in the panel data estimates as the restaurant fixed effects might be computed with less observations than they should have to.

Figure 14: Lifespan of Each Restaurant



Note: The figure depicts if a given restaurant identifier (y-axis) is effectively observed on a given day (x-axis). While the number of scatters makes it difficult to observe when a single scatter disappears, when few restaurants disappear from the sample they are displayed as a horizontal white line/bar. For instance, few of these horizontal bars can be seen towards the end of the sample in April 2022. Vertical empty spaces imply days with no observations. This might be because either the website and/or the computer script crashed. Thus, data collection could not be completed in such days. Days with less than 100,000 observations are considered as atypical and neglected from the analysis (the 5th percentile from the raw dataset is about 106,000). Data from April 1st 2020 to March 31st 2022. Source: Author's own work.

A.2 Machine Learning Dish Classification

This Appendix provides greater details on the classification of dishes (cross-section dimension of the panel) using machine learning techniques. First, it describes the construction of the training set, under which a number of algorithms are trained. Second, text cleaning procedures are outlined. Third, it sketches how dish descriptions are taken into a matrix form. Forth, classifiers are listed and, fifth, hyper-parametrised through k-fold cross-validation. Sixth, some forensic statistics of trained models are discussed. Finally, the winner and runner-up models are compared.

A.2.1 Training Set

As presented in the main text, out of the around 616,000 unique descriptions in the dataset, I manually classify more than 13,000 random dishes based on the descriptions provided by the restaurants.Thus, the manual classification considers a little more than 2% of the dishes in question. The dishes are classified into 19 categories, which are chosen on the basis of (i) well-recognized headers in many restaurants' menus, (ii) categories with direct mapping to Mexico's CPI categories and (iii) research question at hand.

The categories are: (1) Starters, (2) Salads, (3) Soups, (4) Eggs, (5) Mains, (6) Pizzas, (7) Tacos, (8) BBC, (9) Grilled and Roasted Chicken, (10) Desserts, (11) Beverages with Alcohol, (12) Beverages without Alcohol, (13) Meals with Beverages, (14) Meals without Beverages, (15) Group Combos, (16) Dessert Combos, (17) Extras, (18) Others (Non-Food) and (19) Ambiguous.[44]

A.2.2 Text Cleaning

The descriptions in training set are then parsed by text cleaning routines in order to have homogeneous notation in the dish descriptions. Removal of stop words, special characters, hashtags; standardizing numbers' and units' abbreviations, are among some of the cleaning procedures.

A.2.3 Word Tokenising

Once descriptions are clean and homogeneous, words in dish descriptions are ready to be tokenized and used as explanatory variables by the different classifiers. To that end, I convert the collection of dish descriptions into a matrix of token (words) counts. That is, the columns in the matrix represent each and every single word appearing at least once in the collection of descriptions, the rows of the matrix are the dishes in the dataset, and each matrix cell counts the number of times a word (column) appears in the description (row).[45]

I get three different sets of explanatory variables, which will be used one at the time by the classifiers in order to assess how sensitive the performances of the classifiers are to the token count specification. These specifications are: (i) the universe of words found in the descriptions i.e. complete set of single words (unigrams), (ii) subset of unigrams by cutting-off infrequent terms and (iii) subset of unigrams and bigrams cutting-off infrequent terms.[46]

The first one uses all words in the collection of descriptions. Hence, this first specification induces a matrix with over 68,000 words (columns).

The second specification is a subset of the first specification (matrix with lower columns dimension). As words are the set of explanatory variables to be used by the algorithms, which might lead to the curse of dimensionality and intensive computational work, this second matrix comprehends words appearing in the collection of descriptions at least 3 times.[47] Thus, around 23,000 words are considered after implementing this

[44]BBC stands for Barbacoa, Birria and Carnitas, which are common taco fillings, and are considered in the Mexican CPI as a specific product category. Meals with/without Beverages consider two or three times meals. E.g. a Meal with Beverage could be a bundle of starter or salad or main and a soft drink.

[45]This type of matrix is commonly referred as a sparse matrix since each row contains a large number of columns with zeros and only a few with non-zero values.

[46]A bigram is defined as the pair of consecutive words. E.g. the unigram representation of "Today is Monday" is ["Today", "is", "Monday"], while the bigram representation is ["Today is", "is Monday"].

[47]That is, I drop terms that have a frequency lower than 0.0005% of the 616,000 descriptions. The aim of this approach is to neglect restaurant-specific terms that might not be relevant for the clas-

cut-off approach.

The third specification adds bigrams to the matrix of unigrams. This is due to concerns arising from, for example, $description_1$ = "chicken with salad" and $description_2$ = "salad with chicken".[48] The gain of using bigrams is obvious in the previous simple example but it is less clear if, on the aggregate and in the presence of more unigrams, the potential improvement in accuracy outweights the greater number of explanatory variables i.e. matrix dimension. In order to keep dimensions attainable, I also keep only bigrams showing up at least 3 times in the corpus. The matrix of unigrams and bigrams has over 32,000 columns.

In sum, there are three different specifications of matrices of token counts: (i) complete set of words (or unigrams), (ii) subset of unigrams and (iii) subset of unigrams and bigrams. These matrices are used, one by one, in the classifiers, which are then compared in terms of their accuracy on the training set.

A.2.4 Classifiers

The classifiers used for this analysis are (i) decision tree, (ii) random forest, (iii) multinomial naive Bayes and (iv) logistic regression.

A.2.5 Hyper-parameters Tuning

All classifiers require some form of hyper-parameter selection prior to estimation. To that end, I use k-fold cross validation procedures. That is, 80% of the training set is divided intro k-folds, after which the model is fitted using observations in k-1 folds under a specific set of parameters and compute the accuracy in the k-th fold. This process is repeated k times in order to compute the accuracy in every fold. The average accuracy is used to select the hyper-parameter configuration maximizing the performance of each classifier.

The grid of parameters used for this search is detailed in Table 2. Note there are *balanced* versions of the decision tree and random forest classifiers. These versions take into account that category sizes are highly unbalanced in the training set. This could be a problem since the parameters and costs functions developed in these al-

sification task. For instance, suppose a fictional restaurant named XXYY offers a restaurant-specific dish with the description (including stop words) "Burger XXYY with bacon and avocado"; the word "XXYY" might not be representative for the broad classification task and adds an extra column to the matrix of explanatory variables. The threshold of 3 in order to be considered in the analysis is chosen with the goal of neglecting very rare words and interfering the less possible with the vocabulary.

[48]In this simple example, the unigram representation leads to the same vector representation. That is, without loss of generality and assuming no stop words, if column 1 counts the word "chicken" and column 2 counts the word "salad", the unigram representation would be $description_1 = [1, 1]$ and $description_2 = [1, 1]$. By using bigrams, without loss of generality, column 1 counts "chicken", column 2 counts "salad", column 3 counts the bigram "chicken salad" and column 4 counts "salad chicken", resulting in a vector representation of $description_1 = [1, 1, 1, 0]$ and $description_2 = [1, 1, 0, 1]$.

gorithms could end up focusing (over specializing) on large categories only. Hence, I impose greater penalties on errors made in smaller categories.[49] The penalties come in the form of weighting observations, where the weights are inversely proportional to category frequencies in the data.

Table 2: Grid of Parameters
By Classifier

Classifier	Parameter	Values
Decision Tree	Max Depth	[500, 550, 600, 625, 650, 675, 700, 750, 800, 900, 1000]
	Min Samples Split	[4,5,6,7,8,10]
	Criterion	[Gini, Entropy]
Balanced Decision Tree	*Same as Above*	*(Various)*
	Class Weight	[Balanced]
Random Forest	Max Depth	[600, 750, 900, 1050, 1200, 1350]
	Min Samples Split	[3,4,5,6,7,10]
	Criterion	[Gini, Entropy]
	N Estimators	[75, 100, 125, 150, 175, 200, 300, 500]
Balanced Random Forest	*Same as Above*	*(Various)*
	Class Weight	[Balanced]
Multinomial Naive Bayes	α	[0.00001,0.0001,0.001,0.01,0.1,0,1,2,3,4,5,10]
	Fit Prior	[True,False]
Logistic Regression	C	[0.00001,0.0001,0.001,0.01,0.1,1,2,3,4,5,10,20]

Note: The grid-search implements an exhaustive search over specified parameter values for each classifier. As mentioned above, k-fold cross validation is used for hyper-parameter selection. That is, 80% of the training set is divided intro k-folds (stratified by category sizes), after which the model is fitted using observations in k-1 folds under a specific set of parameters and compute the accuracy in the k-th fold. This process is repeated k times in order to compute the accuracy in every fold. The average accuracy is used to select the hyper-parameter configuration maximizing the performance of each classifier.
Source: Author's own work.

A.2.6 Classifiers Forensics

As a result of the k-fold cross-validation, Table 3 reports the hyper-parameters that maximize the accuracy score in classifying 80% of the training set. The accuracy scores of these models are depicted in Figure 15a.

Figure 15a shows that, for this specific task for classifying dishes, the use of different specifications on the matrix of token counts generate little gains in terms of accuracy. However, as seen in the various panels of Table 3, the hyper-parameter configuration does change depending the matrix specification as expected.

[49] Previous versions of this paper included an exercise upsampling small categories by bootstrapping with replacement. However, there seems to be no gain in accuracy at the expense of computation time (as the dataset grows due to the bootstrap with replacement). Results not reported but available upon request.

Moreover, Figure 15a highlights that the *logistic regression* and *balanced decision tree* (both with unigrams and bigrams) achieve the greatest and lowest accuracy scores, respectively. Nonetheless, there are only minor differences across models' performance over the sample under which they were trained.

Table 3: Parameters Maximizing Accuracy in Testing Set
By Matrix of Token Counts and Classifiers

Classifier	Parameters
	A. Unigrams
Decision Tree	'max˙depth': 625, 'min˙samples˙split': 5
Balanced Decision Tree	'max˙depth': 750, 'min˙samples˙split': 4
Random Forest	'max˙depth': 600, 'min˙samples˙split': 3, 'n˙estimators': 200
Balanced Random Forest	'max˙depth': 900, 'min˙samples˙split': 3, 'n˙estimators': 500
Naive Bayes	'alpha': 0.1, 'fit˙prior': True
Logistic Regression	'C': 1
	B. Unigrams (Cut-off)
Decision Tree	'max˙depth': 1000, 'min˙samples˙split': 6
Balanced Decision Tree	'max˙depth': 800, 'min˙samples˙split': 4
Random Forest	'max˙depth': 1200, 'min˙samples˙split': 3, 'n˙estimators': 200
Balanced Random Forest	'max˙depth': 1200, 'min˙samples˙split': 3, 'n˙estimators': 175
Naive Bayes	'alpha': 0.1, 'fit˙prior': True
Logistic Regression	'C': 2
	C. Unigrams and Bigrams (Cut-off)
Decision Tree	'max˙depth': 700, 'min˙samples˙split': 7
Balanced Decision Tree	'max˙depth': 500, 'min˙samples˙split': 6
Random Forest	'max˙depth': 900, 'min˙samples˙split': 4, 'n˙estimators': 125
Balanced Random Forest	'max˙depth': 900, 'min˙samples˙split': 4, 'n˙estimators': 150
Naive Bayes	'alpha': 0.1, 'fit˙prior': True
Logistic Regression	'C': 2

Source: Author's own elaboration.

Trained algorithms are then deployed over the remaining (unseen) 20% of the manually constructed training set. The models' accuracy scores classifying unseen data are highlighted in Figure 15b.

Similarly as in the sample over which models were trained, there are no stark differences in terms of accuracy over the unseen sample. This is the case neither across classifiers nor specification of tokens.

A.2.7 Model Selection

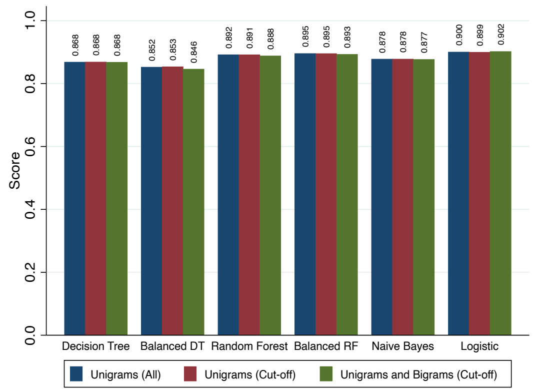
Since it is the one with greatest accuracy (average point estimate), as well with the lowest computational time, the *logistic regression* using unigrams and bigrams is picked as the winner across models. The runner up is the *balanced random forest*, also using unigrams and bigrams, but with significantly more computational time.

Figure 3 in the main text depicts the confusion matrix on the prediction of dish labels using the logistic regression fitted under the complete training set. It provides a graphical representation on whether the prediction matches with the true value. Each cell reports the share of each instance such that every row (true labels) adds up to one.

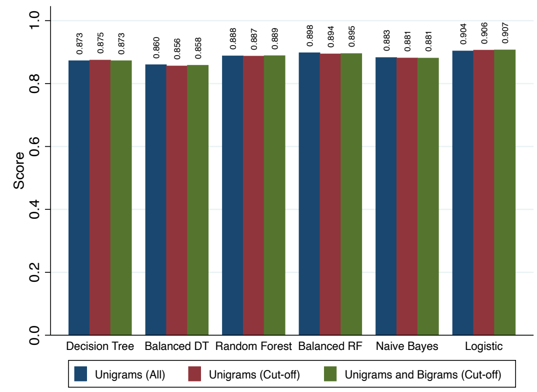
Figure 15: Accuracy Score

By Classifier and Explanatory Variables

(a) Training Set: 80% of manually classified dishes



(b) Test Set: 20% of manually classified dishes



Note: As a result of the k-fold cross-validation, the accuracy scores of the models that maximize the accuracy score in classifying 80% of the training set are depicted in Figure 15a. Trained algorithms are then deployed over the remaining (unseen) 20% of the manually constructed training set. The models' accuracy scores classifying unseen data are highlighted in Figure 15b. Source: Author's own estimates.

Correct predictions lay in the diagonal, values outside the diagonal highlight prediction errors. As shown in Figure 3, most cells on the diagonal report values close to one. As a bypass, Figure 16 shows the confusion matrix on the prediction of dish labels using the balanced random forest trained under the complete training set.

Finally, Table 1 included in the main text adds on the impact of the machine learning techniques used in this research. The first bloc of columns reports the composition of the manually classified dataset. The second bloc of columns summarizes the outcome labels generated through the logistic regression.

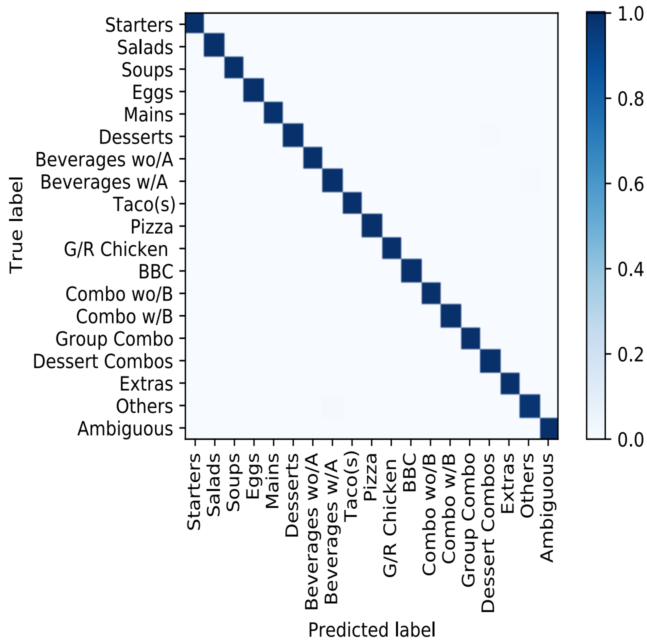
A.3 Manual Restaurant Classification

The composition by type of restaurant is summarized in Figure 17. First, Panel 17a shows that, although restaurant chains have multiple outlets across Mexico City, they constitute a small fraction of restaurants in the sample. In fact, the relative size of independent restaurants has been growing since the pandemic started. Presumably, before the pandemic, restaurant chains were more likely to outsource their online ordering and delivery services to platforms like the one under study. As the pandemic advanced and temporal retail closures were ordered, independent restaurants had no other option than use the online ordering and delivery services. Panel 17b depicts that restaurant with branches and belonging to a franchise chain offer in general more dishes than independent restaurants. Also, the figure suggests a small trend on the median number of dishes offered by restaurants regardless its type.

Figure 18 complements the restaurant composition illustrated in Figure 17. It breaks down multi-outlet eateries into restaurant chains and franchised restaurants. First, it

Figure 16: Balanced Random Forest Confusion Matrix

Predictions Over the Entire Training Set



Source: Author's own estimates.

can be seen in Panel 18a that the reduction on the share of multi-outlet eateries in the dataset is mainly driven by the decrease in the share of franchised restaurants. Second, Panel 18b shows that the number of products chained and franchised restaurants offer is fairly similar between them, while independent restaurants tend to offer less products than the former two.

Figure 19 highlights that price-resetting is not fully synchronized within restaurants. That is, when a restaurant decides to reset one price, it might not reset all prices in the menu. This is important as it adds on the idea that restaurants might be strategic on the set of prices they decide to adjust. Figure 20 reports price moments including instances when there was not a single price change.

A.4 Experimental Price Indices

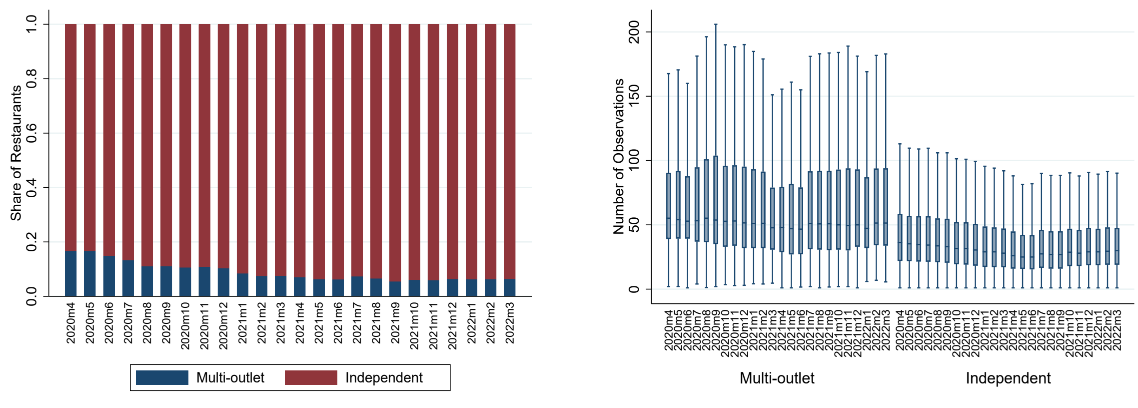
A.4.1 Average Price Index (API)

The second index is named *"Average Price Index"* or *API*, which is calculated as:

$$x_t = \Pi_{i \epsilon \Theta}(p_{i,t})^{\frac{1}{N_t}}$$
$$API_t = \frac{x_t}{x_{t-1}} API_{t-1}$$

Figure 17: Dataset Composition by Type of Restaurant

(a) Share of Restaurants (b) Number of Meals

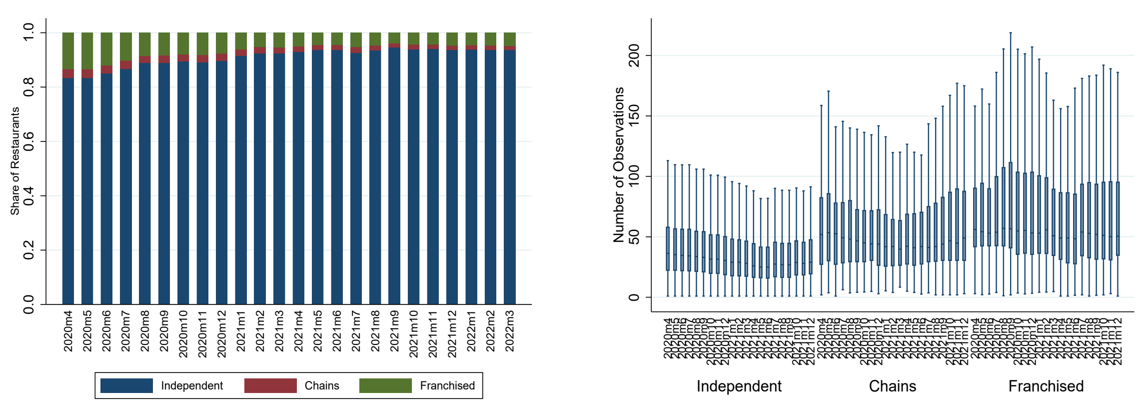


Note: In Panel 17a, monthly shares are calculated using one observation per restaurant in a given month. That is, I count the number of restaurants by its type (unweighted i.e. not taking into account the number of items they offer nor the number of days each restaurant appears in the month); then I compute the proportion relative to the total number of restaurants in the month. For Panel 17b, I first count the number of items (observations) each restaurant offers every day. I then compute, per restaurant, the average number of items it offers every month. Having one observation per restaurant per month, the box plot is generated. Each box shows the 25th percentile (lower side of the box), the median (horizontal line within the box), the 75th percentile (upper side of the box). The whiskers extend two-thirds the the width of the box. Days with less than 100,000 observations, restaurants appearing less than 5 days over the period of study and/or eateries offering less than five items per day, on average while in the sample, are neglected from the analysis in both panels. Source: Author's own work.

Figure 18: Dataset Composition by Type of Restaurant

Breaking Up Multi-Outlet Restaurants

(a) Share of Restaurants (b) Number of Meals



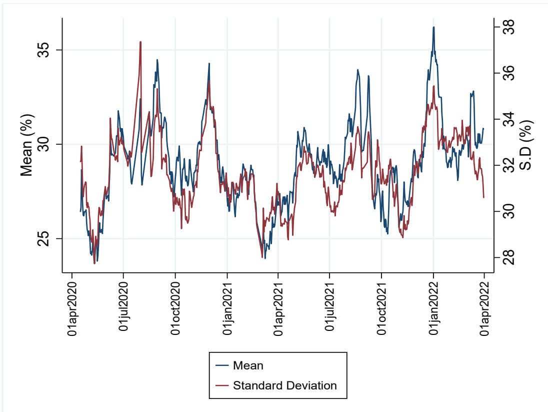
Note: Same computation procedure as Figure 17 but using three types of restaurants, as instead of two. Source: Author's own estimates.

The term x_t computes the geometric average of prices in fortnight t relative to t-1 from dishes observed in at least 75% of fortnights, $i \in \Theta$. Then, the variation in x_t is chain

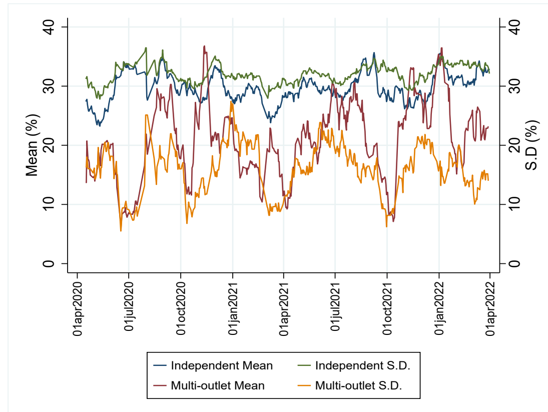
Figure 19: Price-Resetting Synchronization within Restaurants

Average and S.D. on the Fraction of Products Changing Prices in a Restaurant

(a) All Restaurants



(b) By Type of Restaurant

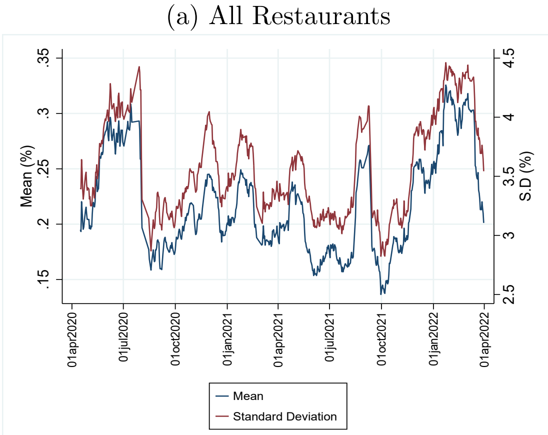


Note: Price statistics are computed as follows. First, for every restaurant, I calculate the fraction of items changing prices on a given day. I consider items in subset θ from Equation 1 only. Second, I calculate the average and standard deviation of non-zero fractions across restaurants. That is, I only consider instances when a given restaurant changed at least one price, and neglect cases when it did not to change a single one. Third, for illustration purposes, I smooth series using a 28-days moving average. Panel 19a calculates price moments by pooling restaurants altogether. Panel 19b computes price moments by type of restaurant. Source: Author's own estimates.

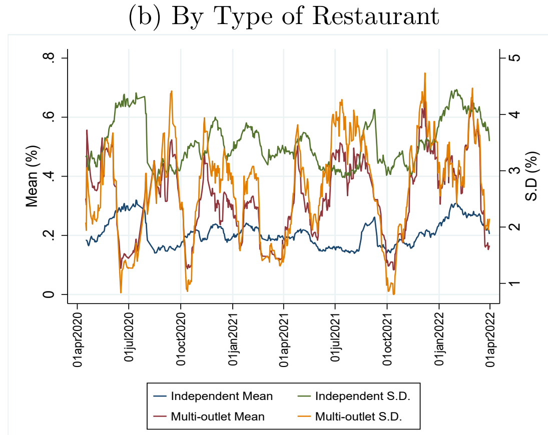
Figure 20: Fraction of Products Changing Prices at a Given Restaurant

Considers instances when a restaurant not changed a single price. Items in subset θ from Equation 1 only.

(a) All Restaurants



(b) By Type of Restaurant

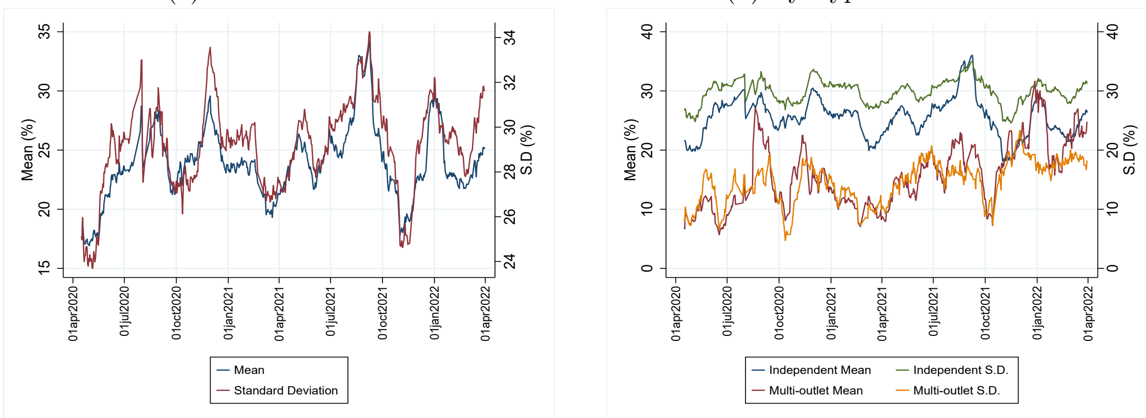


Note: Statistics computed as: (i) using items in subset θ from Equation 1, a dummy variable signals whether an item's price change (daily); (ii) for every restaurant, I calculate the fraction of items changing prices on a given day; (iii) I compute the average and standard deviation of fractions across restaurants i.e. a given restaurant change none, a subset or all its prices; (iv) I report the 28-days moving average for illustration purposes. Panel 20a pools restaurants altogether. Panel 20b computes price moments by type of restaurant. Source: Author's own calculations.

Figure 21: Fraction of Products Changing Prices at a Given Restaurant

Neglects instances when a restaurant not changed a single price.

(a) All Restaurants (b) By Type of Restaurant

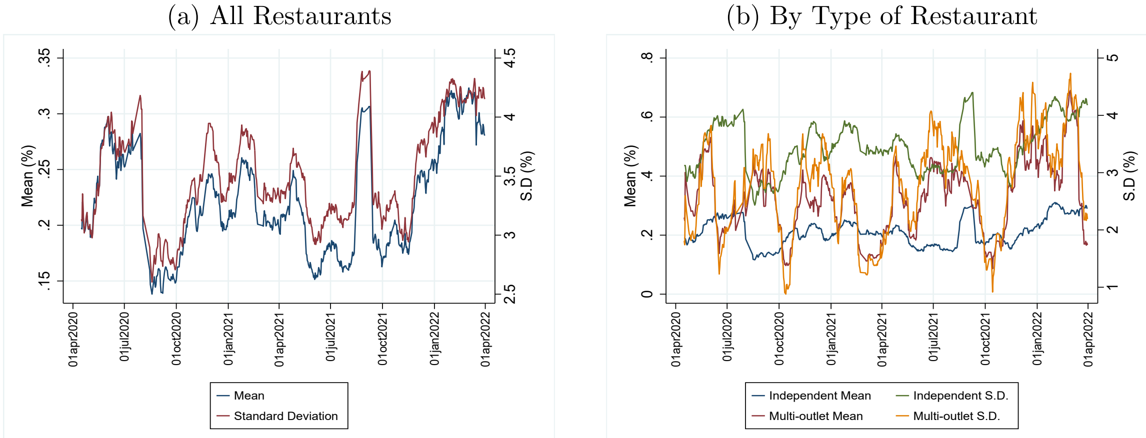


Note: This figure is computed following the the same steps as those described in Figure 19 but it considers all products in the dataset and not only those in subset θ from Equation 1. Source: Own elaboration.

Figure 22: Fraction of Products Changing Prices at a Given Restaurant

Considers instances when a restaurant not changed a single price.

(a) All Restaurants (b) By Type of Restaurant



Note: This figure is computed following the the same steps as those described in Figure 20 but it considers all products in the dataset and not only those in subset θ from Equation 1. Source: Own elaboration.

linked to a Jevons index $Apr2020 = 100$. Hence, API index is a Unit Value Index.[50] Contrary to *AVI*, *API* does consider the entry and exit of goods from one period to the next one (limited by the definition of Θ though).

[50] Recent studies using Unit Value Indices in the context of price data are Diewert (2020); Diewert and Fox (2020); Flower and Karachalias (2019); among others.

A.4.2 API by Dish Category

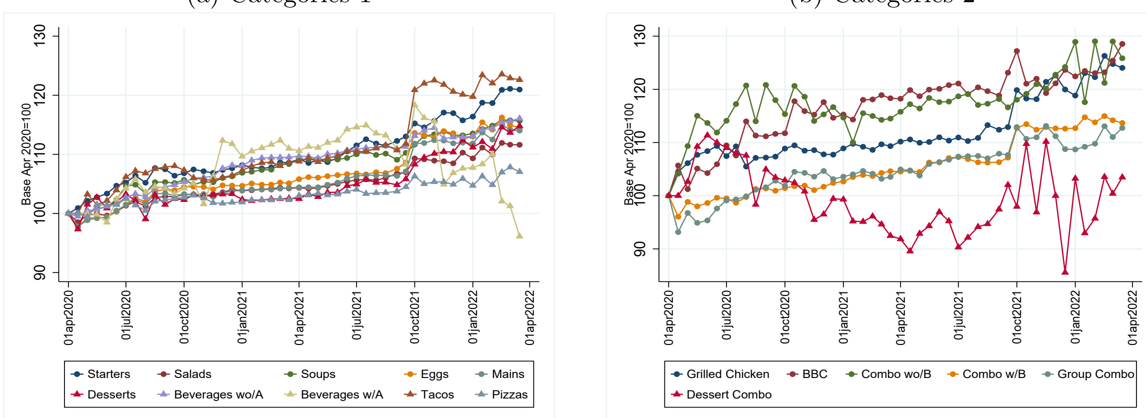
By allowing a more flexible stance in terms of entry and exit of goods, as API does, Panel 23a shows that Pizza and Salads have been consistently the categories with the lowest cumulative inflation since the start of the pandemic. Tacos, Starters and Beverages Without Alcohol have shown the greatest cumulative inflation two years into the pandemic.

Panel 23b shows that unit value indexes, like API, might exhibit greater volatility than bilateral price indexes, like AVI, when the category sizes are small.

Figure 23: Average Price Index

By Dish Type

(a) Categories 1 (b) Categories 2

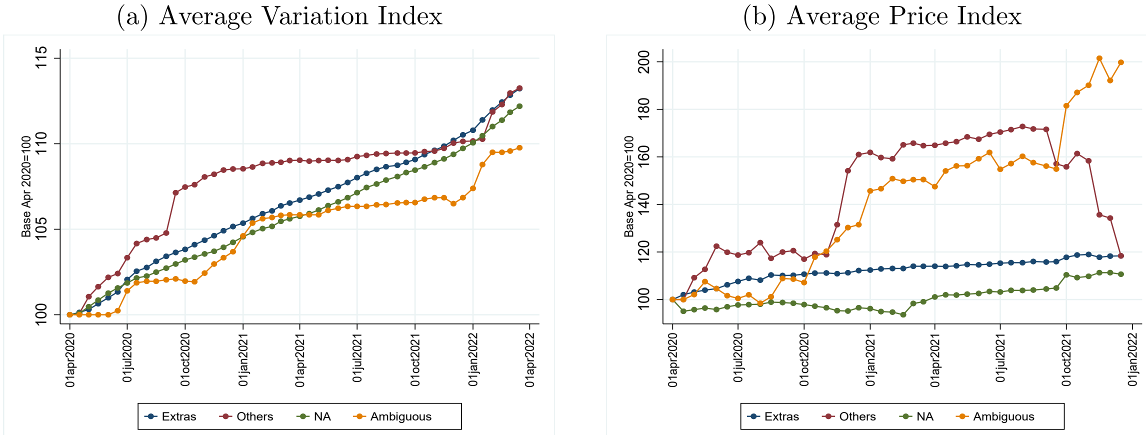


Source: Author's own elaboration with data from an OFOD platform.

Figure 24: Experimental Price Indices

Remainder Dish Types

(a) Average Variation Index (b) Average Price Index



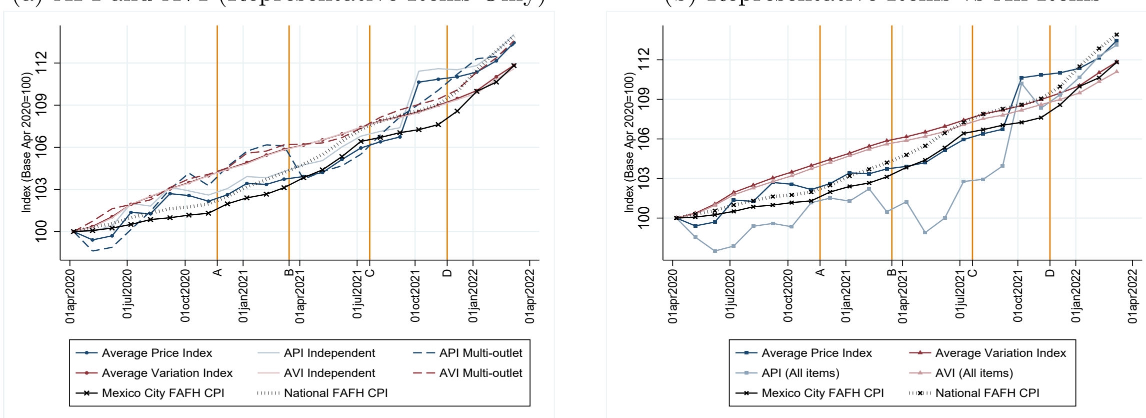
Source: Author's own calculations based on data from an OFOD platform.

A.4.3 API by Restaurant

API has shown greater divergence between indices. Since October 2020, API Multi-outlet (restaurants with branches) has exhibited greater average price than API Independent (single-location restaurants). The temporal inclusion of pricy items could be behind this differential. Though, the gap between API Multi-outlet and API Independent is smaller since April 2021.

Figure 25: Experimental Price Indices

(a) API and AVI (Representative Items Only) (b) Representative Items vs All Items



Source: Author's own work with data from an OFOD platform.

A.5 Stylized Facts

Benchmark results are compared to (i) estimates using seasonal fixed effects and (ii) estimates using the complete dataset (as not only representative dishes). They take form of:

$$P\left(y_{i,j,t}=1|x\right)=\beta_1 x_{dishtype}+\beta_2 x_{dow}+\beta_3 x_{day}+\beta_4 x_{month}+\beta_5 x_{year}+\beta_6 x_j+\varepsilon_{i,j,t}$$
$$\mid \Delta y_{i,j,t} \mid=\beta_1 x_{dishtype}+\beta_2 x_{dow}+\beta_3 x_{day}+\beta_4 x_{month}+\beta_5 x_{year}+\beta_6 x_j+\varepsilon_{i,j,t}$$

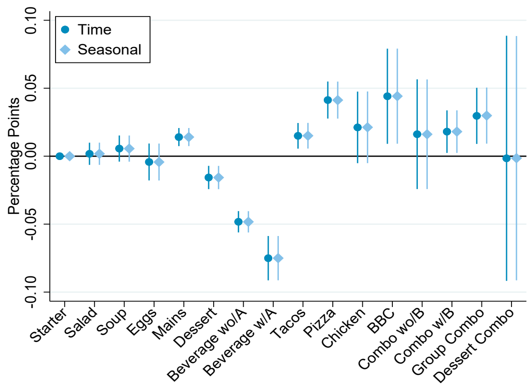
where $P\left(y_{i,j,t}=1|x\right)$, $\mid \Delta y_{i,j,t} \mid$ and x_j are defined as in the main text. x_{dow}, x_{day}, x_{month}, x_{year} represent day of the week, calendar day, month and year fixed effects, respectively. These fixed effects are not reported on the basis of confidentiality.

Figure 26: Stylized Facts of Price Adjustments

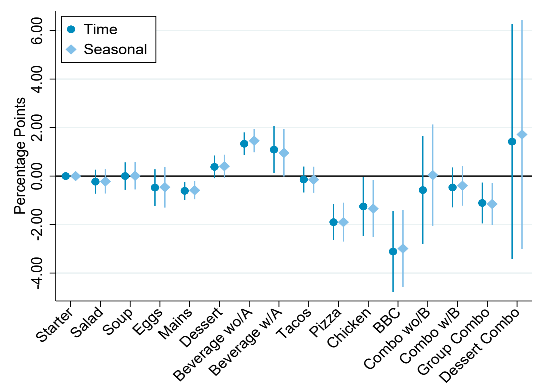
Representative Dishes Using Different Set of Time FE

Price Changes Regardless Sign of Adjustment

(a) Frequency of Changes



(b) Size of Adjustments



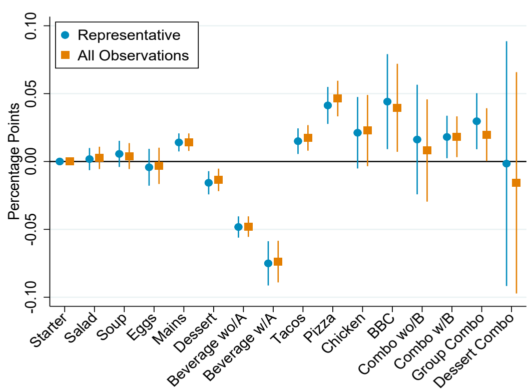
Note: Scatters represent point estimates from the econometric model. Whiskers illustrate point estimates' 95% confidence intervals. Source: Author's own estimates with OFOD platform's data.

Figure 27: Stylized Facts of Price Adjustments

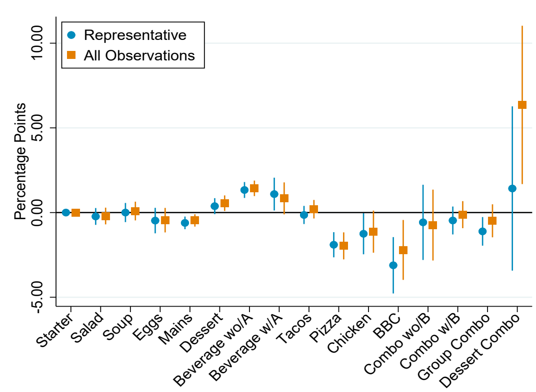
Comparison By Dish Sample

Price Changes Regardless Sign of Adjustment

(a) Frequency of Changes



(b) Size of Adjustments



Note: Scatters represent point estimates from the econometric model. Whiskers illustrate point estimates' 95% confidence intervals. Source: Author's own estimates with OFOD platform's data.

Table 4: Stylized Facts of Price Changes

Representative Dishes

(a) Frequency of Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}<0}$	$\mathbb{1}_{\Delta p_{it}<0}$
Salad	0.00	0.00	0.00	0.00	0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Soup	0.01	0.01	0.00	0.00	0.00	0.00
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Eggs	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.007)	(0.007)	(0.006)	(0.006)	(0.002)	(0.002)
Mains	0.01***	0.01***	0.01***	0.01***	0.00	0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Dessert	-0.02***	-0.02***	-0.02***	-0.02***	0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Beverage wo/A	-0.05***	-0.05***	-0.04***	-0.04***	-0.00**	-0.00**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Beverage w/A	-0.08***	-0.08***	-0.06***	-0.06***	-0.01***	-0.01***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)
Tacos	0.01**	0.02**	0.01**	0.01**	0.00	0.00
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Pizza	0.04***	0.04***	0.03***	0.03***	0.01**	0.01**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)
Chicken	0.02	0.02	0.03*	0.03*	-0.00	-0.00
	(0.013)	(0.013)	(0.013)	(0.013)	(0.004)	(0.004)
BBC	0.04*	0.04*	0.04*	0.04*	0.00	0.00
	(0.018)	(0.018)	(0.017)	(0.017)	(0.004)	(0.004)
Combo wo/B	0.02	0.02	0.02	0.02	-0.00	-0.00
	(0.021)	(0.021)	(0.019)	(0.019)	(0.007)	(0.007)
Combo w/B	0.02*	0.02*	0.01	0.01	0.01**	0.01**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)
Group Combo	0.03**	0.03**	0.02**	0.02**	0.01	0.01
	(0.011)	(0.011)	(0.009)	(0.009)	(0.005)	(0.005)
Dessert Combo	-0.00	-0.00	-0.02	-0.02	0.02	0.02
	(0.046)	(0.046)	(0.049)	(0.049)	(0.016)	(0.016)
Extras	-0.02***	-0.02***	-0.01***	-0.01***	-0.00	-0.00
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Others	-0.03	-0.03	-0.03	-0.03	-0.00	-0.00
	(0.021)	(0.021)	(0.018)	(0.018)	(0.006)	(0.006)
NA	-0.04***	-0.04***	-0.03***	-0.03***	-0.00*	-0.00*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Ambiguous	-0.05**	-0.05**	-0.06***	-0.06***	0.01	0.01
	(0.019)	(0.019)	(0.014)	(0.014)	(0.013)	(0.013)
Observations	97,818,922	97,818,922	97,818,922	97,818,922	97,818,922	97,818,922
Adjusted R^2	0.005	0.004	0.005	0.004	0.003	0.002
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

(b) Size of Price Adjustments

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mid\Delta p_{i,n}\mid$	$\mid\Delta p_{i,n}\mid$	$\mid\Delta p^{(+)}_{i,n}\mid$	$\mid\Delta p^{(+)}_{i,n}\mid$	$\mid\Delta p^{(-)}_{i,n}\mid$	$\mid\Delta p^{(-)}_{i,n}\mid$
Salad	-0.23	-0.22	-0.12	-0.10	-1.76*	-1.41
	(0.253)	(0.255)	(0.239)	(0.237)	(0.874)	(0.906)
Soup	0.00	0.01	0.17	0.17	-1.70	-0.87
	(0.288)	(0.289)	(0.295)	(0.292)	(0.994)	(1.002)
Eggs	-0.47	-0.46	-0.49	-0.52	-0.59	0.08
	(0.384)	(0.428)	(0.353)	(0.375)	(0.994)	(1.260)
Mains	-0.61**	-0.58**	-0.52**	-0.50**	-1.44*	-1.19
	(0.190)	(0.191)	(0.182)	(0.182)	(0.655)	(0.672)
Dessert	0.38	0.41	0.44	0.49*	-0.52	-0.49
	(0.240)	(0.242)	(0.228)	(0.231)	(0.785)	(0.813)
Beverage wo/A	1.33***	1.46***	1.40***	1.53***	0.33	0.25
	(0.239)	(0.245)	(0.228)	(0.236)	(0.818)	(0.861)
Beverage w/A	1.09*	0.96	1.20*	1.05*	-1.96	-1.73
	(0.494)	(0.498)	(0.503)	(0.503)	(1.998)	(1.814)
Tacos	-0.14	-0.15	-0.18	-0.17	-0.75	-0.54
	(0.273)	(0.274)	(0.255)	(0.256)	(0.954)	(0.988)
Pizza	-1.90***	-1.90***	-1.70***	-1.75***	-1.10	-0.51
	(0.378)	(0.409)	(0.350)	(0.393)	(1.279)	(1.292)
Chicken	-1.25*	-1.34*	-1.35*	-1.47*	-0.65	-0.06
	(0.618)	(0.601)	(0.584)	(0.574)	(2.731)	(2.621)
BBC	-3.11***	-2.99***	-2.48**	-2.48***	-10.19	-11.49
	(0.848)	(0.809)	(0.812)	(0.752)	(6.443)	(7.026)
Combo wo/B	-0.58	0.04	-0.61	0.21	0.21	0.84
	(1.133)	(1.065)	(1.037)	(0.951)	(3.270)	(3.104)
Combo w/B	-0.47	-0.40	-0.57	-0.47	-0.07	-0.33
	(0.420)	(0.419)	(0.372)	(0.367)	(1.465)	(1.453)
Group Combo	-1.11**	-1.15**	-0.97*	-1.12*	0.54	1.19
	(0.430)	(0.446)	(0.450)	(0.439)	(1.383)	(1.643)
Dessert Combo	1.42	1.71	3.85*	3.65*	-0.89	-0.87
	(2.474)	(2.408)	(1.956)	(1.729)	(1.271)	(1.118)
Extras	0.87***	0.91***	1.07***	1.10***	-1.22	-0.99
	(0.230)	(0.232)	(0.226)	(0.229)	(0.736)	(0.759)
Others	2.42*	2.41	2.60**	2.81**	3.89	1.70
	(1.079)	(1.326)	(0.896)	(1.074)	(4.623)	(4.951)
NA	0.60**	0.66**	0.71***	0.78***	-0.84	-0.83
	(0.199)	(0.201)	(0.188)	(0.191)	(0.661)	(0.668)
Ambiguous	-0.57	-0.80	-0.91	-1.16	-2.52	-0.77
	(1.405)	(1.395)	(1.536)	(1.606)	(2.299)	(1.740)
Observations	204,897	204,897	179,890	179,891	24,077	24,097
Adjusted R^2	0.458	0.430	0.496	0.461	0.602	0.547
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

Note: DOW and DOC stand for day of the week and calendar respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Own calculations.

Table 5: Stylized Facts of Price Changes

All Dishes (Representative or Not)

(a) Frequency of Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbf{1}_{\Delta p_{it}\neq 0}$	$\mathbf{1}_{\Delta p_{it}\neq 0}$	$\mathbf{1}_{\Delta p_{it}>0}$	$\mathbf{1}_{\Delta p_{it}>0}$	$\mathbf{1}_{\Delta p_{it}<0}$	$\mathbf{1}_{\Delta p_{it}<0}$
Salad	0.00	0.00	0.00	0.00	0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Soup	0.00	0.00	0.01	0.01	-0.00	-0.00
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Eggs	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)
Mains	0.01***	0.01***	0.01***	0.01***	0.00	0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Dessert	-0.01**	-0.01**	-0.01**	-0.01**	-0.00	-0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Beverage wo/A	-0.05***	-0.05***	-0.04***	-0.04***	-0.01***	-0.01***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Beverage w/A	-0.07***	-0.07***	-0.06***	-0.06***	-0.01***	-0.01***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.003)	(0.003)
Tacos	0.02***	0.02***	0.01***	0.01***	0.00	0.00
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Pizza	0.05***	0.05***	0.04***	0.04***	0.01**	0.01**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)
Chicken	0.02	0.02	0.02*	0.02*	-0.00	-0.00
	(0.013)	(0.013)	(0.012)	(0.012)	(0.005)	(0.005)
BBC	0.04*	0.04*	0.04*	0.04*	0.00	0.00
	(0.017)	(0.017)	(0.016)	(0.016)	(0.005)	(0.005)
Combo wo/B	0.01	0.01	0.02	0.02	-0.01	-0.01
	(0.019)	(0.019)	(0.018)	(0.018)	(0.007)	(0.007)
Combo w/B	0.02*	0.02*	0.01	0.01	0.01*	0.01*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)
Group Combo	0.02*	0.02*	0.01	0.01	0.01	0.01
	(0.010)	(0.010)	(0.008)	(0.008)	(0.004)	(0.004)
Dessert Combo	-0.02	-0.02	-0.04	-0.04	0.02	0.02
	(0.042)	(0.042)	(0.038)	(0.038)	(0.022)	(0.022)
Extras	-0.02***	-0.02***	-0.01***	-0.01***	-0.00*	-0.00*
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Others	-0.05*	-0.05*	-0.03*	-0.03*	-0.01*	-0.01*
	(0.018)	(0.018)	(0.016)	(0.016)	(0.005)	(0.005)
NA	-0.04***	-0.04***	-0.04***	-0.04***	-0.00**	-0.00**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Ambiguous	-0.04	-0.04	-0.06**	-0.06**	0.02	0.02
	(0.024)	(0.024)	(0.019)	(0.019)	(0.017)	(0.017)
Observations	134,179,813	134,179,813	134,179,813	134,179,813	134,179,813	134,179,813
Adjusted R^2	0.009	0.008	0.008	0.007	0.005	0.005
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

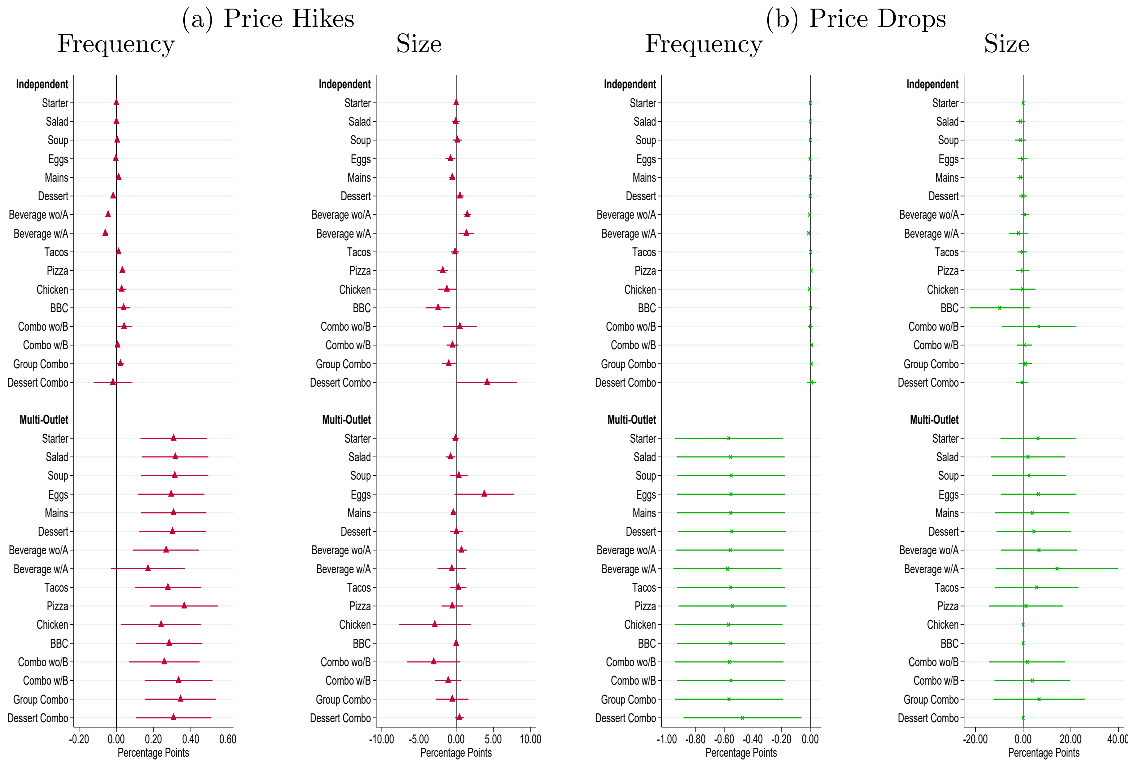
(b) Size of Price Adjustments

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mid \Delta p_{i,n} \mid$	$\mid \Delta p_{i,n} \mid$	$\mid \Delta p^{(+)}_{i,n} \mid$	$\mid \Delta p^{(+)}_{i,n} \mid$	$\mid \Delta p^{(-)}_{i,n} \mid$	$\mid \Delta p^{(-)}_{i,n} \mid$
Salad	-0.20	-0.10	-0.11	0.00	-1.35	-0.71
	(0.252)	(0.249)	(0.236)	(0.236)	(0.842)	(0.862)
Soup	0.09	0.14	0.31	0.30	-1.58	-0.67
	(0.282)	(0.282)	(0.291)	(0.286)	(0.916)	(0.927)
Eggs	-0.45	-0.48	-0.45	-0.50	-1.03	-0.07
	(0.369)	(0.396)	(0.345)	(0.353)	(0.946)	(1.272)
Mains	-0.46*	-0.37*	-0.39*	-0.32	-1.18*	-0.81
	(0.186)	(0.188)	(0.178)	(0.182)	(0.588)	(0.617)
Dessert	0.55*	0.66**	0.60**	0.71**	-0.08	0.17
	(0.234)	(0.238)	(0.225)	(0.233)	(0.716)	(0.749)
Beverage wo/A	1.43***	1.58***	1.49***	1.63***	0.25	0.41
	(0.233)	(0.240)	(0.225)	(0.236)	(0.738)	(0.771)
Beverage w/A	0.84	0.97*	0.81	0.92	-1.71	-1.29
	(0.481)	(0.484)	(0.472)	(0.480)	(1.800)	(1.742)
Tacos	0.20	0.28	0.11	0.20	-0.43	-0.25
	(0.279)	(0.287)	(0.257)	(0.265)	(0.866)	(0.894)
Pizza	-1.97***	-2.00***	-1.73***	-1.88***	-0.50	-0.08
	(0.407)	(0.467)	(0.393)	(0.472)	(1.103)	(1.086)
Chicken	-1.13	-1.03	-1.39*	-1.29*	-0.21	0.13
	(0.633)	(0.608)	(0.595)	(0.577)	(2.479)	(2.461)
BBC	-2.21*	-1.88*	-2.15**	-1.96**	-4.33	-6.36
	(0.902)	(0.880)	(0.767)	(0.752)	(6.115)	(5.932)
Combo wo/B	-0.74	0.03	-0.66	0.39	0.08	0.47
	(1.067)	(1.041)	(1.007)	(0.928)	(3.310)	(2.976)
Combo w/B	-0.12	0.09	-0.45	-0.13	1.55	1.18
	(0.407)	(0.414)	(0.372)	(0.390)	(1.280)	(1.305)
Group Combo	-0.49	-0.28	-0.18	-0.25	-0.50	0.28
	(0.497)	(0.529)	(0.479)	(0.501)	(1.391)	(1.529)
Dessert Combo	6.36**	9.71*	5.25**	4.41*	8.30	12.96*
	(2.384)	(4.262)	(1.941)	(1.792)	(5.715)	(5.496)
Extras	1.01***	1.06***	1.20***	1.29***	-0.63	-0.62
	(0.224)	(0.228)	(0.223)	(0.227)	(0.669)	(0.702)
Others	2.77**	2.69*	3.08***	3.22**	0.38	0.87
	(1.001)	(1.212)	(0.861)	(0.985)	(4.187)	(4.600)
NA	0.91***	1.11***	0.96***	1.13***	-0.33	-0.07
	(0.196)	(0.208)	(0.188)	(0.208)	(0.600)	(0.633)
Ambiguous	-1.63	-1.46	-2.29	-2.47	0.14	0.02
	(1.654)	(1.505)	(1.774)	(1.887)	(1.881)	(1.628)
Observations	282,910	282,910	240,864	240,864	40,356	40,356
Adjusted R^2	0.467	0.436	0.496	0.462	0.615	0.562
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

Note: DOW and DOC stand for day of the week and calendar respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own work.

A.6 Stylized Facts by Type of Restaurant

Figure 28: Stylized Facts of Price Changes by Sign of Adj. and Restaurant Type



Note: Scatters represent point estimates from Equation 5. Whiskers illustrate point estimates' 95% confidence intervals. Results based on dishes (and therefore restaurants) appearing in at least 75% of fortnights in the sample. Estimates are reported in columns (3) and (5) of Table 6 and Table 7. I use web scraped prices from an OFOD platform operating in Mexico City from April 2020 to March 2022. Source: Own calculations.

Table 6: Stylized Facts of Price Changes by Restaurant Type

Linear Probability Model

Representative Dishes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}<0}$	$\mathbb{1}_{\Delta p_{it}<0}$
A. Independent						
Salad	0.00	0.00	0.00	0.00	0.00	0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Soup	0.00	0.00	0.00	0.00	0.00	0.00
	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
Eggs	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.007)	(0.007)	(0.006)	(0.006)	(0.002)	(0.002)
Mains	0.01***	0.01***	0.01***	0.01***	0.00	0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Dessert	-0.02***	-0.02***	-0.02***	-0.02***	-0.00	-0.00
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Beverage wo/A	-0.05***	-0.05***	-0.04***	-0.04***	-0.01**	-0.01**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Beverage w/A	-0.07***	-0.07***	-0.06***	-0.06***	-0.01***	-0.01***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)
Tacos	0.01**	0.01**	0.01**	0.01**	0.00	0.00
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Pizza	0.04***	0.04***	0.03***	0.03***	0.01**	0.01**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)
Chicken	0.02	0.02	0.03*	0.03*	-0.00	-0.00
	(0.014)	(0.014)	(0.013)	(0.013)	(0.005)	(0.005)
BBC	0.04*	0.04*	0.04*	0.04*	0.00	0.00
	(0.018)	(0.018)	(0.017)	(0.017)	(0.004)	(0.004)
Combo wo/B	0.04	0.04	0.04*	0.04*	-0.00	-0.00
	(0.023)	(0.023)	(0.021)	(0.021)	(0.009)	(0.009)
Combo w/B	0.02*	0.02*	0.01	0.01	0.01**	0.01**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)	(0.004)
Group Combo	0.03**	0.03**	0.02*	0.02*	0.01	0.01
	(0.011)	(0.011)	(0.009)	(0.009)	(0.005)	(0.005)
Dessert Combo	-0.01	-0.01	-0.02	-0.02	0.01	0.01
	(0.049)	(0.049)	(0.053)	(0.053)	(0.016)	(0.016)
Extras	-0.02***	-0.02***	-0.01***	-0.01***	-0.00	-0.00
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Others	-0.04	-0.04	-0.03	-0.03	-0.01	-0.01
	(0.021)	(0.021)	(0.018)	(0.018)	(0.006)	(0.006)
B. With Branches						
Starter	-0.26*	-0.25*	0.31***	0.31***	-0.57**	-0.57**
	(0.113)	(0.114)	(0.091)	(0.091)	(0.192)	(0.191)
Salad	-0.24*	-0.23*	0.32***	0.32***	-0.56**	-0.55**
	(0.112)	(0.114)	(0.091)	(0.091)	(0.192)	(0.191)
Soup	-0.24*	-0.23*	0.31***	0.32***	-0.55**	-0.55**
	(0.114)	(0.115)	(0.092)	(0.093)	(0.192)	(0.192)
Eggs	-0.26*	-0.25*	0.29**	0.30**	-0.55**	-0.55**
	(0.113)	(0.115)	(0.091)	(0.092)	(0.192)	(0.192)
Mains	-0.25*	-0.24*	0.31***	0.31***	-0.55**	-0.55**
	(0.112)	(0.113)	(0.090)	(0.091)	(0.192)	(0.191)
Dessert	-0.25*	-0.24*	0.30***	0.31***	-0.55**	-0.55**
	(0.111)	(0.113)	(0.091)	(0.092)	(0.192)	(0.192)
Beverage wo/A	-0.29**	-0.29*	0.27**	0.27**	-0.56**	-0.56**
	(0.112)	(0.113)	(0.090)	(0.091)	(0.192)	(0.191)
Beverage w/A	-0.41**	-0.40**	0.17	0.17	-0.58**	-0.58**
	(0.125)	(0.127)	(0.102)	(0.103)	(0.193)	(0.192)
Tacos	-0.28*	-0.27*	0.28**	0.28**	-0.55**	-0.55**
	(0.112)	(0.114)	(0.091)	(0.092)	(0.192)	(0.191)
Pizza	-0.18	-0.17	0.36***	0.37***	-0.54**	-0.54**
	(0.115)	(0.116)	(0.093)	(0.093)	(0.192)	(0.192)
Chicken	-0.33*	-0.32*	0.24*	0.24*	-0.57**	-0.57**
	(0.128)	(0.129)	(0.110)	(0.111)	(0.192)	(0.191)
BBC	-0.27*	-0.26*	0.28**	0.29**	-0.55**	-0.55**
	(0.112)	(0.114)	(0.091)	(0.092)	(0.192)	(0.191)
Combo wo/B	-0.31**	-0.30*	0.26**	0.26**	-0.56**	-0.56**
	(0.117)	(0.119)	(0.097)	(0.098)	(0.193)	(0.192)
Combo w/B	-0.22	-0.21	0.33***	0.34***	-0.55**	-0.55**
	(0.115)	(0.116)	(0.093)	(0.094)	(0.192)	(0.192)
Group Combo	-0.22	-0.22	0.34***	0.35***	-0.57**	-0.57**
	(0.118)	(0.120)	(0.097)	(0.097)	(0.193)	(0.192)
Dessert Combo	-0.17	-0.16	0.31**	0.31**	-0.47*	-0.47*
	(0.138)	(0.139)	(0.104)	(0.104)	(0.210)	(0.209)
Extras	-0.29**	-0.28*	0.27**	0.27**	-0.56**	-0.56**
	(0.113)	(0.114)	(0.091)	(0.092)	(0.192)	(0.191)
Others	-0.11	-0.10	0.40***	0.41***	-0.51**	-0.51**
	(0.126)	(0.127)	(0.107)	(0.108)	(0.194)	(0.193)
Observations	97,818,922	97,818,922	97,818,922	97,818,922	97,818,922	97,818,922
Adjusted R^2	0.005	0.004	0.005	0.004	0.003	0.002
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

Note: DOW and DOC stand for day of the week and calendar, respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own calculations.

Table 7: Stylized Facts of Price Changes by Restaurant Type

Size of Price Adjustments

Representative Dishes

	(1) $\mid \Delta p_{i,n} \mid$	(2) $\mid \Delta p_{i,n} \mid$	(3) $\mid \Delta p_{i,n}^{(+)} \mid$	(4) $\mid \Delta p_{i,n}^{(+)} \mid$	(5) $\mid \Delta p_{i,n}^{(-)} \mid$	(6) $\mid \Delta p_{i,n}^{(-)} \mid$
A. Independent						
Salad	-0.09	-0.08	-0.06	-0.03	-1.16	-0.88
	(0.277)	(0.278)	(0.264)	(0.261)	(0.985)	(1.023)
Soup	0.06	0.05	0.16	0.14	-1.14	-0.23
	(0.311)	(0.312)	(0.319)	(0.316)	(1.146)	(1.155)
Eggs	-0.74*	-0.79*	-0.77*	-0.84*	-0.27	0.05
	(0.364)	(0.397)	(0.341)	(0.356)	(1.069)	(1.320)
Mains	-0.60**	-0.57**	-0.53**	-0.52*	-1.08	-0.82
	(0.207)	(0.207)	(0.202)	(0.203)	(0.723)	(0.743)
Dessert	0.46	0.46	0.51*	0.51*	-0.08	-0.05
	(0.259)	(0.261)	(0.251)	(0.254)	(0.879)	(0.908)
Beverage wo/A	1.43***	1.54***	1.48***	1.58***	0.73	0.64
	(0.259)	(0.264)	(0.251)	(0.259)	(0.896)	(0.940)
Beverage w/A	1.26*	1.11*	1.37*	1.19*	-1.98	-1.49
	(0.524)	(0.527)	(0.538)	(0.535)	(2.050)	(1.882)
Tacos	-0.09	-0.08	-0.16	-0.15	-0.34	-0.11
	(0.289)	(0.289)	(0.273)	(0.275)	(1.015)	(1.049)
Pizza	-1.89***	-1.93***	-1.80***	-1.90***	-0.25	0.41
	(0.410)	(0.441)	(0.378)	(0.422)	(1.422)	(1.440)
Chicken	-1.11	-1.19	-1.24*	-1.37*	-0.22	0.37
	(0.642)	(0.617)	(0.609)	(0.590)	(2.746)	(2.637)
BBC	-3.04***	-2.92***	-2.44**	-2.45**	-9.82	-11.11
	(0.851)	(0.812)	(0.815)	(0.754)	(6.449)	(7.037)
Combo wo/B	0.70	1.12	0.50	0.99	6.63	7.12
	(1.336)	(1.325)	(1.152)	(1.183)	(7.947)	(6.668)
Combo w/B	-0.30	-0.24	-0.50	-0.40	0.47	0.18
	(0.459)	(0.457)	(0.404)	(0.399)	(1.615)	(1.595)
Group Combo	-1.09*	-1.15*	-0.99*	-1.18*	0.95	1.50
	(0.457)	(0.476)	(0.482)	(0.471)	(1.443)	(1.651)
Dessert Combo	1.41	1.72	4.16*	3.91*	-0.49	-0.49
	(2.689)	(2.613)	(2.055)	(1.811)	(1.335)	(1.176)
Extras	0.94***	0.97***	1.08***	1.10***	-0.63	-0.36
	(0.246)	(0.247)	(0.246)	(0.248)	(0.799)	(0.822)
Others	1.52	1.05	1.94*	1.66*	4.26	-0.16
	(0.963)	(1.050)	(0.839)	(0.829)	(5.332)	(5.262)
B. With Branches						
Starter	3.98	-0.22	-0.09	-0.26	6.26	1.37
	(3.172)	(3.490)	(0.232)	(0.222)	(8.045)	(2.415)
Salad	2.69	-1.52	-0.76*	-0.95*	2.00	-2.02
	(3.162)	(3.482)	(0.331)	(0.397)	(7.968)	(2.231)
Soup	3.66	-0.34	0.36	0.37	2.51	-2.01
	(3.196)	(3.504)	(0.626)	(0.582)	(7.960)	(2.172)
Eggs	8.03*	4.72	3.78	4.10	6.39	8.51
	(3.873)	(4.380)	(2.039)	(2.255)	(8.042)	(6.098)
Mains	3.50	-0.70	-0.40*	-0.48**	3.84	-0.88
	(3.155)	(3.465)	(0.167)	(0.172)	(7.935)	(2.053)
Dessert	3.96	0.02	0.03	0.15	4.47	-0.51
	(3.194)	(3.510)	(0.434)	(0.429)	(7.985)	(2.269)
Beverage wo/A	4.68	0.80	0.71	0.95*	6.65	1.60
	(3.176)	(3.485)	(0.377)	(0.416)	(8.077)	(2.615)
Beverage w/A	3.50	-0.74	-0.59	-0.71	14.23	3.99
	(3.302)	(3.614)	(0.979)	(1.059)	(13.045)	(4.913)
Tacos	4.10	-0.44	0.29	-0.03	5.70	0.40
	(3.200)	(3.500)	(0.557)	(0.484)	(8.938)	(3.956)
Pizza	2.41	-1.40	-0.53	-0.32	1.21	-3.71
	(3.226)	(3.559)	(0.726)	(0.960)	(7.965)	(2.062)
Chicken	0.88	-3.91	-2.87	-3.37	0.00	0.00
	(4.125)	(5.032)	(2.470)	(3.453)	(.)	(.)
Combo wo/B	0.92	-2.27	-3.01	-1.61	1.72	-2.60
	(3.555)	(3.711)	(1.822)	(1.243)	(8.102)	(2.962)
Combo w/B	2.36	-1.69	-1.07	-1.14	3.85	-1.11
	(3.258)	(3.535)	(0.903)	(0.813)	(8.103)	(2.567)
Group Combo	3.18	-0.84	-0.53	-0.41	6.69	3.90
	(3.343)	(3.627)	(1.110)	(1.019)	(9.755)	(9.884)
Dessert Combo	6.64	2.62	0.44	0.63	0.00	0.00
	(3.551)	(3.798)	(0.304)	(0.333)	(.)	(.)
Extras	4.52	0.37	1.11*	1.12*	1.68	-3.63
	(3.174)	(3.495)	(0.457)	(0.475)	(8.034)	(2.565)
Others	16.27***	16.73**	10.13***	15.65***	9.15	16.06***
	(4.265)	(5.236)	(2.585)	(3.836)	(9.049)	(4.657)
Observations	204,897	204,897	179,890	179,891	24,077	24,097
Adjusted R^2	0.459	0.430	0.497	0.461	0.602	0.547
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	.	Yes	.	Yes	.
DOW FE	.	Yes	.	Yes	.	Yes
DOC FE	.	Yes	.	Yes	.	Yes
Month FE	.	Yes	.	Yes	.	Yes
Year FE	.	Yes	.	Yes	.	Yes

Note: DOW and DOC stand for day of the week and calendar, respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own calculations.

A.7 COVID-19 in Mexico City

In this section, I provide a brief description on the COVID-19 pandemic fallout in Mexico City. The aim of this section is to provide an overview on how the FAFH industry was affected by social distancing and other health-related measures implemented to contain the virus. Furthermore, I outline the relief programs that, to the author's knowledge, could have benefited restaurants in Mexico City. Though, with the variables in the OFOD dataset, as well as the public data on relief program recipients, it is not possible to have an idea on the share (or number) of restaurants (owners and/or staff) in the sample under study benefited by any of the programs. Hence, this research does not leverage any relief program data, specially in terms of recipients (restaurant owners or staff).

The first COVID-19 in Mexico was recorded on February 17th, 13 days before the World Health Organization (WHO) declared COVID-19 as a pandemic. As the number of cases started to increase, in addition to the uncertainty on the burden COVID-19 might represent to the health system, Mexico's federal government announced on March 14th, 2020 the closure of non-essential activities starting March 23rd, 2020. Temporal closures considered on-site services of restaurants, bars, eateries and the like. As shown in Figure 29, restaurants and the like suffered a fall in their revenue. However, and importantly for this research, restaurants were not prevented to offer their products through takeaways or delivery services. Therefore, some restaurants kept their kitchens open for takeaways and/or deliveries and, thus, both restaurants and customers saw OFOD platforms as their only channel to stayed in touch.

In April 2020, both national and local authorities started to roll out a number of relief programs oriented to minimize the negative effects of halting non-essential economic activities.[51] Relevant for this research, I only focus on relief programs that might have benefited restaurants' owners or staff:

- First, Mexico City's Economic Development Secretariat started offering firm loans.[52] These business loans ranged from 3,000 to 0.5 million MXN (approximately 150 to 25,000 USD), had fixed interest rates and payments had to be made in a fortnightly basis. Second, Mexico City's Labor Development Secretariat provided cash transfers to employees without fixed salary.[53] Although not all, many workers in the FAFH industry are under these payment scheme (e.g. waiters). Also, not all recipients of this program come from the FAFH industry (e.g. freelancers). Moreover, in order to be elegible as a potential program recipient, workers must have been registered to Mexico City's local authorities by March 23rd, 2020. Third, federal government's Ministry of Trade provided two loans programs aimed at family business and entrepreneurs.[54] These loans were up to 25,000 MXN (approximately

[51] Loans, online platforms for firms to interact, among others.

[52] In Spanish, *Secretaria Desarrollo Económico* in April 2020 offered the program *"Financiamiento para microempresas afectadas por la emergencia sanitaria del COVID-19 en la Ciudad de México"*.

[53] In Spanish, *Secretaria de Trabajo y Desarrollo al Empleo* in April 2020 offered the program *"Apoyo para trabajadoras eventuales, personas desempleadas y no asalariadas"*.

[54] In Spanish, *Secretaria de Economía* in April 2020 offered two programs: (i) *"Créditos Solidarios*

1,250 USD).

- Intuitively, the first and third programs sought to ameliorate the fall in firms' revenue, while the second aimed at lowering (labor) costs. Without firms' demographics (e.g. size, average revenue), as well as the lack of a consistent restaurant identifier across the OFOD dataset and the public data on relief program recipients, it is difficult to grasp an idea on the impact these relief programs on the restaurants in the sample, specially on their price-setting decisions.

On June 5th, 2020, the federal government announced a new risk-tier system based on four colors. From the highest to the lowest risk-tier, colors were red, orange, yellow and green. Regarding the guidelines imposed to FAFH providers as part of the strategies to contain the virus:

- The "Red" stage implied that restaurants could (i) offer their services outdoors only (e.g. parking lots, streets or sidewalks); (ii) serve on-site dining until six in the afternoon and takeaways/deliveries thereafter; (iii) align dining tables in zigzag and 1.5 meters apart; (iv) QR codes for menus were mandatory; and (v) no more than four people per table.
- In the "Orange" stage, restaurants could (i) serve indoors but limited to 30% of capacity; (ii) use natural ventilation but inside air recirculation was partially forbidden (only 30% of air could be recirculated); (iii) music was not allowed; and (iv) implement sanitation stations at the entrance.
- The "Yellow" stage allowed for (i) indoor dining; (ii) up to 50% seating capacity; (iii) playground areas were allowed to reopen with mandatory face mask usage and constant cleaning; (iv) inside air recirculation was partially forbidden (up to 40%).
- "Green" relaxed all the aforementioned measures, while still required the use of face masks, antibacterial gel and set dining tables 1.5 meters apart.

Importantly for this research, it seems all health related restrictions did not affect restaurants' takeaways/deliveries services. However, they affected their on-site dining operations.

The vaccination program started in Mexico on December 24th, 2021.[55] At the program kickoff, inoculation was targeted to health personnel, then to teachers and the elderly (+65) only. After that, ten-year cohorts followed i.e. $65 - 50$, then $49 - 40$, $39 - 30$ and finally $29 - 18$ years old. As Figure 29 shows, the number of fully vaccinated people gained momentum around April 2021 and with a fairly steady increase until January 2022. By the end of the sample in March 2022, nearly 80 million people in Mexico had been fully vaccinated according to *Our World in Data: COVID-19 Vaccination Dataset*.[56]

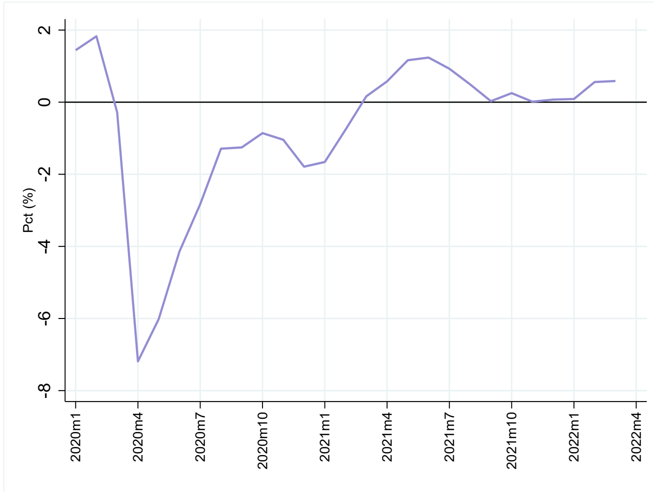
a la Palabra" and (ii) *"Apoyo Solidario a la Palabra"*.

[55] At the time of writing in September 2023, see link https://www.gob.mx/salud/prensa/266-arranca-vacunacion-contra-covid-19-en-mexico.

[56] See Mathieu et al. (2021) for more on how this global public dataset is regularly updated and in-

Figure 29: National FAFH Expenditure Gap on on-site PoS

Excls. transactions in OFOD



Note: This figure uses public data from Banco de Mexico's SIE. Expenditure Gap is calculated as follows. First, total expenditure per month is calculated as the sum of daily expenditures on restaurants' (on-site) PoS from January 2010 to July 2022. Importantly, these transactions are made using physical PoS i.e. on-site, and do not encompass transactions made through OFOD platforms. Monthly statistics are then deflated and seasonally adjusted. Finally, through the use of a HP filter, I plot the cyclical component of the series from January 2020 to March 2022. Source: Author's own work with data from Banco de México.

cludes data on the total number of vaccinations administered, first and second doses administered, daily vaccination rates and population-adjusted coverage for all countries for which data is available. At the time of writing this paper in September 2023, see link https://ourworldindata.org/covid-vaccinations.

A.8 Price-setting Across Pandemic Stages

Table 8: Stylized Facts of Price Changes at Different Stages in the Pandemic
Representative Dishes

(a) Frequency of Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}\neq 0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}>0}$	$\mathbb{1}_{\Delta p_{it}<0}$	$\mathbb{1}_{\Delta p_{it}<0}$
1st Wave (2/2)	-0.02	-0.02	-0.03	-0.02	0.00	0.00
	(0.024)	(0.025)	(0.022)	(0.022)	(0.006)	(0.006)
2nd Wave	0.01	0.02	-0.00	0.00	0.02**	0.02**
	(0.020)	(0.021)	(0.019)	(0.019)	(0.006)	(0.006)
3rd Wave	-0.05***	-0.05**	-0.05***	-0.05***	0.00	0.00
	(0.015)	(0.015)	(0.014)	(0.014)	(0.005)	(0.005)
4th Wave	0.08***	0.08***	0.07***	0.07***	0.00	0.01
	(0.023)	(0.023)	(0.021)	(0.021)	(0.006)	(0.006)
Observations	97818922	97818879	97818922	97818879	97818922	97818879
Adjusted R^2	0.004	0.002	0.004	0.001	0.002	0.001
Restaurant FE	Yes	.	Yes	.	Yes	.
Type of Dish FE	Yes	.	Yes	.	Yes	.
Product FE	.	Yes	.	Yes	.	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
DOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Size of Price Adjustments

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mid \Delta p_{i,n} \mid$	$\mid \Delta p_{i,n} \mid$	$\mid \Delta p^{(+)}_{i,n} \mid$	$\mid \Delta p^{(+)}_{i,n} \mid$	$\mid \Delta p^{(-)}_{i,n} \mid$	$\mid \Delta p^{(-)}_{i,n} \mid$
1st Wave (2/2)	-0.63	-1.27	-1.65*	-1.90	5.25*	1.88
	(0.783)	(0.996)	(0.838)	(1.085)	(2.244)	(4.523)
2nd Wave	-0.40	-0.95	-0.49	-0.57	0.46	-2.71
	(0.876)	(1.127)	(0.896)	(1.139)	(2.316)	(4.407)
3rd Wave	-1.92**	-2.17**	-2.13***	-2.19**	0.98	-0.37
	(0.598)	(0.742)	(0.612)	(0.765)	(1.783)	(3.783)
4th Wave	-1.42	-1.74	-1.41	-1.26	0.02	-1.88
	(0.927)	(1.213)	(0.964)	(1.251)	(2.593)	(4.835)
Observations	204897	130159	179891	108522	24097	10736
Adjusted R^2	0.430	0.524	0.461	0.519	0.548	0.781
Restaurant FE	Yes	.	Yes	.	Yes	.
Type of Dish FE	Yes	.	Yes	.	Yes	.
Product FE	.	Yes	.	Yes	.	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
DOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: DOW and DOC stand for day of the week and calendar, respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own elaboration.

A.9 Stylized Facts Using the Color-Tier System

I follow the same empirical strategy as in Subsection 3.2.3, but I substitute $Pandemic_k$ by $RiskColor_n$, which is the color-tier system in Mexico City as shown in Panel 10b:

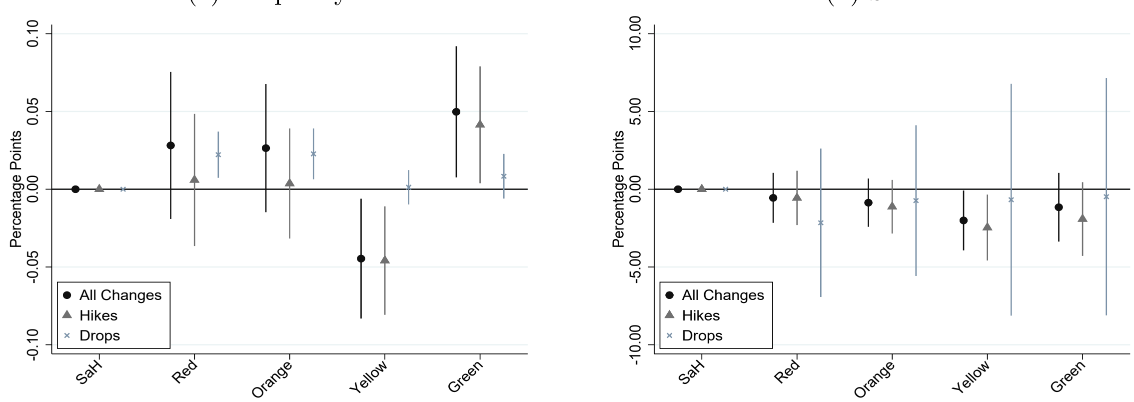
$$z_{i,j,t} = \beta_1 x_{dishtype} \times RiskColor_n + \theta_j + \theta_N + \varepsilon_{i,n} \tag{7}$$

In terms of color-tier system, "Red" and "Orange" states do not report a statistically significant difference to the "Stay at Home" or "SaH" base category. Nonetheless, their point estimates are positive implying somewhat more frequent price changes. It seems that for these two states price changes were mainly driven by price drops. Then, the "Yellow" state sees statistically significant (10%) less frequent price changes. The "Green" state is the one with more price changes (10%) with respect to the the other states. For these last two states price hikes were relevant drivers behind price adjustments.

Moving on to the size of price changes, point estimates from all states changed by smaller margins on average relative to the base category. Only the "Yellow" state reported a statistically significant smaller intensive margin of adjustment (10%). As described above, the number of price drops are not as many as price hikes, toppled with aggressive discount strategies, lead to wide confidence intervals for the central moment of price drops estimates.

Figure 30: Stylized Facts of Price Changes at Different Risk-Tier Colors
Sorted from Highest (left) to Lowest (right) Risk
Coefficients as Deviations From Base Category

(a) Frequency (b) Size



Note: Scatters in Panel 30a and in Panel 30b represent point estimates from Equation 7. Regression results are reported in Table 9. Whiskers in both panels illustrate the 95% confidence intervals of point estimates. Estimates obtained using products observed in at least 75% of fortnights between April 2020 and March 2022. *1st Wave (1/2)* is the base category. Data comes from web scraped prices as displayed on an OFOD platform operating in Mexico City. For more on the data, see Section 2. Source: Author's own estimates.

Table 9: Stylized Facts of Price Changes at Different Risk-Tier Colors
Frequency of Price Adjustments
Representative Dishes

(a) Frequency of Price Changes

	(1) $\mathbb{1}_{\Delta p_{it}\neq 0}$	(2) $\mathbb{1}_{\Delta p_{it}\neq 0}$	(3) $\mathbb{1}_{\Delta p_{it}>0}$	(4) $\mathbb{1}_{\Delta p_{it}>0}$	(5) $\mathbb{1}_{\Delta p_{it}<0}$	(6) $\mathbb{1}_{\Delta p_{it}<0}$
Red	0.03	0.03	0.01	0.01	0.02**	0.02**
	(0.024)	(0.024)	(0.022)	(0.022)	(0.008)	(0.008)
Orange	0.03	0.03	0.00	0.01	0.02**	0.02**
	(0.021)	(0.021)	(0.018)	(0.018)	(0.008)	(0.009)
Yellow	-0.04*	-0.04	-0.05**	-0.04*	0.00	0.00
	(0.020)	(0.020)	(0.018)	(0.018)	(0.006)	(0.006)
Green	0.05*	0.05*	0.04*	0.04*	0.01	0.01
	(0.022)	(0.022)	(0.019)	(0.019)	(0.007)	(0.007)
Observations	97818922	97818879	97818922	97818879	97818922	97818879
Adjusted R^2	0.004	0.002	0.004	0.001	0.002	0.001
Restaurant FE	Yes	.	Yes	.	Yes	.
Type of Dish FE	Yes	.	Yes	.	Yes	.
Product FE	.	Yes	.	Yes	.	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
DOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Size of Price Adjustments

	(1) $\mid \Delta p_{i,n} \mid$	(2) $\mid \Delta p_{i,n} \mid$	(3) $\mid \Delta p_{i,n}^{(+)} \mid$	(4) $\mid \Delta p_{i,n}^{(+)} \mid$	(5) $\mid \Delta p_{i,n}^{(-)} \mid$	(6) $\mid \Delta p_{i,n}^{(-)} \mid$
Red	-0.55	-1.04	-0.56	-1.22	-2.16	-0.05
	(0.819)	(1.025)	(0.891)	(1.196)	(2.434)	(5.242)
Orange	-0.86	-2.05*	-1.12	-2.31*	-0.73	0.50
	(0.792)	(0.920)	(0.879)	(1.133)	(2.471)	(4.560)
Yellow	-2.01*	-3.12***	-2.46*	-3.02***	-0.68	-2.95
	(0.981)	(0.809)	(1.080)	(0.907)	(3.800)	(4.879)
Green	-1.16	-2.38**	-1.92	-2.54*	-0.48	-0.33
	(1.127)	(0.910)	(1.209)	(1.049)	(3.891)	(4.823)
Observations	204897	130159	179891	108522	24097	10736
Adjusted R^2	0.430	0.524	0.461	0.519	0.547	0.781
Restaurant FE	Yes	.	Yes	.	Yes	.
Type of Dish FE	Yes	.	Yes	.	Yes	.
Product FE	.	Yes	.	Yes	.	Yes
DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
DOC FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: DOW and DOC stand for day of the week and calendar, respectively. Estimates multiplied by 100 for illustration purposes. Standard errors clustered at restaurant level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's own calculations.