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COVID-19 AND THE DEMAND FOR ONLINE FOOD SHOPPING SERVICES: EMPIRICAL EVIDENCE FROM TAIWAN

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ABSTRACT

We investigate how the coronavirus pandemic affected the demand for online food shopping services using data from the largest agri-food e-commerce platform in Taiwan. We find that an additional confirmed case of COVID-19 increased sales by 5.7% and the number of customers by 4.9%. The demand for grains, fresh fruit and vegetables, and frozen foods increased the most, which benefited small farms over agribusinesses. Online food shopping was highly responsive to COVID-19 media coverage and online content. Because Taiwan did not impose a stay-at-home order, the demand for online food shopping may be similar in other countries after they lift mobility restrictions.

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A data appendix is available at http://www.nber.org/data-appendix/w27427

1. Introduction

The coronavirus disease (COVID-19) pandemic has created unprecedented challenges for the agri-food industry. After public health officials across the globe recommended social distancing and governments implemented stay-at-home orders and travel restrictions, retail food establishments and farmers experienced both demand and supply shocks (WHO 2020; The World Bank 2020). Due to widespread prohibitions on dining inside restaurants, demand for restaurant food has decreased dramatically since the beginning of the pandemic, and restaurants unable to offer take-out services have closed (Mohammed 2020). The resulting shift in demand away from food eaten away from home (FAFH) towards the food purchased at supermarkets, grocery stores and convenience stores has resulted in shortages and declining inventory levels of some food products (Uhler 2020). In the U.S., for example, just over half of food expenditures prior to the pandemic where for FAFH (Saksena et al. 2018). With FAFH options limited to take-out in much of the U.S., grocery and beverage store sales increased more than 25% in March 2020 (Redman 2020a). Likewise, March grocery store sales increased by 20% in the U.K., setting a four-week sales record (Mattinson 2020).

COVID-19 has also caused disruptions to the agri-food supply chain that have exacerbated difficulties in bringing food to market in sufficient quantity to meet surging demand. One significant short-term difficulty has been shifting agricultural products from restaurants to a retail food sector that has different storage capacity and transportation infrastructure (Hart et al. 2020; Hobbs 2020). Keeping food processing plants operational while maintaining adequate protection for employees has also been a major challenge, and the spread of the coronavirus at some facilities has caused them to close (Hailu 2020; Gallagher and Kirkland 2020). Numerous media outlets report similar difficulties at food warehouses and shipping companies (Newton 2020; Narayan 2020; Davis 2020). International shipping of commodities across national borders has also slowed due to reductions in demand for manufactured goods that have limited capacity for reciprocal trade in agricultural products (Gray 2020; King 2020). Additional inspections and food safety investigations at national borders also slow agricultural trade in both directions, and international travel restrictions stand to limit seasonal farm labor migration during upcoming harvests (Hobbs 2020; Hooper and Le Coz 2020).

Despite the difficulties experienced by food shoppers due to COVID-19, such as limited public transportation, food stockouts (i.e. exhausted inventories), and reduced hours at supermarkets and grocery stores, most shoppers in developed countries such as the U.S. have maintained adequate access to food (U.S. FDA 2020).[1] This is in no small part due to the availability of online e-commerce platforms that allow consumers to shop for food over the internet and have it either delivered to their home, or set aside for curbside pick-up. Prior to the pandemic, online food shopping was gaining popularity in many countries, but travel restrictions and the fear of infection have quickly led consumers to choose online shopping as their preferred means of purchasing food (Singh 2019; Debter 2020). As a consequence, online grocery sales in the U.S. are projected to grow 40% in 2020, and e-commerce sales at Walmart increased 74% in April 2020 despite a drop in foot traffic at stores (Redman 2020b; Nassauer 2020a). Likewise, e-commerce sales at U.S. Target stores rose 141% in each month of the first quarter of 2020 while comparable in-store sales increased less than 1% (Nassauer 2020b). Online food shopping in China and Europe has also increased significantly since the start of the pandemic (Cheng 2020; von Abrams 2020). In many cases, nascent e-commerce platforms have had difficulty accommodating the surge in online customers, leading to long processing and delivery wait times for consumers (Gray 2020; Debter 2020).

By allowing consumers to obtain food from home, it is very likely that online food shopping has helped to slow the transmission of the coronavirus and protect at-risk consumers with pre-existing conditions. E-commerce platforms may both provide customers with convenient options and generate positive externalities in the form of lower infection rates and reduced health care costs. It is therefore important to understand what drives the use of online food shopping services. In this paper, we analyze several critical aspects of consumers' online food shopping decisions using transaction data from the largest online platform selling agri-food products in Taiwan. First, we measure how online shopping responds to the number of COVID-19 cases in an individual's local area. In doing so, we consider not only how case counts affect financial measures of the e-commerce platform, but also what types of foods consumers purchase and which suppliers benefit the most from the increase in demand brought about by the pandemic.

Since there may be a delay between the growth in infections and consumer awareness of infection rates in their local area, we next measure how the use of online shopping responds to a measure of internet searches about the coronavirus. Last, we consider how the focus of news media on COVID-19 affects consumer participation in online food shopping. Past research suggests that news articles may both reflect consumers' sentiment and shape opinions (Zucker 1978; Happer and Philo 2013;

[1] Due to limited availability of fresh fruits and vegetables, some consumers in developed countries have shifted to pre-prepared foods that are less health (Wunsch 2020; Miriri and Hunt 2020). In developing countries where food shortages are more acute, the potential exists for more serious and widespread malnutrition (Dahir 2020; World Food Program USA 2020).

Hopkins, Kim and Kim 2017). By analyzing both the effect of actual COVID-19 case counts and news coverage of the pandemic we can infer whether consumers' response to news media is consistent with their response to the actual number of COVID-19 cases in their community.

The online food shopping industry is in a unique stage of its development. Prior to the coronavirus pandemic the use of online shopping was increasing at a steady state as platforms became more user-friendly. While some projected that online food shopping would soon challenge a dominant retail food industry, online purchases were typically less than 5% of total sales (Redman 2020b; IGD 2017; Nielsen 2015). As the first paper to investigate the demand for online food shopping services during the COVID-19 period, we provide evidence of how COVID-19 has caused a shift in the mode of food delivery that could ultimately lead to a realignment of the retail food sector.

2. COVID-19 and agri-food e-commerce in Taiwan

Because Taiwan is only 81 miles from mainland China, and there is steady travel between the two countries[2], the number of COVID-19 cases in Taiwan was expected to be high (Wang, Ng and Brook 2020). Despite such inherent risk, Taiwan's confirmed case count and the case-fatality rate is relatively low (JHU CSSE 2020). Following the first confirmed case of COVID-19 in Taiwan on January 21, 2020, the government initiated a coordinated response involving central disease surveillance, border control policies, and contact tracing that largely contained the virus. Although Taiwan has had ongoing success with disease control, anxiety over the spread of COVID-19 was high at the beginning of the outbreak (Wang, Ng and Brook 2020).

Prior to the coronavirus pandemic, the agri-food e-commerce industry in Taiwan was growing steadily but still much smaller than the traditional retail sector. By 2016, online sales of food reached NT $15 billion (Liu, 2016). In addition, Taiwan's Council of Agriculture sponsored training programs for farmers in key areas such as internet marketing and e-commerce business models in order to promote farm-to-consumer internet sales. The programs, in conjunction with the Taiwan Agriculture and Food Traceability System[3], help organic and small producers become more competitive by bypassing wholesalers and highlighting the origin or healthfulness of products (Taiwan Today 2016).

[2] For example, there were over 2.7 million visitors to Taiwan from China in 2019 (Wang and Lin 2020).

[3] The Taiwan Agriculture and Food Traceability System, established in 2007, provides consumers with information on the origin agricultural produce and ingredients.

3. Data

We used data from several sources to conduct our analysis, including administrative sales records from a large agri-food e-commerce platform, information about coronavirus cases in Taiwan, search data from Google, and data on COVID-19 news articles from Taiwan's largest newspapers.

3.1. Administrative sales records from the Ubox platform

We created several measures of online food shopping using data from the administrative transaction records of Ubox[4], the largest business-to-consumer agri-food e-commerce platform in Taiwan. Ubox is a non-profit corporation established in 1999 by the Council of Agriculture to sell food from agricultural business cooperatives and individual farms directly to consumers. Prior to the advent of Ubox, other e-commerce platforms rarely offered agri-food products due to their perishable nature. Although Taiwan's farm associations initially sponsored Ubox, the platform does not restrict the source of its products. Ubox delivers food ordered on its platform directly to a consumer's home through an express delivery shipping service. Similar to other e-commerce platforms, Ubox's revenue is derived from a 10-15% charge applied to the sales value of each transaction (Wu 2017).

Transaction records from Ubox include the amount of each food product sold to consumers and the associated expenditure at the individual transaction-level. The records also contain the date of the transaction and the purchaser's zip code, allowing us to aggregate sales data to the county level for each week.[5] In addition to sales transactions, the data contain the payments received by each seller and the profit made on the platform from each transaction. We can identify whether a seller is a member of one of the following three categories: farmer association/marketing cooperative, agribusiness cooperative and individual farm. The data also contain the following six product identifiers: frozen food, fresh fruit or vegetables, whole grains, non-alcoholic drinks, other types of food products and non-food products. By aggregating individual transactions within these product categories, we created a panel dataset at the product category-county-week level.

Since Taiwan confirmed its first case of the COVID-19 on January 21, 2020, we constructed a treated sample using Ubox transactions over the 11-week period from January 21, 2020 to April 6, 2020.[6] We then constructed a control sample using Ubox transactions from 2017, 2018, and 2019 that occurred during the same week range. There are 2,686 observations in both samples combined. We don't include

[4] https://www.ubox.org.tw/

[5] There are 21 counties in Taiwan. The average size of each county is 1,723 square kilometers.

[6] There were between 6,522 and 13,427 transactions during the 11-week periods in 2017 - 2020.

transactions that occurred in the weeks just prior to January 21, 2020 in our control sample because both the demand for many food products and their supply is seasonal, and we believe it is more appropriate to have the control sample during the same season as our treated sample.

We created several variables at the product category-county-week level that we used as dependent variables in our empirical models. These include total sales, total payments received by producers, total Ubox profits, the number of consumers that used the platform, the number of producers who sold products on the platform, and a product variety index. Following Chu and Manchanda (2016), we constructed the latter as: $V_p = 1 - HHI_p = 1 - \sum_{i=1}^{N} S_{ip}^2$, where p indicates product category and $i = 1, \ldots, N$ indexes individual products within a given product category. HHI is the Herfindahl-Hirschman index, which we calculated from the squared shares of the quantity of individual products sold within each product category. The HHI ranges between 0 and 1, where a value of 1 indicates that only 1 item was sold in the product category, and the value of 0 is achieved when the number of items sold in the product category becomes infinitely large. Therefore, higher values of V_p indicate greater diversity in the number of individual foods sold within a product category.

The control variables we constructed from the Ubox records include six variables that indicate product category and three variables that capture the product seller. The latter are the ratios of products sold by farmer associations/marketing cooperatives, agribusinesses, or individual farms in each product category in every county during each week.

3.2. COVID-19 case counts

From the Center of Disease Control (CDC) in Taiwan, we obtained the number of confirmed and suspected cases of COVID-19 in each county and week between January 21, 2020 and April 6, 2020. Confirmed cases were validated by a COVD-19 test, while suspected cases are non-confirmed cases that were reported to the CDC because the healthcare provider felt that the patient exhibited symptoms consistent with a COVID-19 infection. Only confirmed cases are reported to the public during CDC press conferences. We created measures of the weekly number of confirmed and total cases and the cumulative number of confirmed and total cases and merged the associated variables to the UBox data by county identification number and week. Figure 1 shows the geographical distribution of cumulative confirmed COVID-19 cases in Taiwan, as of April 6, 2020 at the county level. There is a clear correlation between case counts and population density, with the largest number of cases concentrated in Taipei and the western part of the island.

3.3. *COVID-19 web searches and newspaper articles*

While case count data allows us to track the spread of the virus across counties and time, they don't perfectly correlate to consumer information about the spread of COVID-19. This is because there can be a delay between when case counts are reported and when consumers learn about the infection rate in their local area. In order to better measure consumer receipt of information about the virus we obtained two variables that measure web search activity on Google.com from the Google Trends data.[7] Using these data one can extract index values that measure the popularity of web searches for particular terms in a given location across time. We extracted one index that measures the popularity of web searches for "COVID-19" or "Coronavirus" during each week of our treatment period across Taiwan. The second index is based on the number of new article searches for these same terms during the treatment period.

Web searches provide one measure of information seeking by consumers, but many consumers access information on a regular basis without the aid of the internet. This is particularly true of older consumers. In order to better measure the availability of information about COVID-19 we aggregated the number of times during each week of the treatment period that the text "COVID-19" or "Coronavirus" appeared in each of Taiwan's five largest newspapers. This last variable provides a measure of media influence on the intensity of online food shopping. We merged all three variables to the Ubox data using week identifiers in year 2020.

3.4. *Descriptive statistics*

In Table 1 we report week-by-week changes in the number of confirmed COVID-19 infections and the number of total (confirmed and suspected) COVID-19 cases for the 11-week period following the first confirmed case on January 21, 2020. Confirmed cases never exceed 2% of total cases in any week of the sample period. Weekly confirmed cases peek at 129 in the 9th week following the initial infection at the same time that total cases are at their highest point. However, confirmed cases continue to decline in the 11th week despite an increase in suspected cases over the 10th week. During the 11th week cumulative cases were only 372, or 15.6 per million. In comparison, confirmed cases in the U.S. 11 weeks after the first known case were 634 per million.[8]

Table 1 also contains the weekly index values measuring Google keyword

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7 https://trends.google.com/trends/?geo=US

8 This calculation is based on the daily COVID-19 case counts provided by the CDC (https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html), and the projected 2020 population of the U.S. from the United Nations Population Division (Available at https://www.worldometers.info/world-population/population-by-country/).

searches, Google news searches and newspaper mentions of COVID-19/Coronavirus. Keyword searches initially peak in the second week following the first reported case, decline, and peak again to their highest level in the 9th week when infections also peak. Newspaper mentions of COVID-19 follow a similar patter, as do news searches, although the latter are still rising in the 11th week. It is interesting that the second surge in Google searches and newspaper mentions correlates with the weekly number of confirmed cases, rather than the cumulative confirmed case count. This is consistent with the contemporaneous infection rate driving consumers' desire for COVID-19 information, rather than past levels of infection.

We report the mean and standard deviation for all variables during the COVID-19 period and the control period in Table 2. The measures of online food shopping are higher in the COVID-19 period than the control period, and there is a corresponding shift in the ratio of products sold by farm cooperatives at the expense of those sold by individual farms (the ratio business cooperative sales is unchanged). Finally, there is a small increase in the proportion of frozen food and grain products purchased during the COVID-19 period, and a small decrease in other food purchases.

4. Empirical Model

We used a panel data model to identify the impact of the coronavirus pandemic on several different measures of online food shopping (Wooldridge 2010). The Ordinary Least Squares (OLS) estimating equation is:

$$(1) \qquad Y_{ijt} = \alpha + \gamma \cdot COVID19_{jt} + \ \beta' X_{ijt} + t_{year} + t_{week} + c_j + \varepsilon_{ijt}$$

where Y_{ijt} is one of the following the outcome variables for a Ubox transaction in product category i in county j during time t: platform sales, payments to producers, platform profits, product variety, number of customers, or number of producers $COVID19_{jt}$ is a continuous variable measuring one of the following in county j and during week t: the weekly number of confirmed COVID-19 cases, the cumulative number of confirmed COVID-19 cases, the weekly number of total (confirmed and suspected) COVID-19 cases, or the cumulative number of total COVID-19 cases. X_{ijt} is a vector of explanatory variables that includes the ratio of products sold by food cooperatives, agribusinesses and individuals farms, and indicator variables for product category (see Table 2 for more information); t_{year} and t_{week} are time fixed effects for year and week, respectively; c_j is a county-level fixed effect; ε_{ijt} is a random error component. The parameter γ, which measures the impact of an additional case of COVID-19 on the outcome variable, is identified using variation in COVID-19 cases over time within county (across both the COVID-

19 and non-COVID-19 period).

We used the same specification to estimate the effect of a 100-unit change in the index measuring weekly COVID-19 Google web searches and news searches or the number COVID-19/Coronavirus mentions in newspaper articles. However, in this case the explanatory variables of interest do not vary by county. For both sets of models, we used the two-way-cluster-robust variance approach proposed by Cameron and Miller (2015) to cluster the standard errors of the coefficients at both the county and week level.

5. **Empirical Results**

5.1. The effect of the COVID-19 pandemic on online food shopping through Ubox

Table 3 contains our estimates of the impact of weekly and cumulative confirmed COVID-19 cases on Ubox platform sales, payments to producers who sell their food products on Ubox, and Ubox platform profits. Full estimation results for the platform sales model are also reported in Appendix Table A1. An additional confirmed case of COVID-19 during a one-week timeframe increased Ubox sales by NT$ 249 per week (the point estimate is 0.249 in NT$1,000/week). By dividing this estimate by the mean sales value in the non-COVID-19 period (NT$ 4,392), we find that sales increased by 5.7% due to an additional COVID-19 case. The marginal effect of one additional confirmed case per week had a similar effect on payments to producers and platform profits. In the case of the former, this is because Ubox charges a similar commission to producers, irrespective of their size. Ubox platform sales, payments and profits are all less responsive to an increase in the cumulative number of confirmed cases than a contemporaneous increase in weekly cases. A one unit increase in the cumulative case count increased the three measures by only 1.5% – 1.7%.

In Table 4 we report fixed effect estimates for two additional measures of online food shopping, the number of Ubox customers and suppliers, and our measure of the variety of food products sold on Ubox. At 4.9% and 5.0%, the effect of an additional weekly confirmed case of COVID-19 on the number of consumers and suppliers, respectively, are only slightly smaller than the marginal effects for the financial measures of Ubox use. In contrast, product variety increased only 1.0% per additional case. Again, all three measures are much less responsive to a change in the cumulative number of confirmed COVID-19 cases than the contemporaneous number of cases.

We next consider the impact of confirmed COVID-19 cases on Ubox sales separately for each type of food product and supplier. The estimates in panel A of Table 5 indicate that purchases of grain rose the most during the COVID-19 period (13.1% per additional confirmed case), followed by fruits and vegetables (9.6%) and frozen food (5.6%). Point estimates for purchases of drinks, other food and non-food products are all positive, but imprecisely estimated. In panel B we report estimates from supplier-specific models. Individual farms experienced the largest increase in demand from COVID-19, with sales increasing 8.9% per additional confirmed case. Agribusinesses and farm cooperatives experienced a slightly smaller increase in demand, with sales increasing by 5.4% and 4.4% per case, respectively.

Because there were two counties in Taiwan without any COVID-19 cases, we have the opportunity to test whether the presence of infections in other parts of the country influenced the online shopping behavior of those living in areas that were free of COVID-19. To investigate the existence of such "spillover effects", we regressed Ubox sales from the two counties without COVID-19 cases on the total number of weekly or cumulative confirmed cases aggregated over all other counties in Taiwan. The results, reported in Table 6, indicate a small spillover effect of infections in other parts of the country in the two counties without any COVID-19 cases. Specifically, an additional weekly case of COVID-19 was associated with a 1.7% increase in Ubox sales in the counties without cases. Likewise, sales increased by 0.7% with the addition of one cumulative case.

5.2. The effect of information seeking and availability on Ubox sales

Panel A of Table 7 contains estimates of the effect Google web and news searches and newspaper mentions of COVID-19/Coronavirus on Ubox sales in all counties of Taiwan. In order to compare the effects of a 100 index unit change in Google searches to a 100 word change in newspaper mentions, we report elasticities computed using the mean values during the COVID-19 period.[9] We find that Ubox sales are more strongly associated with the frequency that COVID-19 was mentioned in newspapers than Google searches for COVID-19. In particular, a 1% increase in Google web searches is associated with a 0.8% increase in Ubox sales, and the elasticity for Google news searches is slightly smaller in magnitude. In contrast, a 1% increase in newspaper mentions of COVID-19 is associated with a much larger 3.8% increase in Ubox sales. In panel B of Table 7 we present estimates for Google searches and newspaper mentions from models where the dependent variable is Ubox sales in the two counties in Taiwan without any COVID-19 infections. The elasticity estimates are all much smaller than for full sample in panel A, but they are still statistically significant, suggesting there is some spillover effect of information about COVID-19 in counties with confirmed cases.

[9] In other tables, when we express marginal effects in percentage terms we use the mean of the non-COVID-19 period in order to accurately characterize the percentage increase in the marginal effect due to COVID-19. In this case, however, it is the elasticity during the COVID-19 period that is of interest, not the elasticity during the average period (when COVID-19 is present only 25% of the time).

5.3. Specification tests and robustness checks

We subjected our models to several tests in order to validate our specification and gage the robustness of our results. First, we tested whether our key regressors, weekly and cumulative confirmed COVID-19 cases, exhibit a linear or nonlinear relationship with Ubox platform sales by estimating Robinson's semiparametric partial linear model (Robinson 1988; Verardi and Debarsy 2012). Under this specification, weekly or cumulative cases enter the model as a Gaussian kernel-weighted polynomial. Hardle and Mammen (1993) developed a test of whether the nonparametric component of the model can be approximated by a parametric polynomial. Implementing the test for a polynomial of order one is a test of the typical linear parametric specification. Appendix Table A2 contain estimates from the semiparametric partial linear model and the test results for linearity of the weekly and cumulative case variables. For both regressors, we fail to reject the null hypothesis that the model is linear in the key regressor. Plots of the nonparametric relationship between weekly and cumulative COVID-19 cases and Ubox sales in Figure A1 provide further evidence of a linear relationship between the regressors and outcome variable.

We next investigated whether the treatment and control periods in our fixed effect model are properly defined. The beginning of our treatment period is the day of the first confirmed case of COVID-19 in Taiwan. However, prior to this date there were numerous confirmed cases of COVID-19 in China, and it is possible that consumers in Taiwan could have changed their food shopping habits in response to media reports about the outbreak in China. To test for evidence of such an "anticipation effect" we estimated our model of Ubox sales on Google web and news searches and COVID-19 newspaper mentions using the three weeks prior to the first confirmed case of COVID-19 in Taiwan.[10] As shown in Table A3, the coefficient estimates for all three information variables are statistically insignificant, suggesting consumers in Taiwan did not increase their use of Ubox prior to the advent of coronavirus cases in Taiwan.

In our main models we pool the January 21 – April 6 period for 2017, 2018 and 2019 to create the non-COVID-19 (control) period in our model. In order to test whether years earlier in time provide the same control properties as years closer in time to the treatment period, we re-estimated the models for Ubox sales separately using each of the three control years. The estimates in Table A4 are similar across all three years, suggesting that pooling the three yearly samples in the control period is appropriate.

[10] An anticipation effect occurs if consumers in Taiwan change their food shopping behavior prior to confirmation of any COVID-19 cases in Taiwan under the assumption that there are undetected cases in the community.

Throughout the analysis we use confirmed rather than confirmed and suspected (i.e. total) cases of COVID-19 to measure the impact of the pandemic on the outcome variables. Our rationale is that only conformed cases are included in weekly CDC press conferences on infections rates. In addition, we are unsure of the accuracy of un-confirmed COVID-19 diagnoses. In Table A5 we report estimates for models of Ubox financial outcomes that use total (confirmed and suspected) cases. We divided the two COVID-19 case count variables by 100 to put them on roughly the same scale as the confirmed case counts.[11] The magnitude of an additional 100 weekly cases is approximately three times larger, and an additional 100 cumulative cases one and half times larger than estimates from the models that use confirmed cases. By implication, total cases may be more highly correlated with consumer information about the threat of the coronavirus pandemic than confirmed cases. However, we prefer using confirmed cases for our main results because this measure is not subject to the differential beliefs of healthcare providers. In addition, the non-monotonic trend in weekly total cases in Table 1 suggests that there could be a significant amount of measurement error in suspected cases.

Both Ubox sales and confirmed cases of COVID-19 are trending upward over time. We include week and year fixed effects in our models to account for the deterministic trend in Ubox sales, but we wanted to investigate whether our estimates might still reflect a spurious correlated in two positively trending variables. We therefore conducted a falsification test by regressing the financial measures of Ubox performance in the control period on weekly and cumulative cases. The estimates, reported in Table A6, are statistically insignificant in all cases, which is consistent with the failure of our models to reflect a spurious correlation.

A final concern is that confirmed COVID-19 cases counts could be correlated with time-varying unobservable factors that determine consumer preferences for online food shopping. For example, those with a higher tolerance for risk may be more likely to contract COVID-19 and less likely to order food from Ubox. In order to assess the potential for this type of endogeneity to bias our estimates we implemented the sensitivity analysis proposed by Oster (2019), which is based on earlier work by Altonji et al. (2005). Under the assumption that selection on the observed covariates is proportional to selection on unobservable factors, Oster (2019) constructs an estimator for the degree of selection on unobservables relative to observables (δ) needed for the true effect of the treatment variable to be a statistical null. We report estimates of δ for both weekly and cumulative confirmed cases in the models of Ubox platform profits, payments to producers and profits in Table A7[12].

[11] The COVID-19 period mean of total cases is 300 and the mean on just confirmed cases is 3.17.

[12] To implement the sensitivity analysis, we include all of the explanatory variables and the fixed

The values range from 2.4 – 2.8, suggesting that a very high level of selection on unbservables is required for our non-zero estimates to represent a spurious correlation. Both Oster (2019) and Altonji et al. (2005) suggest one as a reasonable upper bound for δ.

6. Discussion and Conclusions

By analyzing several financial performance measures of Ubox, an online food shopping platform, we find that the COVID-19 pandemic significantly increased online food shopping in Taiwan. Given that Ubox sales increased by 5.7% per additional case, there was an 18% increase in sales during the average week after COVID-19 arrived in Taiwan. Likewise, Ubox customers grew 16% in a typical week during the COVID-19 period. Such a rapid increase in demand raises the question of whether food supply chain restrictions may have limited Ubox's ability to meet the requests of all potential customers. If in fact Ubox was operating at capacity during the COVID-19 period then our models will underestimate the latent demand for online food shopping services during the pandemic.

Both the increase in demand for online Ubox products and the consequent effects on the supply chain were not uniform across food product categories. Grain products experienced the largest surge in demand, which could be due to the storable nature of raw grain, and an increase in home production of grain-based foods like breads and bakery items. In a typical week, sales from grain increased approximately 42% during the COVID-19 period. Fresh fruit and vegetables and frozen food were also in high demand. The latter is storable, much like grain, but this is not the case for fresh fruit and vegetables. Nonetheless, consumers in Taiwan typically purchase fresh fruit and vegetables in outdoor markets, which could be risky to patronize during the pandemic. COVID-19 did not benefit all producers equally. Products sold by individual farms experienced stronger demand than those sold by larger agribusinesses and farm cooperatives. The benefit to individual farms may be due in part to their proportionally larger share of fresh fruits and vegetables sold through the Ubox platform.[13]

We find that the variety of food products purchased on Ubox increased during the COVID-19 period. This could be due to the use of the platform by new customers with different preferences than existing customers. Alternatively, it could reflect the substitution of food prepared at home for FAFH as customers sought to limit their exposure to others in the community. In order to replace meals typically purchased at

effects. Therefore, we tested the remaining bias due to the unobserved time variant factors.

[13] Individual farms supplied 42% of fresh fruit and vegetables to Ubox, while farm cooperatives and agribusinesses supplied 36% and 22% of the product, respectively.

restaurants with home cooked meals households may have needed to purchase a wider variety of food products than previously.

A key question for the food industry is to what extent the increased use of online shopping platforms will persist after COVID-19 restrictions are lifted and the pandemic finally abates (Hobbs 2020). Unlike the U.S. or most countries in Europe, Taiwan did not shutdown businesses or impose a stay-at-home order. The country did adopt strict restrictions on international travel from China and other countries with high rates of infections, and it did mandate the use of facemasks in public. Nonetheless, the mobility of Taiwanese citizens within the country was relatively unaffected by COVID-19. As a result, we believe that the increase in online food shopping that was experienced in Taiwan may be similar to what will be experienced in the U.S. and Europe after stay-at-home orders and business restrictions are reduced. The number of COVID-19 infections will continue to grow after restrictions are removed in the U.S. and Europe, but consumers will regain their mobility, which mirrors the environment we used to generate our estimates in Taiwan.

A recent study of Sweden and Denmark found that most of the economic contraction brought on by the coronavirus pandemic was due to changes in consumer behavior, and not mandated social distancing and restrictions on economic activities (Andersen et al. 2020). By implication, if consumer preferences are more important in driving economic behavior than restrictions, the greater use of online food shopping identified in this study may be largely translatable to other countries, even if they do have restrictions. Our estimates of the effect of Google searchers and newspaper mentions of COVID-19 are consistent with the notion that consumer preferences drive consumption shifts observed during the coronavirus pandemic. Ranging between 0.7 and 0.8, the elasticity of Ubox sales to web searches is much larger than the elasticity with respect to confirmed weekly COVID-19 cases of 0.2. The elasticity of sales to suspected and confirmed cases combined is 0.4, which is more similar to web searches, but clearly the switch to online food shopping is more sensitive to consumer perceptions of COVID-19 risks than actual case counts. The source of these perceptions is typically information in the news media since most consumers do not have personal knowledge of an infected person or their experiences. The high level of responsiveness of Ubox sales to newspaper mentions highlights the significant impact the media can have on consumer purchasing decisions. It also helps to explain why most individuals overestimate the risk of a COVID-19 infection (Akesson et al. 2020).

Estimating the extent of a permanent shift to online food shopping after the development of a COVID-19 vaccine is more difficult.[14] One study of the Korean

[14] A study of antibody levels in Sweden, a country without any mobility or business restrictions, found that a modest percentage of the Swedish population had developed COVID-19 antibody levels by

experience found that employment losses caused by local outbreaks in regions without stay-at-home and business restrictions were concentrated in the accommodation/food service industry, among several others (Aum, Lee and Shin 2020). By implication, demand for FAFH in Taiwan will presumably recover after the threat of COVID-19 diminishes. If some of the increased demand for Ubox products was due to a substitution from FAFH, that demand could dissipate over the long run. Ultimately, whether consumers continue to use online food shopping platforms, such as Ubox, depends on whether they find the experience superior to shopping at retail establishments under normal circumstances. We are not aware of any scientific studies that estimate the persistence of online food shopping following initial exposure, but given the steady increase in the use of online platforms in several countries, we expect that many consumers who were motivated to use online platforms for the first time due to COVID-19, will continue to use them in the future, even if only occasionally.

Our study has some limitations that should be recognized. We analyze transactions from one large online food shopping platform in Taiwan, and the shift in food consumption patterns we identify might not be generalizable to online platforms in other countries with different consumer characteristics. In addition, our panel data fixed effect approach may not fully account for consumer selection into the use of the online platform. In particular, it is possible that there was selection into online food shopping by consumers in counties with higher exposure to COVID-19 based on unobservable time-varying factors. Finally, increasing trends in both COVD-19 and online food shopping could lead to spurious correlations. Although we have presented robustness checks that our consistent with our model's ability to account for both selection and time trends, not all forms of bias can be captured using available tests.

Despite these limitations, we believe this study makes an important contribution to the literature as the first to identify the impact of COVID-19 on consumers' use of online food shopping. This is an important topic because the ability to have food delivered at home is an important strategy that individuals can use to reduce their likelihood of exposure to COVID-19. Due to the high risk faced by the elderly or those with chronic medical conditions, the need to isolate oneself from others in the community can be pressing and doing so is only possible if food can be obtained from home. In addition, the use of online food shopping platforms can generate a positive public health externality because individuals that stay at home do not infect others in the community if they are carriers of the virus.

Our results also have relevance for agricultural policy. The Ubox platform was created by the Taiwanese Council of Agriculture in part to provide smaller, individual

April, 2020 (Ahlander and Pollard 2020). It is, therefore, likely that a vaccine will be developed before any region develops herd immunity to the virus (Branswell 2020).

farms with a low-cost outlet to reach consumers. Similar mechanisms have been adopted in other countries to help promote small farms, and studies have found that famers that sell food directly to consumers are more likely to survive than those that only sell through wholesalers (Gerrard 2017; Key, 2017). Our results indicate that individual farms benefited most from the increase in demand due to COVID-19. Importantly, small farmers lack many of means of financial insurance afforded to employees of larger agribusinesses, putting them at greater risk of income loss during the pandemic. Our findings suggest that online direct-to-consumer platforms, such as Ubox, can be used to protect small farmers during the pandemic or at other times when their income streams are disrupted by sudden shifts in demand.

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Table 1. Confirmed and suspected cases of COVID-19, Google COVID-19 web searches and COVID-19 newspaper mentions in Taiwan, by week.

Date in 2020	Week	COVID-19 cases				Google searches and newspaper mentions		
		Confirmed cases	Cumulative confirmed cases	Confirmed & suspected cases	Cumulative confirmed & suspected cases	Google keyword search index	Google news search index	Newspaper mentions
01/21-01/27	1	5	5	514	514	899	588	3,202
01/28-02/03	2	5	10	676	1,190	1,056	952	6,248
02/04-02/10	3	8	18	1,094	2,284	847	674	7,144
02/11-02/17	4	2	20	1,497	3,781	722	678	4,409
02/18-02/24	5	10	30	4,508	8,289	869	897	4,391
02/25-03/02	6	10	40	2,962	11,251	825	642	3,602
03/03-03/09	7	4	44	2,754	14,005	749	692	4,492
03/10-03/16	8	21	65	3,308	17,313	853	690	6,397
03/17-03/23	9	129	194	7,788	25,101	1,242	698	8,228
03/24-03/30	10	111	305	6,038	31,139	960	830	6,993
03/31-04/06	11	67	372	7,229	38,368	824	881	4,600
	All	372	--	38,368	--	9,846	8,222	59,706

Table 2. Sample statistics of the selected variables.

Sample		Full sample		COVID-19 period		Non-COVID-19 period	
N·T (unbalanced panel)		2,686		575		2,111	
Variable	Definition	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outcome variables							
Platform sales	Ubox platform sales value (NT$ 1,000/week).	4.56	8.78	5.16	13.13	4.39	7.15
Payments to producers	Payments to product suppliers (NT$ 1,000/week).	3.28	6.82	3.77	10.92	3.15	5.16
Platform profits	Ubox platform profits (NT$ 1,000/week).	1.24	2.11	1.30	2.35	1.23	2.03
Product variety	Product variety index: 1-HHI (0-1). Higher values indicate more variety.	0.52	0.34	0.49	0.34	0.52	0.34
Customers	No. of customers (10/week).	5.61	8.51	4.73	6.64	5.85	8.94
Suppliers	No. of suppliers (10/week).	4.07	5.26	4.01	4.95	4.09	5.35
Measures of COVID-19 cases, tests and information seeking							
Weekly cases	No. of confirmed COVID-19 cases in the week.	0.68	3.51	3.17	7.06	0	0
Cumulative cases	Cumulative number of COVID-19 cases.	1.92	9.34	8.98	18.57	0	0
Weekly total cases	No. of confirmed and suspected COVID-19 cases in the week.	64	210	300	369	0	0
Cumulative total cases	Cumulative number of confirmed and suspected COVID-19 cases.	250	889	1,169	1,620	0	0
Keyword search index	Popularity of Google keyword searches for COVID-19/Coronavirus (rescaled).	1.94	3.79	9.08	1.53	0	0
News search index	Popularity of Google news searches for COVID-19/Coronavirus (rescaled).	1.61	3.13	7.52	1.13	0	0
Newspaper mentions	No. of times COVID-19/Coronavirus mentioned in newspapers (100/week).	12.07	24.24	56.37	15.73	0	0
Control variables							
Farm cooperative	Ratio of products sold by a farm assoc. or marketing cooperative.	0.43	0.36	0.41	0.38	0.44	0.35

Table 2. Sample statistics of the selected variables, con't.

Agribusiness	Ratio of products sold by an agribusiness.	0.37	0.35	0.37	0.37	0.37	0.35
Individual farm	Ratio of products sold by an individual farm.	0.20	0.29	0.22	0.32	0.19	0.29
Frozen food	Frozen food product (0/1).	0.10	0.31	0.13	0.33	0.10	0.30
Fresh fruit or vegetable	Fresh fruit or vegetable (0/1).	0.20	0.40	0.20	0.40	0.20	0.40
Grain	Whole grains (0/1).	0.21	0.40	0.22	0.41	0.20	0.40
Non-alcoholic drink	Non-alcohol drink (0/1).	0.20	0.40	0.19	0.40	0.20	0.40
Other food	Other food product (0/1).	0.19	0.39	0.16	0.37	0.19	0.39
Non-food	Non-food product (0/1).	0.11	0.31	0.10	0.30	0.11	0.31
Year 2017	Year 2017 (0/1).	0.28	0.45	0	0	0.36	0.48
Year 2018	Year 2018 (0/1).	0.30	0.46	0	0	0.38	0.49
Year 2019	Year 2019 (0/1).	0.20	0.40	0	0	0.26	0.44
Year 2020	Year 2020 (0/1).	0.21	0.41	1	0	0	0

Table 3. Effect of confirmed COVID-19 cases on Ubox platform sales, payments to producers and profits.

	Platform sales				Payments to producers				Platform profits			
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Weekly cases	0.249 ***	0.042			0.181 **	0.031			0.064 ***	0.010		
Effect in %	5.67%				5.74%				5.23%			
Cumulative cases			0.072 **	0.018			0.052 *	0.013			0.019 **	0.004
Effect in %			1.64%				1.66%				1.52%	
R^2	0.056		0.053		0.050		0.048		0.066		0.062	
N·T	2,686		2,686		2,686		2,686		2,686		2,686	

Notes: Standard errors are cluster-corrected at the county and week level. All models include county, week and year fixed effects, and controls for type of producer and product category. Marginal effects in percentage terms are evaluated at the mean of the non-COVID-19 sample. Platform sales, payments to producers and profits are in NT$ 1,000/week. ***,**,* indicate significance at the 1%, 5% and 10% level.

Table 4. Effect of confirmed COVID-19 cases on Ubox product variety, number of consumers and suppliers.

	Product variety				No. of consumers				No. of suppliers			
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Weekly cases	0.013 ***	0.003			0.289 ***	0.048			0.205 ***	0.048		
Effect in %	1.03%				4.93%				5.01%			
Cumulative cases			0.008 **	0.001			0.073 ***	0.027			0.065 ***	0.019
Effect in %			1.53%				1.25%				1.58%	
R^2	0.086		0.082		0.074		0.068		0.060		0.056	
N·T	2,686		2,686		2,686		2,686		2,686		2,686	

Notes: Standard errors are cluster-corrected at the county and week level. All models include county, week and year fixed effects, and controls for type of producer and product category. Marginal effects in percentage terms are evaluated at the mean of the non-COVID-19 sample. ***,**,* indicate significance at the 1%, 5% and 10% level.

Table 5. Effect of confirmed COVID-19 cases on Ubox platform sales, by product type and supplier.

Panel A. Estimates by type of product				
	Weekly cases	S.E.	Cumulative cases	S.E.
Frozen food	0.248 ***	0.038	0.077 **	0.017
Effect in %	5.64%		1.76%	
Fresh fruit or vegetable	0.423 ***	0.013	0.155 ***	0.005
Effect in %	9.62%		3.52%	
Grain	0.577 ***	0.051	0.133 ***	0.020
Effect in %	13.13%		3.02%	
Non-alcoholic drink	0.121	0.059	0.031	0.024
Effect in %	2.75%		0.71%	
Other food	0.067	0.067	0.012	0.028
Effect in %	1.54%		0.27%	
Non-food product	0.028	0.046	0.010	0.020
Effect in %	0.64%		0.23%	
R^2	0.062		0.056	
N·T	2,686		2,686	
Panel B. Estimates by type of supplier				
Farm cooperative	0.193 *	0.062	0.060 *	0.024
Effect in %	4.40%		1.35%	
Agribusiness	0.236 **	0.052	0.054 *	0.024
Effect in %	5.37%		1.24%	
Individual farm	0.392 ***	0.061	0.126 ***	0.027
Effect in %	8.92%		2.87%	
R^2	0.056		0.053	
N·T	2,686		2,686	

Notes: Standard errors are cluster-corrected at the county and week level. All models include county, week and year fixed effects, and controls for either type of producer (panel A models) or product category (panel B models). Marginal effects in percentage terms are evaluated at the mean of the non-COVID-19 sample. ***,**,* indicate significance at the 1%, 5% and 10% level.

Table 6. Effect of confirmed COVID-19 cases on Ubox platform sales in counties without cases.

	Coeff.	S.E.	Coeff.	S.E.
Aggregate weekly cases	0.076 *	0.036		
Effect in %	1.73%			
Aggregate cumulative cases			0.030 *	0.014
Effect in %			0.68%	
R^2	0.110		0.100	
N·T	599		599	

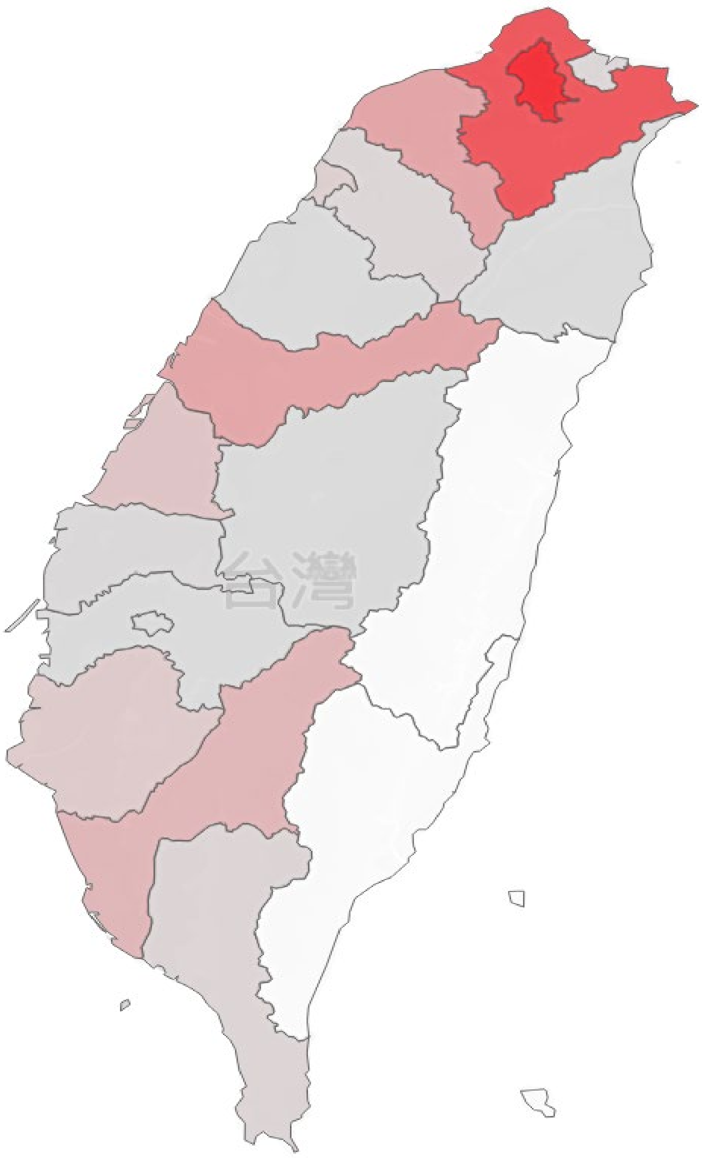
Notes: Standard errors are cluster-corrected at the county and week level. All models include county, week and year fixed effects, and controls for type of producer and product category. Marginal effects in percentage terms are evaluated at the mean of the non-COVID-19 sample. ***,**,* indicate significance at the 1%, 5% and 10% level.

Table 7. Effect of COVID-19 Google web and news searches and COVID-19 newspaper mentions on Ubox platform sales.

	Panel A: All counties								
	Coeff.	S.E.	Elas.	Coeff.	S.E.	Elas.	Coeff.	S.E.	Elas.
Keyword search	0.471 ***	0.065	0.83						
News search				0.472 ***	0.062	0.69			
Newspaper mentions							0.347 **	0.192	3.79
R^2		0.049			0.049			0.048	
N·T		2,686			2,686			2,686	
	Panel B: Counties without COVID-19 cases								
Keyword search	0.103 **	0.048	0.18						
News search				0.093 **	0.040	0.14			
Newspaper mentions							0.110 *	0.053	1.20
R^2		0.094			0.087			0.101	
N·T		599			599			599	

Notes: Standard errors are cluster-corrected at the county and week level. All models include county, week and year fixed effects, and controls for type of producer and product category. Elasticites are evaluated at the means of the COVID-19 sample. ***,**,* indicate significance at the 1%, 5% and 10% level.

Figure 1. Cumulative confirmed COVID-19 cases in Taiwanese counties, April 6, 2020.



Notes: Darker colors indicate more cases, and white indicates no case. Nineteen out of 21 counties in Taiwan reported a positive number of COVID-19 cases.