Market Response to Typhoons: The Roles of Information and Expectations*

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Abstract

This study investigates typhoons' effects on Taiwan's wholesale vegetable market during the 1996-2014 period. We first identify effects on prices and quantities during storms' striking periods and further separate price effects into those due, respectively, to supply and demand shifts. The results show that for typhoons that make landfall, prices rise significantly during the striking period, and the decomposition results indicate that most of the price effects during periods with warnings but no landfall are due to demand shifts, which supports evidence of precautionary purchases by consumers. However, during the landfall period, the price effect is mainly driven by decreased supply. In addition, we find that typhoon effects differ between specific vegetables, and the magnitude of precautionary purchase is correlated with expected damage to those vegetables. Consumers also make more precautionary purchases when they face higher-intensity typhoons or learn typhoons will make landfall within 24 hours, and such prior information related to intensity or landfall urgency can also amplify early harvest effects by farmers.

Keywords: Typhoon, Reaction to Forecast Information, Vegetable Market
JEL Classification: Q11, Q13, Q54

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1 Introduction

Typhoons (also called hurricanes[1]) often cause severe damage to agricultural sectors due to heavy downpours and storm surges. Food and Agriculture Organization (FAO) of the United Nations has reported that crop and livestock production damage from extreme storms is estimated to be more than USD 19 billion in its combined least-developed and lower-middle-income country categories from 2008-2018.[2] In Florida in 2018, Hurricane Irma alone caused an estimated USD 1.3 billion in crop losses.[3] The destructiveness of storms on agriculture is further predicted to be amplified in coming years from a combination of natural cycles and climate change (Chen and McCarl, 2009). As damage to agricultural production usually leads to market shortages, both consumers and producers may make precautionary reactions that affect equilibrium prices and quantities. This paper attempts to use transaction price and quantity data recorded in markets in Taiwan to identify relevant consumer and producer behavior, especially during the storms striking periods, which stretch from initial warnings through landfall.

When a typhoon forms and has a possibility of striking, the Taiwanese government usually reveals such forecast to the population so they can prepare. People may acquire emergency supplies and hoard storable foods before, during or after storm landfalls. For example, Beatty, Shimshack and Volpe (2019) find that sales of emergency supplies (bottled water, batteries and flashlights) increase when a location is

[1] Typhoons are known as hurricanes in the Atlantic and northeastern Pacific Oceans and are usually referred to as tropical cyclones in the western part of the Northern Pacific Ocean between 180° and 100°E in the Northern Hemisphere. Typhoons occur mostly from July through October since during this period, the environment features high temperatures with sufficient water mass to form typhoons. When a typhoon is formed, it starts to move westward to the northwest or north with the direction of surrounding guiding airflow and the clockwise circulation direction of the high atmospheric pressure south edge. The typhoon reaches the west edge of the high atmospheric pressure region when it is between 20° and 30°N, gradually turning north into the westerly belt, and further turning to the northeast.

[2] Available at: https://www.fao.org/documents/card/en/c/cb3673en. Accessed December 2021.

[3] It is estimated by the University of Florida's Institute of Food and Agricultural Sciences (FAO), Economic Impact Analysis Program. Available at: https://fred.ifas.ufl.edu/economicimpactanalysis/DisasterImpactAnalysis/. Accessed December 2021.

warned of a likely hurricane strike, and sales increase immediately prior to forecasted landfall. Their results provide evidence of short-term demand shifts, which indicates that consumers make precautionary purchases to assure adequate supplies after receiving typhoon threat warnings. In addition, consumers may stay sheltered and reduce their purchases once storms make landfall and may have ex post responses once a storm has passed. Besides storable goods, consumers may also need to purchase fresh perishable agricultural products in advance to meet daily needs or avoid short-run price surges after storms. Therefore, it is also important to understand how consumers respond concerning perishable agricultural commodities.

The supply side market reaction is complicated. Many existing studies have investigated the impact of hurricanes on crop production. For instance, Strobl (2012) indicates that hurricane strikes significantly reduce crop production in the Caribbean. Israel and Briones (2012) find that typhoons cause significant negative impacts on rice production in the Philippines. Spencer and Polachek (2015) use data from Jamaica to show that underground crops, such as yams and potatoes, are significantly damaged by excessive rainfall brought by hurricanes. A number of studies have investigated crop yield response to climate change-related shifts in extreme conditions (Schlenker and Roberts, 2009; Attavanich and McCarl, 2014). However, it is not clear how farmers maintain adequate supply levels for the population during storms' striking periods. Given the expectation of potential damage from hurricane strikes, farmers are likely to adopt strategies to respond to hurricane threats. For example, Campbell and Beckford (2009) document coping strategies adopted by Jamaican farmers before and after Hurricane Dean in August 2007. Before the storm, farmers mainly adopted strategies of protecting nurseries, spraying, harvesting, and storage. After the storm, they scaled down production and instituted post-hurricane harvesting and plant restoration practices. Farmers may provide higher or lower levels of supply to the market when they adopt different precautionary approaches.

In this study, we first use daily 1996-2014 transaction data in the Taiwan wholesale vegetable market to identify effects of typhoons on prices and quantities during storms' striking periods. There are two advantages to using Taiwanese data. First, Taiwan is located on the western edge of the Pacific Ocean (see Figure 1), on the normal global track of typhoons, so such storms strike Taiwan frequently every year.[4] There were a total of 366 typhoons from 1911 through 2018 (averaging 3.39 per year).[5] The storms generally occur in summer (from July through October). Instead of using one typhoon to conduct a case study, we can use the historical data to identify typhoons' effects over a certain period. Second, "daily" transaction data in the wholesale vegetable market provides a good opportunity to show typhoons' short-run effects since the landfall of a typhoon usually lasts 1-2 days.

We further divide the effects of typhoons on prices and quantities into those due to supply or demand shifts, respectively, which can be used to investigate the behavior of buyers and sellers during storms' striking periods. Since the supply is almost perfectly inelastic, changes in quantity are driven by supply shifts. If the demand curve is assumed as usual, we can use the price elasticity of demand to quantify price effects due to supply shifts and the remaining effect is driven by the shift in demand.

On the demand side, consumers may make precautionary purchases when they receive warnings, which results in a temporary increase in demand. On the supply side, there are two possible effects to determine supply level when storms have not made landfall after warnings were issued. One is the early harvest effect and the other is the precautionary preparation effect. Farmers can harvest earlier to prevent loss before the typhoons' landfall, which provides a positive effect on supply. In addition,

[4] Landfalling typhoons typically bring sustained high winds and heavy rains. Since the geographical features of Taiwan are fragile—few plains, high mountains, short rivers, and steep slopes, unable to accommodate much rainwater—the torrential rain brought by typhoons is likely to cause earth and rock collapse, landslides and flooding. Related damage to humans and buildings is common. During the 1958 through 2017 period, estimates are that typhoons caused 4,390 deaths, 15,149 injuries; collapse of some 120,000 houses and partial collapse of some 220,000 more across Taiwan. The storms can also cause severe agricultural losses. Such losses from the 2009 Typhoon Morakot alone are estimated at NT$ 20 billion, of which 56% came from lost products and 39% from lost farmland. Detailed damage information was reported in https://cdprc.ey.gov.tw/.

[5] These are counted when the typhoon's center made landfall in Taiwan or when the typhoon caused losses there even if it passed nearby Taiwan without making landfall.

farmers can make some precautionary preparations, such as opening a ditch alongside their fields to prevent water damage, so farmers might not have time to harvest or ship products to market, causing a negative effect on supply. The overall net effect can be observed from changes in quantity and the precautionary purchase effect can be captured after analysis.

When storms make landfall, supply also has two possible channels to affect quantity. One is due to interruption of shipping, which might sharply reduce supply level. The other is from previous early harvest, which can boost quantity level. We can observe the net overall effect from the data based on empirical analysis.

The results show that for typhoons that make landfall, prices rise significantly during the striking period, and the decomposition results indicate that most price effects during warning periods before landfall are due to demand shifts, which supports evidence of precautionary purchase by consumers. However, during landfall periods, price effects are mainly driven by decreased supply. In addition, amounts traded fall slightly when warnings are issued but before actual landfall occurs, which implies that the effect of precautionary preparation in those cases is larger than that of early harvest. During the landfall period, quantity traded drops sharply, which indicates the effect of shipping interruption is much stronger than the early harvest effect.

We also find that typhoons' effects differ between specific vegetables, and magnitude of precautionary purchases are correlated with expected storm damage to specific vegetables. The precautionary purchase effect is largest for green leafy vegetables and smallest for mushrooms. Furthermore, the effect is smaller for imported vegetables. Lastly, consumers make more precautionary purchases when they face higher typhoon intensity or receive information that typhoons will make landfall within 24 hours, and such information related to intensity or landfall urgency can also amplify early harvest effects by farmers.

Such an examination contributes to existing literature in several ways. First, to best of our knowledge, this paper is the first to display daily market responses to typhoons and decompose price effects into those due to supply versus demand shifts. We also use this decomposition to further demonstrate evidence of precautionary strategies by buyers and sellers. Second, we further link precautionary reactions from buyers and sellers to weather information reported by government. Existing literature has investigated effects of precise weather information directly on welfare outcomes (Katz and Murphy, 1997; Gladwin et al., 2007; Letson, Sutter and Lazo, 2007; Zirulia, 2016). In this study, we further demonstrate that this information can directly affect buyer and seller behavior. Third, we examine the effects from many typhoons during a long period rather than the one-time shock of a specific huge typhoon as a case study. While some studies have looked at longer periods and multiple storms, their focus has been much more on aggregate damage due to storm strikes (Strobl, 2012; Weinkle et al., 2018), and they have not addressed effects before actual damage.

The rest of this paper is organized as follows. Section 2 provides data and background on typhoons and wholesale vegetable markets. Section 3 introduces this study's empirical strategy. Section 4 presents and discusses empirical results. Section 5 concludes this research.

2 Data and Background

2.1 Typhoon Landfall and Warning Information Data

The Taiwan Central Weather Bureau (TCWB) monitors all potential typhoons in the Pacific Ocean and issues warnings when they approach Taiwan. The first warning is issued when outer bands of a storm's radius[6] are expected to pass within 100 km of Taiwan during the next 24 hours. Then TCWB issues land and sea warnings as the storm approaches Taiwan. Sea warnings are first put in effect when the storm's radius' outer bands are predicted to be over surrounding waters within 100 km of Taiwan

[6]The storm radius is calculated from the eye of the storm outward to locations where the average wind speed is at least 50 kilometers per hour (km/h), or 14 m/s.

during the following 24 hours. When the outer bands are predicted to be over the island in 18 hours, TCWB switches sea warnings to land warnings. The land warnings are suspended when the storm radius no longer includes land area, and sea warnings are lifted when the storm radius no longer includes waters surrounding Taiwan. All warnings are issued at least every three hours, and each warning provides information on the storm's forecasted track, intensity, central pressure, location in latitude and longitude, radius, maximum sustained winds, forward speed, 24-hour movement, and warning area. We use all information in warnings to define variables used in this study. For instance, forecasted 24-hour movement information can help us determine whether the storm radius is predicted to make landfall in the following 24 hours.

Definition of landfall in our study is different from the TCWB definition. In defining landfall, TCWB considers that it is accomplished only when the center of a typhoon moves from the sea to be over land. However, a storm can cause enormous damage even when its center is not over land as the outer circulation of a typhoon usually brings heavy rain. To better depict the typhoons' effects, we thus expand our definition of landfall in this study so that landfall occurs when a storm's radius starts to cover any parts of the main island of Taiwan. Based on this definition, typhoons can be categorized into two types: landfalling storms (LS) and non-landfalling storms (NLS).

We meanwhile split the warning period into two sub-periods, which we call warning and landfall periods, in the following analysis. The landfall period is defined as the interval starting when the storm's radius begins to cover Taiwan to ending when the storm radius totally leaves the land area of Taiwan. Before the landfall period, the remainder of the period during which warnings are issued is the warning period, defined as the period starting from the first TCWB warning until the beginning of the previously defined landfall period.

Table 1 provides descriptive statistics on all typhoons in Taiwan during the years 1996-2014. Among 111 total typhoons, 35 (32%) were non-landfalling storms, and

76 (68%) landfalling storms. Based on typhoon intensity, we can further classify typhoons into three categories: weak (maximum winds 34-63 knots), medium (64-99 knots), and strong (100 knots or over). During this sample period, 18 are classified as having been strong, 55 medium and 38 weak. In addition, typhoons most often occurred in July (24 storms), August (31), and September (23 storms). Following our previous definition, average warning period was 1.77 days for NLS and 1.24 days for LS. Average landfall period was 1.5 days. Both warning and landfall periods are longer when typhoons are stronger.

2.2 Daily Wholesale Vegetable Market Data

We use daily transaction data from the 1996-2014 period on Taiwan's wholesale vegetable market.[7] The daily wholesale market, as embodied in specific physical markets, starts in the very early morning (3:00am) and products are shipped by farmers and traded either through bargaining or auctions, so equilibrium prices can be viewed as determined by a market mechanism. Since farmers are unable to substantially change supply once vegetables are harvested and not at all after they have been shipped, short-run supply is almost perfectly inelastic in this market, which suggests that market sales are determined solely by the supply side. We then construct average prices and total quantity within each vegetable-market-day combination to proxy daily equilibrium prices and quantities for this study.

Furthermore, we select 66 different vegetables for the following analysis.[8] Based on classifications from the Council of Agriculture, Executive Yuan, vegetables can be grouped into four categories: green leafy vegetables (19 items), flower and fruit vegetables (21 items), root vegetables (20 items) and mushrooms (6 items). Detailed information is listed in Table A1. In addition, we further focus on four major wholesale

[7]The data can be obtained from the website of the Taiwan Agriculture and Food Agency of the Council of Agriculture (AFACA). Link: https://amis.afa.gov.tw/main/Main.aspx.

[8]The data contains 136 vegetables, but we use the following rules to select 66 vegetables for the analysis: (1) vegetables are solely sold during the Taiwan typhoon season, from May through November. (2) transaction data needed to be available for 20 days or more per month.

markets:[9] Taipei City First (Taipei I) and Second (Taipei II) Fruit and Wholesale Vegetable Markets, Taichung Fruit and Vegetable Market, and Kaohsiung Fruit and Vegetable Market. The four markets are distributed between the northern, central and southern sections of Taiwan, and they collectively have more than half of Taiwan's vegetable transaction volumes. The largest two markets are Taipei I and Taipei II, which on average together have daily volumes of 2,200 metric tons, or about 33% of the national total.

Table 2 presents summary statistics on vegetable prices and quantities. Average transaction price was NT$32.94/kg, and average quantity 6321 kg. During days unaffected by typhoons, average price was NT$32.74/kg and this average price rose to NT$36.07/kg (NT$37.74/kg) during NLS (LS) warning periods. When typhoons were making landfall, the average price rose further to NT$38.79/kg. Average quantity sold reacts the opposite way. When there was no typhoon, average quantity was 6,344kg, which reduces to 5,728 kg (5,913 kg) during warning periods for NLS (LS), and yet smaller (5,667 kg) during landfall periods. Average prices across the four markets varied substantially and average quantity for Taipei I is largest among these four markets.

3 Methodology

To examine typhoon effects on market prices and quantities, we use daily data for 66 vegetables in four markets during 1996-2014 and consider the following fixed effects model:

$$\log(Y_{jmdt}) = \beta_0 + \beta_1 W_{dt}^{NLS} + \beta_2 W_{dt}^{LS} + \beta_3 L_{dt} + X_{dt}\gamma + f_j + \theta_m + g_t + \epsilon_{jmdt}, \quad (1)$$

[9] There are 18 wholesale vegetable markets in Taiwan. We only chose the four major wholesale markets, which can represent the entire wholesale markets in Taiwan.

where Y_{jmdt} is the price or quantity of vegetable j in market m on day d in month t. W_{dt}^{NLS} and W_{dt}^{LS} are two dummy variables to indicate whether day d in month t is in a warning period for NLS and LS, respectively. L_{dt} is a dummy variable for whether a typhoon is making landfall[10] during day d in month t.

We also control periods before and after typhoons in X_{dt} to avoid underestimating typhoons' effects. If typhoons have any effect before and after warning and landfall periods, the baseline should also exclude those affected days. More specifically, we include a set of dummies to indicate 1-5 days before warning periods. For NLS, we include dummies for 1-3 days after warning periods, but for LS, we use six dummies for 1-6 weeks after landfall periods. There are two important notes to keep in mind regarding these dummy variables. First, we allow overlapping events[11] on the same day since typhoons' effects could be accumulated after strikes of successive typhoons. Second, results are robust when we extend intervals of these controlled periods; however, typhoons' effects will be underestimated if we do not include enough days or weeks for the periods before and after typhoons.

To avoid conflating effects of typhoons with those of major holidays, we include two sets of holiday dummies in X_{dt}: One is for moon festivals (in September) and the other for lunar new year periods (in January or February). We put day-of-week fixed effects in X_{dt} to capture price and quantity fluctuations within the same week in markets.

Lastly, we specify a set of fixed effects, including commodity fixed effects (f_j), market fixed effects (θ_m) and month-by-year fixed effects (g_t). The identification strategy is to estimate the treatment effect on different days in the same month for the same vegetable in the same market. Since typhoons are exogenous to markets, we directly apply the ordinary least squares to the regression model. Because we believe that error terms of vegetables within the same category (of four) in the same year (of

[10]The definition of landfall is that a typhoon has its radius over the land of Taiwan on that day.

[11]For instance, one day could be in the first week after the landfall period of Typhoon A, while also serving as the third week after the landfall period of Typhoon B.

19) are correlated, the robust standard errors are clustered at the category-by-year level.[12]

4 Empirical Results

4.1 Main Results

The first two columns in Table 3 show estimation results from equation (1). In addition, we further decompose typhoons effects on prices and quantities into effects based on supply or demand shifts, respectively, and so the last three columns in Table 3 present results of our decomposition.

Since the supply curve is a vertical line, the effect on quantities is mainly driven by supply shifts. If we also assume that the demand curve is the same as usual, we can use price elasticity of demand to calculate price effects due to supply shifts, and understand the remaining effect is driven by demand shift. The detailed process of demand estimation is presented in Appendix A and overall price elasticity of demand for all vegetables collectively is -0.952.

For typhoons that do not make landfall, prices significantly rise by 3.8% relative to unaffected days during the warning period while quantity traded remains unchanged. The results indicate a demand shift likely due to precautionary purchase behavior by consumers during the warning period to stock up on vegetables.

For typhoons that make landfall, price rises significantly, by 11.8%, relative to unaffected days during the warning period, about three times more than in the non-land-falling storm case. On the quantity side, amount traded significantly falls by 2%, probably reflecting that the effect of precautionary preparation by farmers is larger than the effect of early harvesting. If we further decompose price effects into supply and demand, most are due to the demand shift of 9.67%, which supports evidence of

[12] Thanks for the suggestions from the reviewer. We also compare the robust standard errors at different cluster levels, such as the commodity level, and the commodity-by-year level, and report the largest one (category-by-year) for the results.

precautionary purchase by consumers.

During landfall periods, prices significantly rise by 11.4% relative to unaffected days, a similar increase as observed during warning periods; however, the decomposition result shows that price effect is mainly driven by a supply shift of 9.27%. This implies that effects of shipping interruption for farmers is much stronger than the early harvest effect.

To further examine effects during those periods before and after warning and landfall periods, Figures 2 and 3 present results for NLS and LS, respectively. First, prices rise significantly one day before warning periods while quantity remains unchanged, which suggests precautionary purchases may respond to media reports of potential typhoons before official warnings. For NLS, price gradually drops back to initial price levels by three days after warnings are issued while quantity remains relatively stable throughout. For LS, reactions in both price and quantity are larger. Since LS might bring more substantial damage, the results suggest vegetable supplies need about six weeks[13] to return to normal levels, which affects both price and quantity in the market.

4.2 Heterogeneous Effects

In this section, we further explore heterogeneous effects for different vegetables. First, we follow government definitions to classify vegetables in four categories: green leafy vegetables, flower and fruit vegetables, root vegetables and mushrooms. In addition, some vegetables are imported so we also split vegetables into two groups on this dimension: (partially) imported and non-imported. Lastly, we directly apply the same methodology to each vegetable and compare results with those from the previous classifications.

[13]Since plug seedlings can shorten the growth period of vegetables in the field, supply can be replenished within six weeks after typhoon strikes. In Taiwan, farmers commonly use the plug seedling method to grow vegetables, especially during summer with frequent showers and occasional typhoons.

Based on information and media articles from the Taiwan Council of Agriculture, green leafy vegetables are damaged most by typhoons. Since most of these vegetables are cultivated directly in the soil, heavy rainfall associated with typhoons could cause damage in quantity and quality directly to them. The second most damaged vegetables are flower and fruit vegetables, which commonly grow on trees, so they could be blown off when facing strong typhoon winds. For root vegetables, the supply during a typhoon period is relatively stable because they can be stored for long periods in well-ventilated places. Lastly, mushrooms usually grow indoors, so they are affected least by typhoons. Consumers usually make precautionary purchases of those vegetables that could be affected severely by typhoons, since they expect high prices or shortages after major damage. Our hypothesis is that the magnitude of precautionary purchases differs across vegetable groups depending on anticipated damage.

Table 4 presents empirical results from equation (1) for four different groups of vegetables.[14] During warning periods for NLS, prices of all vegetable categories except mushrooms significantly increase (7% for green leafy vegetables, 4% for flower and fruit vegetables, and 1.5% for root vegetables) with quantities of all four groups unchanged. This suggests precautionary purchasing by consumers. The magnitude of price increase is consistent with our hypothesis that the largest price increase is for green leafy vegetables and smallest for root vegetables.

During LS warning periods, we have similar but larger price increases for these four groups. Based on decomposition results, price increases due to demand shifts were largest for green leafy vegetables (13.98%), and smallest for mushrooms (0.79%). The order of price effects due to demand shifts are also consistent with the precautionary purchase hypothesis. In addition, quantities traded of green leafy, and flower and fruit vegetables, fall by 4.9% and 2.9%, respectively. Notably, the quantity of root vegetables increases by 1.77%, which might reflect the release of previous storage. In landfall periods, quantities decrease in these four categories and price effects are

[14]The robust standard errors are clustered at the commodity-by-year level.

mainly driven by the supply side, except for the case of flower and fruit vegetables.

Figure 4 presents dynamic patterns of price and quantity during periods before and after LS. The price and quantity patterns of root vegetables and mushrooms are relatively more stable. There are two possible reasons. First, these categories are less affected by typhoons. Mushrooms are mostly grown in greenhouses and are therefore less vulnerable to typhoon damage. Second, some vegetables could be imported from other countries after typhoons. Because root vegetables such as potatoes and radishes are more storable, they can be relatively easily replenished from other countries even while typhoons cause damage to local supplies. Therefore, quantities for root vegetables return to normal within two weeks.

We also use quantity data in the sample period to calculate shares of imported products for each vegetable, and divide the sample into two groups: imported (with at least 5% imported products[15]) and non-imported vegetables (others, with ¡5% imports). Figure 5 shows price and quantity patterns for these two groups, illustrating how patterns are relatively more stable for those vegetables with a significant imported percentage.

In addition, we also apply the model in equation (1) to each vegetable.[16] Figure 6 presents price effects during warning and landfall periods for LS.[17] Each dot represents the estimate for one vegetable, with confidence intervals shown on Figure 6. The horizontal red lines on this figure represent estimates from the main results. The four symbols represent the four vegetable groups, and the solid (hollow) symbol represents non-imported (imported) vegetables. Most estimates for green leafy vegetables (blue circles) and flower and fruit vegetables (red square) are significantly above zero,

[15]There are nine vegetables in the (partly) imported group. These include five root vegetables: asparagus (57.38%), onion (39.18%), burdock root (15.80%), radish (12.46%), and potato (8.93%). Also two flower and fruit vegetables: broccolini (21.21%), and peas (8.21%) and two green leafy vegetables: celery (8.14%), and lettuce (6.14%). Numbers in parentheses represent the share of imported products in each item.

[16]The robust standard errors are clustered at the year level. Since the number of clusters is too few, we use the bootstrap method to calculate clustered standard errors.

[17]The other four estimates are shown in the appendix B.

consistent with previous results for these four groups. Similarly, estimates for partly imported vegetables are relatively smaller than those for non-imported vegetables.

4.3 Further Examinations

In this section, we first present results concerning the effects of information, including on the strength of typhoons and landfall forecasts, and then further focus on the recovery period, especially for the first two weeks after landfall periods.

4.3.1 Effects of Typhoon Strength and Landfall Forecasts

Information on storm intensity and near-term landfall forecasts also appear to have effects on buyers' and sellers' precautionary strategies. To verify that, we create a variable to indicate high-intensity (medium or strong) typhoons and interact with the three main variables (warning periods for NLS and LS, and landfall periods). Results are shown in Table 5. These indicate that first, consumers make more precautionary purchases when they face higher-intensity typhoons. During a warning period, price effects for high-intensity LS (NLS) are 12.3% (4.5%), larger than 10.7% (3.2%) when LS (NLS) is forecasted to be of low intensity. Decomposition also shows similar results for warning periods and that precautionary purchase effects continue until landfall periods when typhoon intensity is higher.

In addition, supply level during LS warning periods is higher when typhoon intensity is higher. Since there are two effects, the early harvest and precautionary preparation effects, to determine supply by farmers during warning periods, results show that farmers exert larger early harvest effects when they face higher-intensity typhoons. This is consistent with results during landfall periods. Although interruption of shipping creates negative shocks to supply, that level is higher during typhoons of higher intensity due to early harvesting by farmers.

Besides typhoon intensity, we also examine effects of landfall forecasts. First, we create a dummy variable to indicate when typhoons are projected to make landfall in 24 hours —public information reported by TCWB —and we make the dummy variable interact with warning periods for both NLS and LS. Results in Table 6 show that price effects are larger when people receive this information, which demonstrates that receiving predictions of landfall within 24 hours can strengthen the consumer precautionary purchase effect. Similarly, information of impending landfall in 24 hours also amplifies farmers' early harvest effects, inducing a higher level of supply during LS warning periods.

In addition, we construct a dummy variable to indicate whether the previous day's forecast projected impending typhoon landfall within 24 hours, and we have this dummy interact with the landfall period. Therefore, we can compare two types of landfall periods: expected and unexpected. During the sample period, TCWB only reports inaccurate predictions 10 out of 95 projected landfall days. Usually for inaccurate predictions, the typhoon's radius only slightly covered Taiwan. Results in Table 6 show that consumers make precautionary purchases when they face expected landfalls but not when landfall is unexpected. Furthermore, as expected landfall may induce more shipping interruption since storm coverage is larger, supply level is lower during expected landfall periods.

4.3.2 Recovery Period after Landfall

In section 4.1, we found that for an LS, prices in the first week after landfall drop slightly but increase sharply in the second week after landfall. To investigate the market further during the first two weeks after landfall, we estimate equation (1) again but replace dummy variables for the first two weeks after landfall with 14 separate daily dummies, one for each day. Figure 7 summarizes results. First, vegetable quantities are lower on the first day after the storm leaves Taiwan, and then increase sharply on the next two days. Such an increase likely reflects producers releasing their storage or shipping their products not previously shipped to other markets due to landfall-caused shipping interruptions.

In addition, prices fall sharply in the three days after storm departure, due not only to increased supply but also due to likely short-term decreased demand. Consumers may not immediately buy as they presumably stocked up during the prior warning period and may still have vegetables at home. However, once six days have passed, vegetable quantities sold become relatively stable. We also see a significant price increase on days six through eight, likely reflecting demand increases due to full return of consumers to the market. Subsequently, starting in days ten through twelve, prices and quantities start to return to normal but do not fully attain that until six weeks after storm departure as by then, new plantings and harvestings bring new supplies of most items to market.

4.4 Placebo Tests

To conduct a placebo test, we look at typhoons' effects specifically on rice, which can be stored for a long time. Ideally, we do not expect to see any typhoon effects on rice since frequency of buying rice is low, and supply would not be expected to experience shortages after typhoons. Because we do not have total daily sales data for rice, we only use wholesale daily price data for rice in Taipei[18] to examine typhoons' effects on rice prices. We use the same framework as in equation (1), and bootstrapping robust standard errors are clustered at the year level. Figure 8 presents the price pattern for NLS and LS. In both situations, typhoon effects on rice are very close to zero, relatively smaller than for vegetables.

5 Conclusion

This paper uses daily transaction data from 1996-2014 in Taiwan wholesale vegetable markets to identify typhoons effects on prices and quantities during warning and

[18] Since wholesale prices do not vary greatly between counties or regions, we only establish data for Taipei, which represents the largest market in Taiwan.

landfall periods. Then we further decompose price effects into those apparently due respectively to supply or demand shifts. Results show that for landfalling storms, price significantly rises by 11.8% (11.4%) relative to unaffected days during warning (landfall) periods. Decomposition results show that most price effects during warning periods are due to demand shifts, which support evidence of precautionary purchase by consumers, but price effects during landfall periods are mainly driven by decreased supply. In addition, for LS during warning periods, amounts traded significantly fall by 2%, likely reflecting effects of precautionary preparation by farmers being larger than early harvest effects. During landfall periods, quantities traded drops, indicating effects of shipping interruptions are stronger than early harvest effects.

We also find that typhoons' effects differ between vegetables, and magnitude of precautionary purchases are correlated with expected damage to those vegetables. Precautionary purchase effects are largest for green leafy vegetables and smallest for mushrooms. In addition, effects are smaller for partly-imported vegetables, whose growth processes are less affected directly by storms in Taiwan. Lastly, information related to storm intensity and near-term landfall forecasts also seem to have effects on buyers' and sellers' precautionary strategies. Consumers make more precautionary purchases when they face higher typhoon intensity and/or receive information that typhoons will make landfall in 24 hours, and such information can also amplify early harvest effects by farmers.

Several implications can be drawn from these results. First, price effects are driven by different channels during warning and landfall periods, respectively; therefore, it is better to use different approaches to mitigate price fluctuations during typhoon periods. For instance, releasing information on short-run diet modifications such as substitution of root vegetables and mushrooms for green leafy vegetables, may help reduce precautionary purchases of green leafy vegetables; however, this strategy could not solve the supply-side shortage during landfall periods.

Second, we find that typhoons' effects are smaller for imported products, which implies that increasing short-run imports during storm threat periods can reduce shortages. For instance, Typhoon Mindulle struck Taiwan in 2004, causing great damage. The government lowered its import tax rate for vegetables in the following month in response to the shortage. If we can increase the proportion of imports for some green leafy vegetables, people might not expect a shortage of those vegetables after storms so they will not feel the need to make precautionary purchases before them.

Third, we should expect typhoons' effects to be amplified in the future due to climate change. Our result, coupled with climate change-based arguments foreseeing a future with more intense storms (Grinsted, Ditlevsen and Christensen, 2019); shifts in locations where typhoons reach peak wind intensity (Kossin, Emanuel and Vecchi, 2014); more rainfall due to slowing typhoon movement (Kossin, 2018) and increasing abruptness of track direction changes (Hall and Kossin, 2019) indicates intensifying threats from typhoons to society. Development of more rapid transport of products to markets as well as improved storage technology, among other measures, are thus needed to lower market disruptions from this rising threat.

Although we have shown typhoons' effects on wholesale vegetable markets, a few caveats remain. Due to data limitations, we do not have specific information on growing areas for each vegetable, so our current analysis only relies on variations over time. In the future, it will be better to explore variations between different vegetables from different geographic areas to further identify typhoons' effects. These could illustrate farmer behaviors regarding this subject more specifically, including precautionary strategies and shipping interruptions.

References

Attavanich, Witsanu, and Bruce A. McCarl. 2014. "How is CO2 affecting yields and technological progress? A statistical analysis." *Climatic Change*, 124(4): 747–762.

Beatty, Timothy K. M., Jay P. Shimshack, and Richard J. Volpe. 2019. "Disaster Preparedness and Disaster Response: Evidence from Sales of Emergency Supplies Before and After Hurricanes." *Journal of the Association of Environmental and Resource Economists*, 6(4).

Campbell, Donovan, and Clinton Beckford. 2009. "Negotiating Uncertainty: Jamaican Small Farmers' Adaptation and Coping Strategies, Before and After hurricanes - A Case Study of Hurricane Dean." *Sustainability*, 1(4): 1366–1387.

Chen, Chi-Chung, and Bruce McCarl. 2009. "Hurricanes and Possible Intensity Increases: Effects on and Reactions from U.S. Agriculture." *Journal of Agricultural and Applied Economics*, 41(1): 125–144.

Gladwin, Hugh, Jeffrey K. Lazo, Betty Hearn Morrow, Walter Gillis Peacock, and Hugh E. Willoughby. 2007. "Social Science Research Needs for the Hurricane Forecast and Warning System." *Natural Hazards Review*, 8(3): 87–95.

Grinsted, Aslak, Peter Ditlevsen, and Jens Hesselbjerg Christensen. 2019. "Normalized US hurricane damage estimates using area of total destruction, 19002018." *Proceedings of the National Academy of Sciences*, 116(48): 23942–23946.

Hall, Timothy M., and James P. Kossin. 2019. "Hurricane Stalling Along the North American Coast and Implications for Rainfall." *npj Climate and Atmospheric Science*, 2(1): 1–9.

Israel, Danilo C., and Roehlano M. Briones. 2012. "Impacts of Natural Disasters on Agriculture, Food, Security, and Natural Resources and Environment in the Philippines." Working paper.

Katz, Richard W, and Allan H. Murphy. 1997. *Economic Value of Weather and Climate Forecast.*

Kossin, James P. 2018. "A Global Slowdown of Tropical-Cyclone Translation Speed." *Nature*, 558: 104–107.

Kossin, James P., Kerry A. Emanuel, and Gabriel A. Vecchi. 2014. "The poleward migration of the location of tropical cyclone maximum intensity." *Nature*, 509: 349–352.

Letson, David, Daniel S. Sutter, and Jeffrey K. Lazo. 2007. "Economic Value of Hurricane Forecasts: An Overview and Research Needs." *Natural Hazards Review*, 8(3): 78–86.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences*, 106(37): 15594–15598.

Spencer, Nekeisha, and Solomon Polachek. 2015. "Hurricane Watch: Battening Down the Effects of the Storm on Local Crop Production." *Ecological Economics*, 120: 234–240.

Strobl, Eric. 2012. "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions." *Journal of Development Economics*, 97(1): 130–141.

Weinkle, Jessica, Chris Landsea, Douglas Collins, Rade Musulin, Ryan P. Crompton, Philip J. Klotzbach, and Roger Pielke. 2018. "Normalized hurricane damage in the continental United States 1900-2017." *Nature Sustainability*, 1(12): 808–813.

Zirulia, Lorenzo. 2016. "Should I Stay or Should I Go?': Weather Forecasts and the Economics of Short Breaks'." *Tourism Economics*, 22(4): 837–846.

Tables and Figures

Table 1: Summary Statistics for Typhoons Threatening Taiwan

	Non-landfalling Storms (NLS)				Landfalling Storms (LS)			
	Weak	Medium	Strong	Total	Weak	Medium	Strong	Total
Total number	13	19	3	35	25	36	15	76
Number by month:								
January-May	1	0	1	2	2	2	0	4
June	4	1	0	5	2	4	0	6
July	3	5	0	8	5	8	3	16
August	4	2	0	6	11	9	5	25
September	1	7	1	9	4	6	4	14
October-December	0	4	1	5	1	7	3	11
Average warning period in days	1.69	1.79	2.00	1.77	0.80	1.44	1.47	1.24
	(0.48)	(0.54)	(0.00)	(0.49)	(0.65)	(0.77)	(0.52)	(0.75)
Average landfall period in days	-	-	-	-	1.28	1.53	1.80	1.50
	-	-	-	-	(0.46)	(0.84)	(0.68)	(0.72)

Note: Standard deviations on the length of landfall and warning periods are shown in parentheses.

Table 2: Summary Statistics on Prices and Quantities

Variables	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Prices (NTD/kg)	1,439,280	32.939	27.461	0.9	803.3
Quantities (kg)	1,439,280	6320.623	14950.655	1	471475
In warning period for NLS	1,439,280	0.010	0.099	0	1
In warning period for LS	1,439,280	0.015	0.120	0	1
In landfall period	1,439,280	0.016	0.124	0	1
Prices by periods					
Days without typhoons	1,381,491	32.738	27.349	0.9	803.3
Days in warning period for NLS	14,159	36.071	27.735	2	379.6
Days in warning period for LS	21,172	37.735	29.795	2.1	389.1
Days in landfall period for LS	22,458	38.790	30.513	2.4	582.4
Quantities by period					
Days without typhoons	1,381,491	6343.571	14989.980	1	471475
Days in warning period for NLS	14,159	5727.837	13289.167	1.8	237439
Days in warning period for LS	21,172	5912.708	14399.041	1.8	346035
Days in landfall period for LS	22,458	5667.241	13968.765	2	298894
Prices by market					
Taipei I	380,885	34.956	28.753	1.4	803.3
Taipei II	369,562	33.673	28.007	1	784.8
Taichung	324,884	24.133	19.403	1	400
Kaohsiung	363,949	37.944	29.756	0.9	625
Quantities by market					
Taipei I	380,885	15624.857	25136.291	1	471475
Taipei II	369,562	4436.058	7843.743	2	177279
Taichung	324,884	1323.546	2279.596	1	54804
Kaohsiung	363,949	2957.762	5272.258	1	96342

Source: The Agriculture and Food Agency Council of Agriculture (AFACA), Executive Yuan in Taiwan (https://amis.afa.gov.tw/main/Main.aspx).
Note: Each observation represents daily auction price/quantity for one commodity in a vegetable market. NLS covers a storm where a warning was issued and the typhoon never made landfall. LS covers a storm where a warning was issued and the typhoon made landfall.

Table 3: Estimation Results and Decomposition

	Estimates		Decomposition		
			Price affected by		Quantity affected by
	log(price)	log(quantity)	demand	supply	supply
In warning period for NLS (1=Yes)	0.038***	-0.009	3.84%	-	-
	(0.012)	(0.012)			
In warning period for LS (1=Yes)	0.118***	-0.020*	9.67%	2.14%	-2.04%
	(0.016)	(0.010)			
In landfall period (1=Yes)	0.114***	-0.088***	2.09%	9.27%	-8.83%
	(0.019)	(0.017)			
Observations	1,439,280	1,439,280			
R-squared	0.712	0.799			

Note: NLS covers a storm where a warning was issued and the typhoon never made landfall. LS covers a storm where a warning was issued and the typhoon eventually did made landfall. The regressions are also controlled by the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. *** p<0.01, ** p<0.05, * p<0.1. The price elasticity of demand for decomposition is -0.952.

Table 4: Estimation Results for Four Categories

	Estimates		Decomposition		
			Price affected by		Quantity affected by
	log(price)	log(quantity)	demand	supply	supply
Panel A: Green Leafy Vegetables					
In warning period for NLS (1=Yes)	0.070***	-0.018	6.96%	-	-
	(0.011)	(0.013)			
In warning period for LS (1=Yes)	0.198***	-0.049***	13.98%	5.82%	-4.95%
	(0.012)	(0.012)			
In landfall period (1=Yes)	0.194***	-0.134***	3.61%	15.75%	-13.39%
	(0.013)	(0.014)			
Observations	426,721	426,721			
R-squared	0.642	0.846			
Panel B: Flower and Fruit Vegetables					
In warning period for NLS (1=Yes)	0.040***	-0.006	4.03%	-	-
	(0.010)	(0.017)			
In warning period for LS (1=Yes)	0.133***	-0.029**	11.14%	2.15%	-2.91%
	(0.010)	(0.012)			
In landfall period (1=Yes)	0.122***	-0.068***	7.13%	5.06%	-6.84%
	(0.011)	(0.016)			
Observations	469,084	469,084			
R-squared	0.654	0.740			
Panel C: Root Vegetables					
In warning period for NLS (1=Yes)	0.015***	-0.003	1.46%	-	-
	(0.005)	(0.010)			
In warning period for LS (1=Yes)	0.051***	0.018*	6.58%	-1.47%	1.77%
	(0.006)	(0.010)			
In landfall period (1=Yes)	0.053***	-0.073***	-0.73%	6.05%	-7.29%
	(0.006)	(0.010)			
Observations	427,708	427,708			
R-squared	0.790	0.788			
Panel D: Mushrooms					
In warning period for NLS (1=Yes)	0.002	-0.011	-	-	-
	(0.004)	(0.016)			
In warning period for LS (1=Yes)	0.008*	-0.018	0.79%	-	-
	(0.005)	(0.016)			
In landfall period (1=Yes)	0.010*	-0.059***	-0.82%	1.86%	-5.91%
	(0.006)	(0.017)			
Observations	115,767	115,767			
R-squared	0.695	0.720			

Note: NLS covers a storm where a warning was issued and the typhoon never made landfall. LS covers a storm where a warning was issued and the typhoon eventually did made landfall. The regressions are also controlled by the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the commodity-by-year level. *** p<0.01, ** p<0.05, * p<0.1. The price elasticity of demand for decomposition for four categories are -0.850 (green leafy vegetables), -1.354 (flower and fruit vegetables), -1.204 (root vegetables), and -3.173 (mushrooms).

Table 5: Estimation Results by the Intensity of Typhoons

	Estimates		Decomposition		
			Price affected by		Quantity affected by
	log(price)	log(quantity)	demand	supply	supply
In warning period for NLS × High intensity	0.045*** [0.016]	-0.002 [0.015]	4.46%	-	-
In warning period for NLS × Low intensity	0.032* [0.019]	-0.017 [0.018]	3.25%	-	-
In warning period for LS × High intensity	0.123*** [0.019]	-0.012 [0.012]	12.33%	-	-
In warning period for LS × Low intensity	0.107*** [0.016]	-0.038** [0.015]	6.79%	3.95%	-3.76%
In landfall period × High intensity	0.119*** [0.017]	-0.042** [0.018]	7.58%	4.37%	-4.16%
In landfall period × Low intensity	0.108*** [0.026]	-0.132*** [0.024]	-2.97%	13.82%	-13.16%
Observations	1,439,280	1,439,280			
R-squared	0.712	0.799			

Note: NLS covers a storm where a warning was issued and the typhoon never made landfall. LS covers a storm where a warning was issued and the typhoon eventually did made landfall. The regressions are also controlled by the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. *** p<0.01, ** p<0.05, * p<0.1. The price elasticity of demand for decomposition is -0.952.

Table 6: Estimation Results by the Information of Landfall

	Estimates		Decomposition		
			Price affected by		Quantity affected by
	log(price)	log(quantity)	demand	supply	supply
In warning period for NLFS × Typhoons will landfall in 24 hours	0.050*** [0.018]	-0.028* [0.016]	2.12%	2.93%	-2.79%
In warning period for NLFS × Typhoons will not landfall in 24 hours	0.033** [0.014]	-0.001 [0.015]	3.34%	-	-
In warning period for LFS × Typhoons will landfall in 24 hours	0.130*** [0.017]	-0.016 [0.013]	13.02%	-	-
In warning period for LFS × Typhoons will not landfall in 24 hours	0.082*** [0.023]	-0.033** [0.014]	4.71%	3.48%	-3.31%
In landfall period × Prediction on the previous day: Typhoons will landfall in 24 hours	0.123*** [0.020]	-0.092*** [0.018]	2.67%	9.66%	-9.20%
In landfall period × Prediction on the previous day: Typhoons will not landfall in 24 hours	0.041* [0.022]	-0.060*** [0.023]	-2.24%	6.30%	-6.00%
Observations	1,439,280	1,439,280			
R-squared	0.712	0.799			

Note: NLS covers a storm where a warning was issued and the typhoon never made landfall. LS covers a storm where a warning was issued and the typhoon eventually did made landfall. The regressions are also controlled by the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. *** p<0.01, ** p<0.05, * p<0.1. The price elasticity of demand for decomposition is -0.952.

Figure 1: Geographic Location of Taiwan

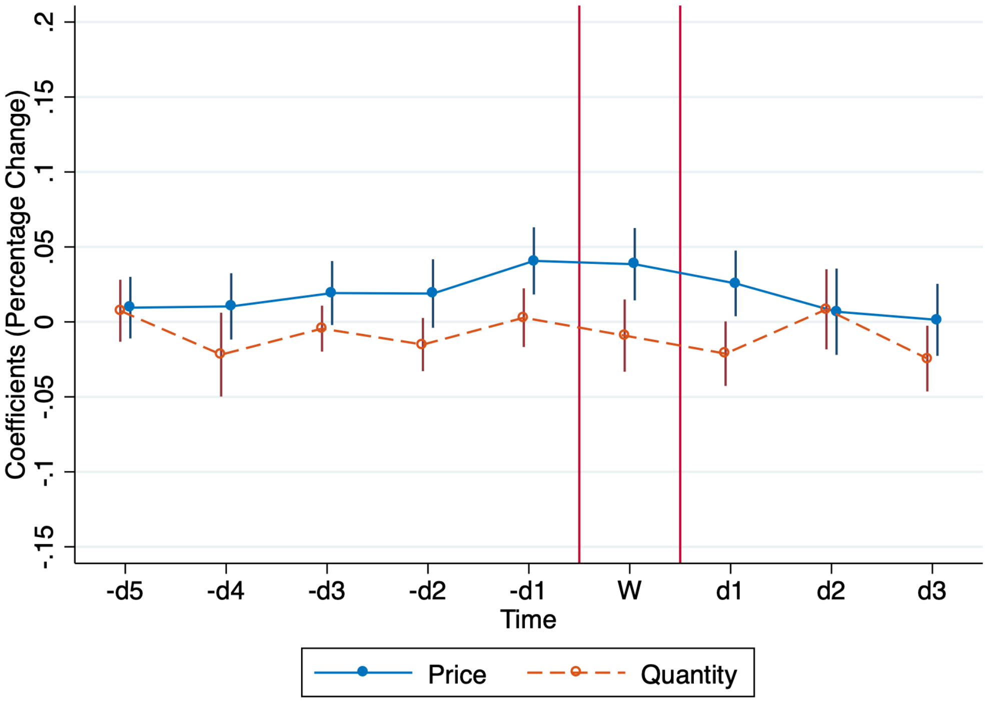


Figure 2: Market Response for Non-Landfalling Storms

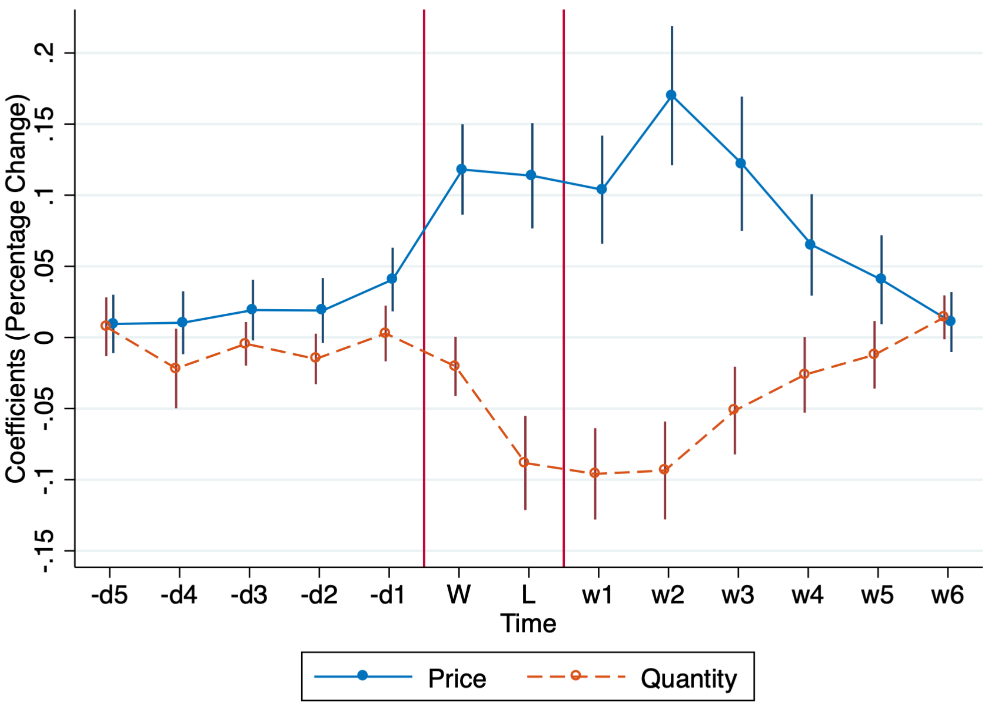
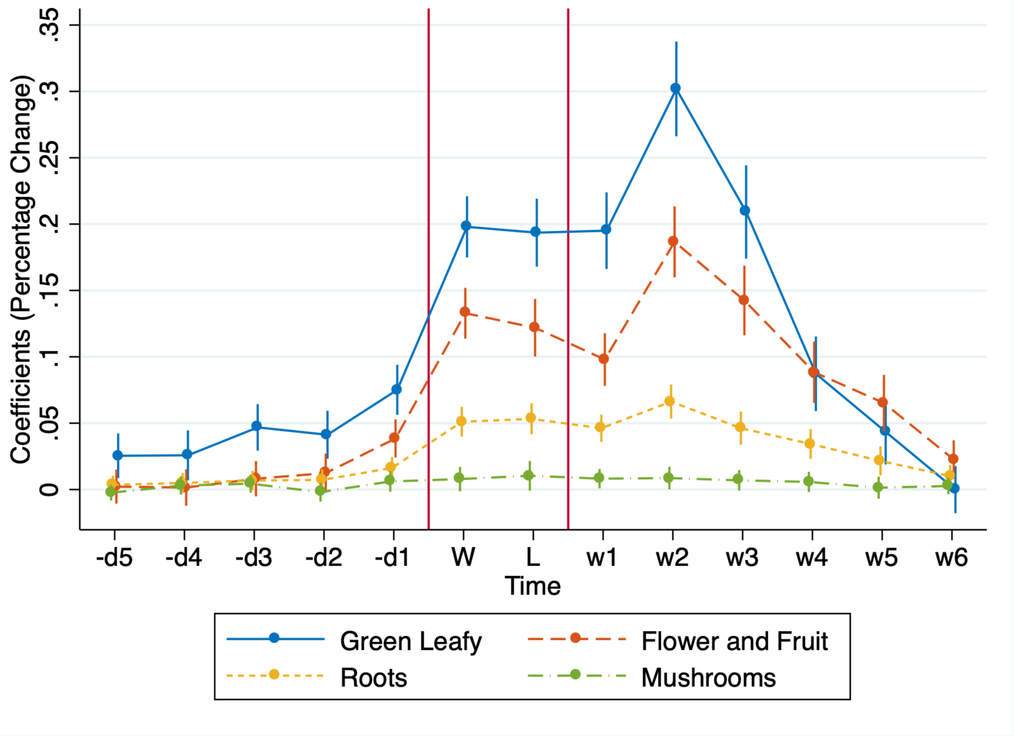
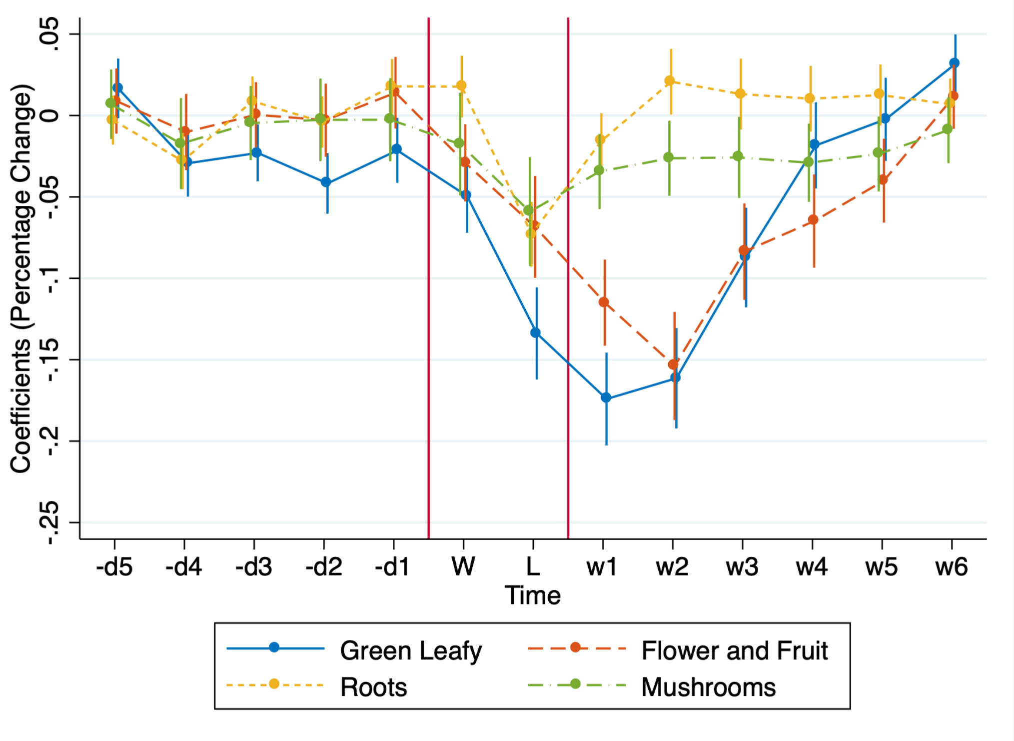


Figure 3: Market Response for Landfalling Storms

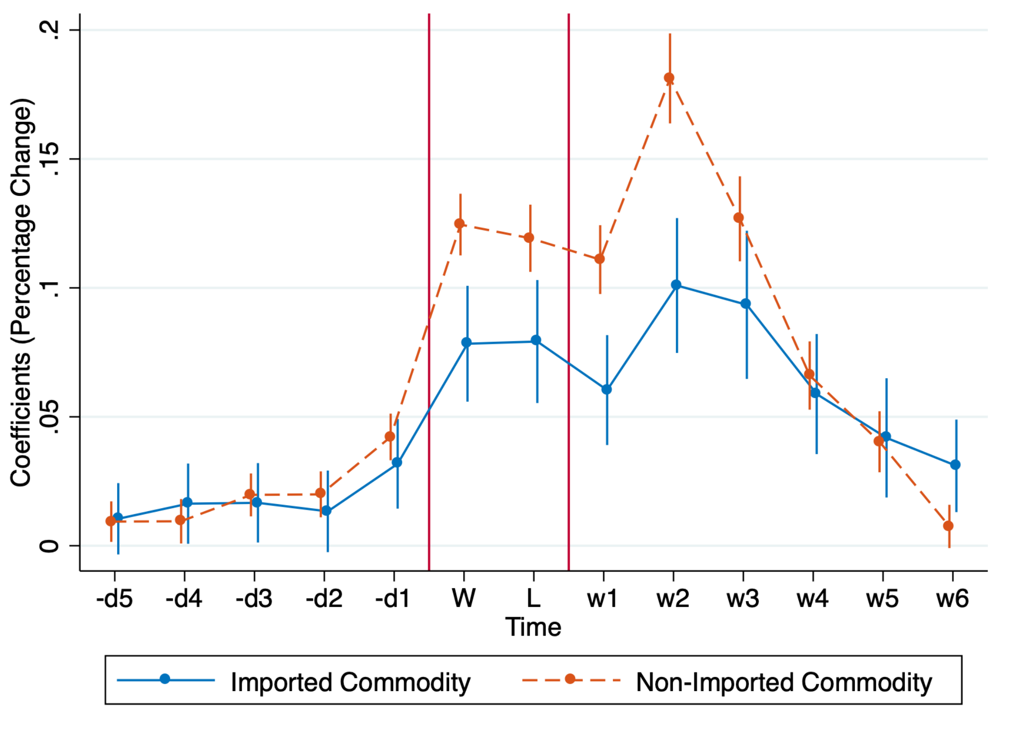


(a) Price Pattern

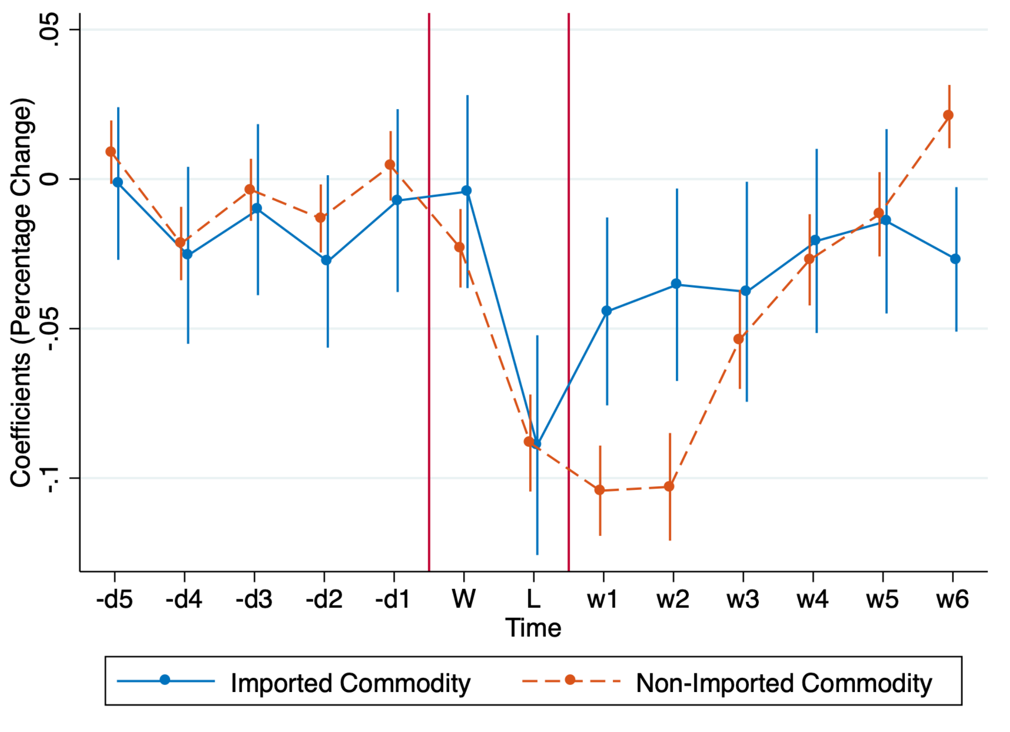


(b) Quantity Pattern

Figure 4: Four Vegetable Categories for Landfalling Storms

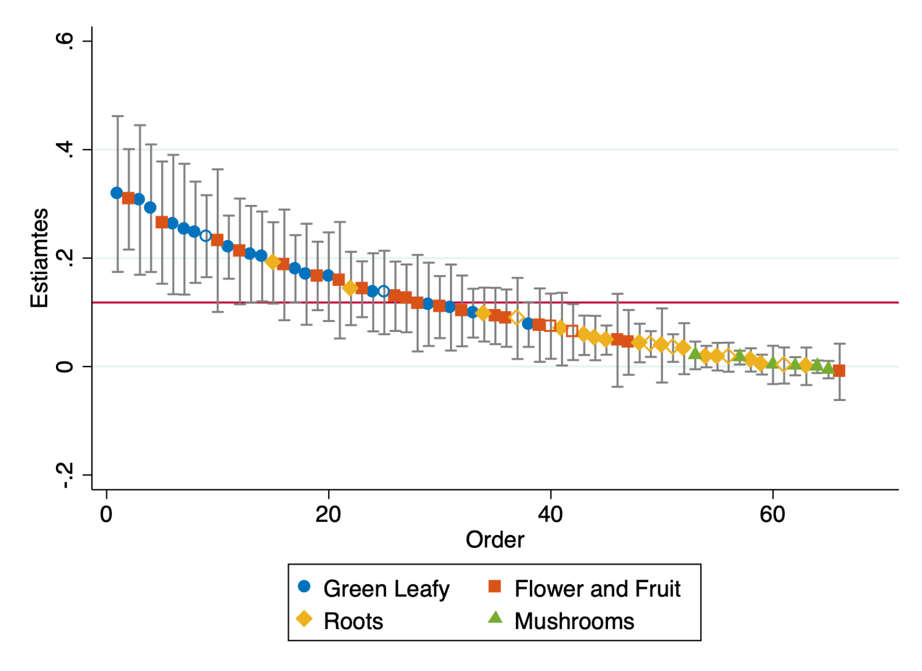


(a) Price Pattern

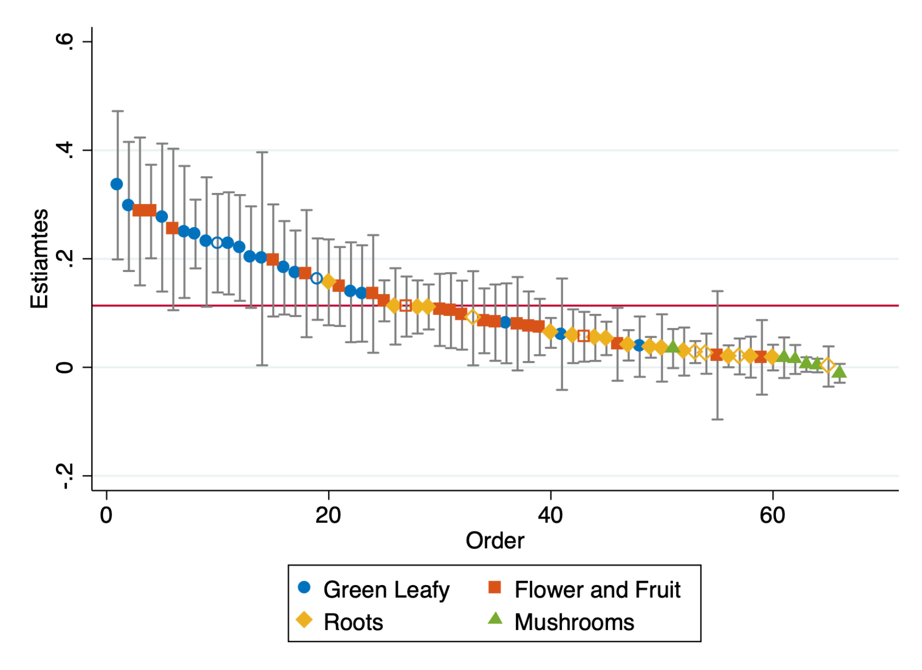


(b) Quantity Pattern

Figure 5: Imported and Non-Imported Commodities for Landfalling Storms



(a) Price in Warning Periods for Landfalling Storms



(b) Price in Landfall Periods for Landfalling Storms

Figure 6: Estimates by 66 Vegetables for Landfalling Storms

Note: Each dot represents the estimate for one vegetable, and the 95% confidence intervals are shown. The horizontal red lines represent the estimates from the main results. Four symbols represent the four groups, and the solid (hollow) symbol indicates the non-imported (imported) vegetable.

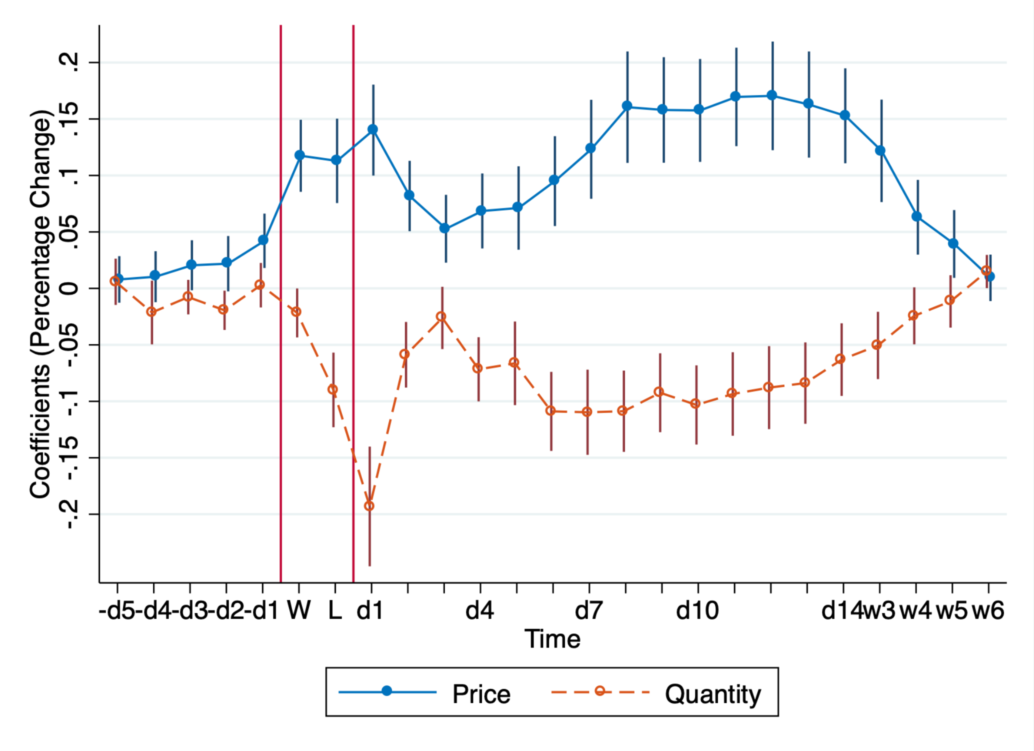
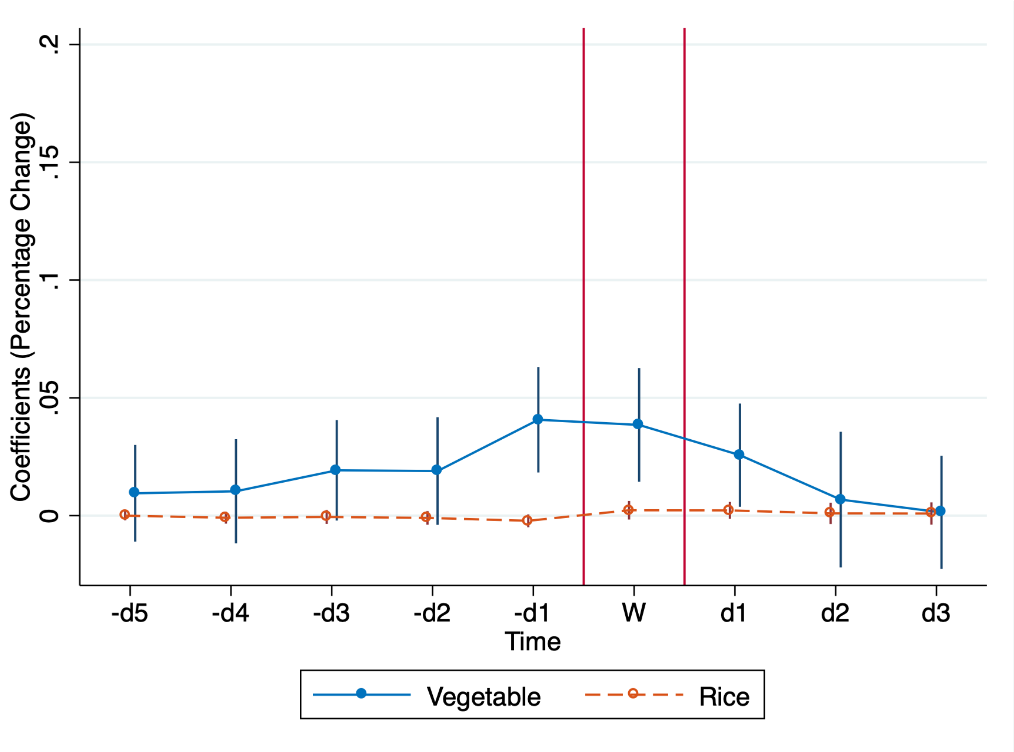
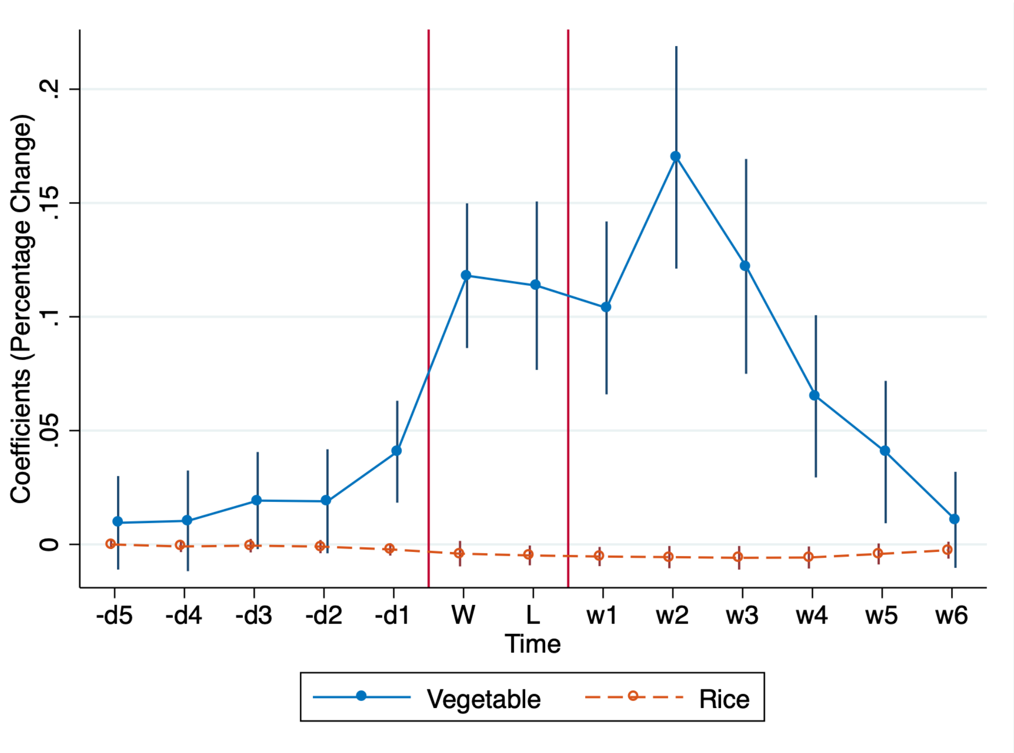


Figure 7: Two Weeks after the Landfall Periods



(a) Price Pattern for Non-Landfalling Storms



(b) Price Pattern for Landfalling Storms

Figure 8: Placebo Test

Appendix

A Demand Estimation

This section presents our demand estimation method for wholesale vegetable markets in Taiwan. In order to obtain price elasticity of demand to decompose typhoons' overall effects on price, we estimate an overall price elasticity of demand, a weighted average of price elasticities of all vegetables. The model is specified as follows:

$$\log(Q_{jmdt}) = \beta_0 + \beta_1 \log(P_{jmdt}) + X_{dt}\boldsymbol{\gamma} + f_j + \theta_m + g_t + \epsilon_{jmdt},$$

where Q_{jmdt} and P_{jmdt} are, respectively, quantity and price of vegetable j in market m on day d in month t. Our main interest is β_1, which refers to a constant price elasticity of demand. To further control possible factors that can affect demand, we control a set of variables X_{dt}, which include warning periods for both NLS and LS, landfall periods, five days before warning periods, three days after warning periods for NLS, six weeks after landfall periods, holiday effects and day-of-week fixed effects. In addition, we include commodity fixed effects (f_j), market fixed effects (θ_m) and month-by-year fixed effects (g_t). Robust standard errors are clustered at the category-by-year level.

Since the price in the demand estimation equation is endogenous, we use two dummy variables which indicate, respectively, the first and second weeks after a day with torrential rain[19] as the instrumental variables to solve the endogeneity problem. Since vegetables might suffer an extremely large loss after large precipitation, we use this to serve as the exogenous supply shift to identify the demand equation.

Table A2 displays results for the demand estimation. The first column shows results from ordinary least squares (OLS), which may have a positive bias due to the

[19]Based on the definition from TCWB, torrential rain is defined as a situation in which accumulated rainfall exceeds 350 millimeters in 24 hours.

endogeneity problem. The second column presents results from the two-stage least squares (2SLS). The estimated price elasticity of demand is -0.952, larger than that based on OLS estimation. We use this value to decompose price effects in Table 3. Notably, we also find significant coefficients on warning periods for both NLS and LS, which further supports evidence of precautionary purchase from the demand side.

In addition, we use this same framework to estimate overall price elasticities of demand for our four vegetable categories and results are shown in Table A3. Since heavy rainfall would probably not have any effect on mushrooms (grown inside), the first-stage F statistics for mushrooms are very small, which cannot pass a relevance test criterion. Besides mushrooms, the largest price elasticity of demand is -1.354 (flower and fruit vegetables) and the smallest is -0.85 (green leafy vegetables). We use these four elasticities to decompose typhoons' effects on prices in Table 4.

B Additional Tables and Figures

Table A1: Vegetables and the Categories

Category	Vegetables
Green Leafy Vegetables (19 vegetables)	Wild Cabbage, Bok Choy I, Bok Choy II, Cabbage, Malabar Spinach, Water Spinach, Celery, Spinach, Lettuce, Leaf Mustard, Chinese Broccoli, Amaranth, Rape, Sweet Potato Leaves, Parsley, Basil, Gynura Bicolor, Eagle Fern, Shepherd's Purse
Flower and Fruit Vegetables (21 vegetables)	Okra, Broccoli, Cucumber I, Cucumber II, Wax Gourd, Luffa, Bitter Melon, Bottle Gourd, Eggplant, Tomato, Sweet Pepper, Peas, Common Bean, Green Bean, Edamame, Broccolini, Pumpkin, Chayote, Chili Pepper, Corn, Peanut
Root Vegetables (20 vegetables)	Radish, Carrot, Potato, Onion, Green Onion, Chives, Hotbed Chives, Flowering Chives, Garlic, Bamboo Shoots, Taro, Water Chestnut, Jicama, Burdock Root, Lotus Root, Sweet Potato, Ginger, Water Bamboo Shoot, Asparagus, Sprouts
Mushrooms (6 vegetables)	Common Mushroom, Straw Mushroom, Wood Ear, Shiitake Mushroom, Enokitake Mushroom, Oyster Mushroom

Table A2: Demand Estimation

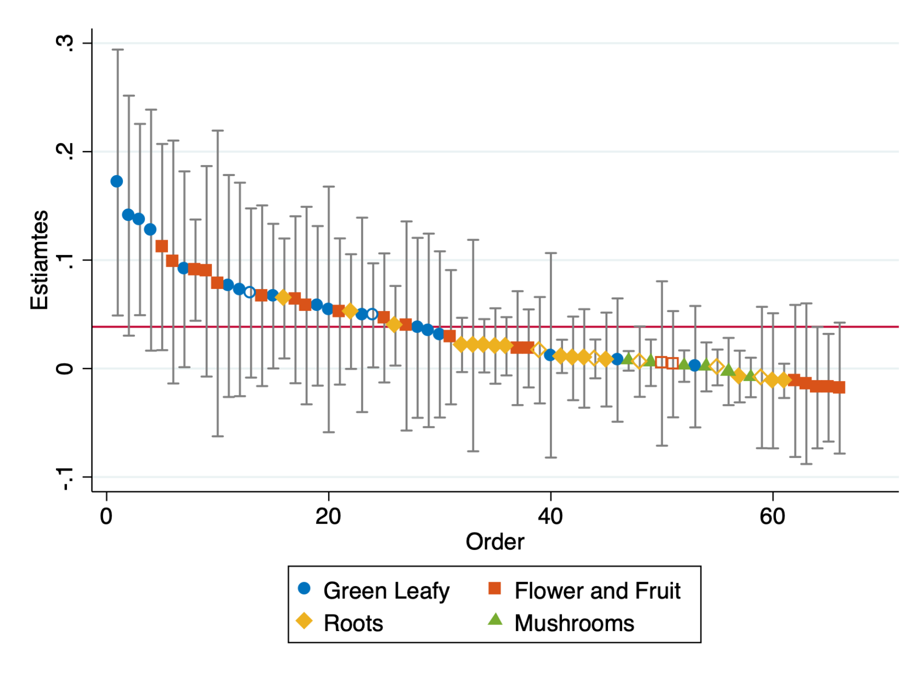
	log(quantity)	
	OLS	2SLS
log(price)	-0.705***	-0.952***
	(0.018)	(0.107)
In Warning Period for NLS (1=Yes)	0.018	0.028**
	(0.011)	(0.013)
In Warning Period for LS (1=Yes)	0.063***	0.092***
	(0.011)	(0.019)
In Landfall Period (1=Yes)	-0.008	0.020
	(0.013)	(0.019)
Observations	1,439,280	1,439,280
R-squared	0.712	0.799
First stage F-value		17.95
p-value		¡0.001

Note: The regressions are also controlled by the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods. The instrumental variables in 2SLS are two dummies which indicate the first and the second week after a day with the torrential rain. Robust standard errors in parentheses are clustered at the category-by-year level. *** p<0.01, ** p<0.05, * p<0.1.

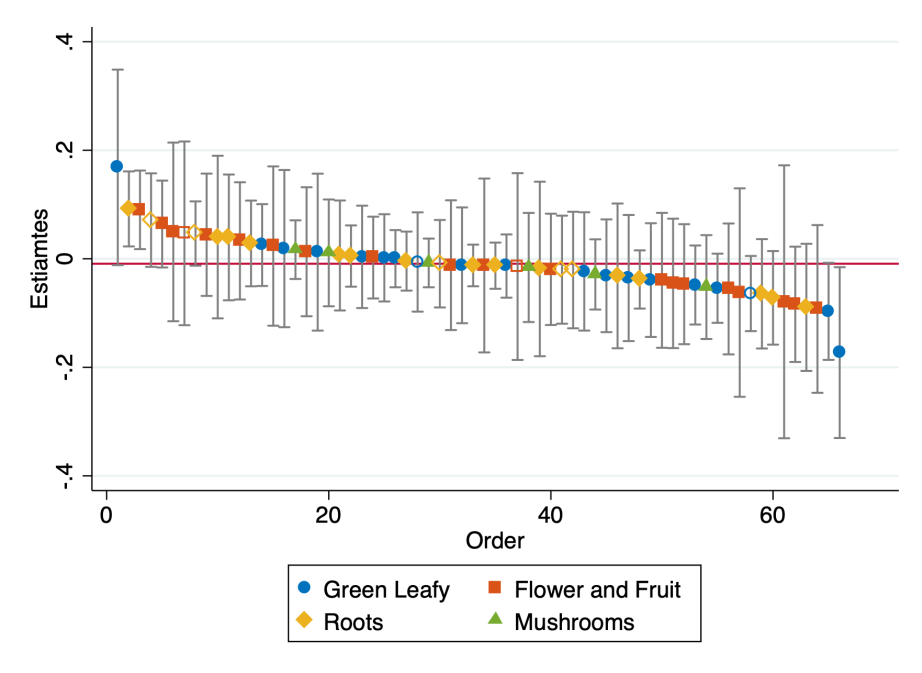
Table A3: Demand Estimation for Four Categories

	log(quantity)			
	2SLS	2SLS	2SLS	2SLS
	Green Leafy Vegetables	Flower and Fruit Vegetables	Root Vegetables	Mushrooms
log(price)	-0.850***	-1.354***	-1.204***	-3.173***
	(0.053)	(0.121)	(0.195)	(1.220)
Observations	426,721	469,084	427,708	115,767
R-squared	0.865	0.753	0.805	0.539
First stage F-value	110.43	55.80	11.24	1.77
p-value	¡0.001	¡0.001	¡0.001	0.091

Note: The regressions are controlled by the warning periods for both NLS and LS, landfall periods, commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, five days before warning periods, three days after warning periods for NLS and six weeks after landfall periods. The instrumental variables in 2SLS are two dummies which indicate the first and the second week after a day with the torrential rain. Robust standard errors in parentheses are clustered at the commodity-by-year level. *** p<0.01, ** p<0.05, * p<0.1.



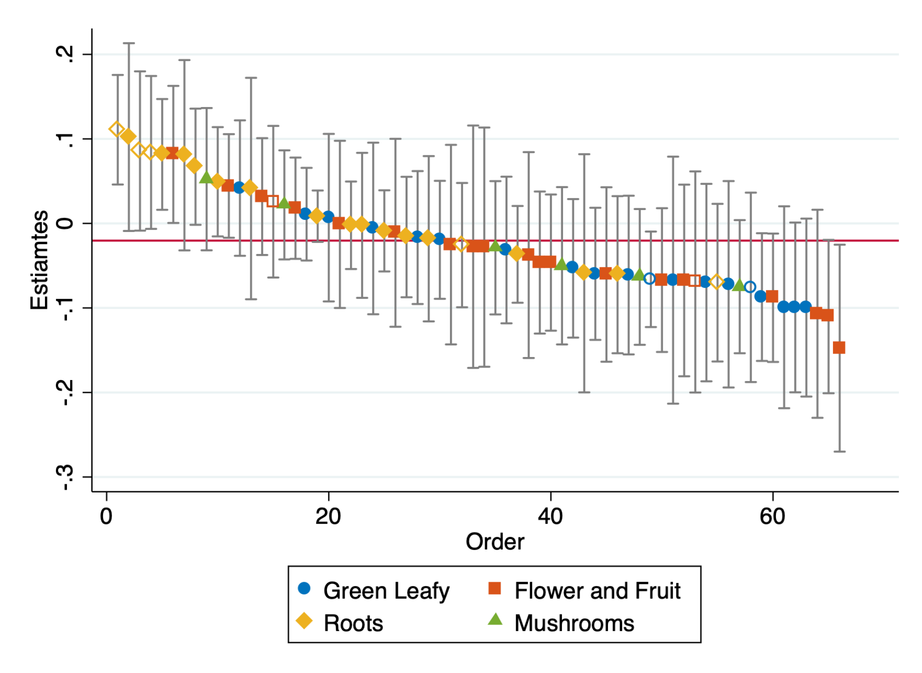
(a) Price in Warning Periods for Non-Landfalling Storms



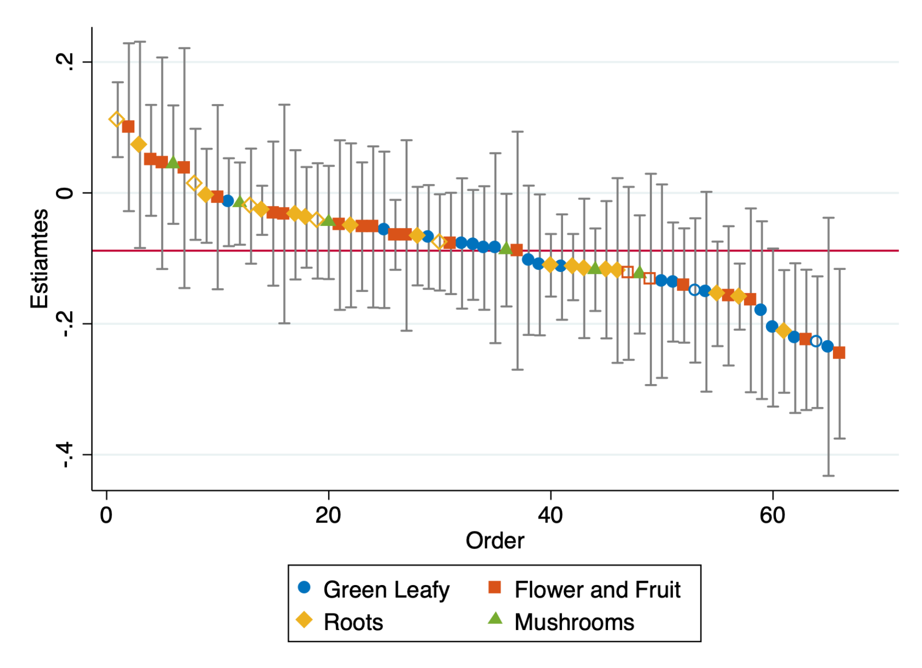
(b) Quantity in Warning Periods for Non-Landfalling Storms

Figure A1: Estimates by 66 Vegetables for Non-Landfalling Storms

Note: Each dot represents the estimate for one vegetable, and the 95% confidence intervals are shown. The horizontal red lines represent the estimates from the main results. Four symbols represent the four groups, and the solid (hollow) symbol indicates the non-imported (imported) vegetable.



(a) Quantity in Warning Periods for Landfalling Storms



(b) Quantity in Landfall Periods for Landfalling Storms

Figure A2: Estimates by 66 Vegetables for Landfalling Storms

Note: Each dot represents the estimate for one vegetable, and the 95% confidence intervals are shown. The horizontal red lines represent the estimates from the main results. Four symbols represent the four groups, and the solid (hollow) symbol indicates the non-imported (imported) vegetable.