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RESEARCH ARTICLE

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Market response to typhoons: The role of information and expectations

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Abstract

Damages from tropical storms are enormous and predicted to increase with climate change. This study uses high-frequency data to investigate typhoons' effects through information channels 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 h, and such prior information related to intensity or landfall urgency can also amplify early harvest effects by farmers.

KEYWORDS

reaction to forecast information, typhoon, vegetable market response

JEL CLASSIFICATION
Q11, Q13, Q54

1 | INTRODUCTION

Typhoons (also called hurricanes[1]) often cause severe damage to agricultural sectors due to heavy downpours and storm surges.[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 & 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 uses 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 government reveals such information to the population so that they can prepare. People may acquire emergency supplies and hoard storable foods before, during or after storm landfalls (Beatty et al., 2019). On the supply side, besides the direct impact of hurricanes on production,[4] farmers are likely to adopt strategies when they expect damage from storms (Campbell & Beckford, 2009). For instance, Jamaican farmers mainly adopted strategies of protecting nurseries, spraying, harvesting, and storage before the storm. Information related to typhoons can directly affect the market outcome, which is also linked to the costs of typhoons; therefore, it is important to understand how the market responds to typhoons.

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, on the normal global track of typhoons, so such storms strike Taiwan frequently every year.[5] There were a total of 366 typhoons from 1911 through 2018 (averaging 3.39 per year).[6] 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

[1]Tropical cyclones are called hurricanes in the Atlantic Ocean and typhoons in the northwest Pacific Ocean.

[2]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. 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.

[4]Many existing studies have investigated the impact of hurricanes on crop production (Israel & Briones, 2012; Spencer & Polachek, 2015; Strobl, 2012a) and the crop yield response to climate change-related shifts in extreme conditions (Attavanich & McCarl, 2014; Schlenker & Roberts, 2009).

[5]Landfalling typhoons typically bring sustained high winds and heavy rains, which cause severe agricultural losses. Detailed damage information was reported in https://cdprc.ey.gov.tw/

[6]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.

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 in the very short run, 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. Farmers can also 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. 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.

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 h, 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.[7] We also use this decomposition to further provide 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 (Gladwin et al., 2007; Katz & Murphy, 1997; Letson et al., 2007; Regnier & Harr, 2006; 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

[7]This augments the literature that has principally dealt with longer term peak market responses and distortions for non-agricultural commodities (Götz et al., 2016; Maystadt & Ecker, 2014). Also, a several studies have addressed the effects on real estate (housing) markets (Hallstrom & Smith, 2005; Ortega & Taşpınar, 2018), labor markets (Belasen & Polachek, 2009; McIntosh, 2008) and financial markets (Hewitt, 2012).

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, 2011; Strobl, 2012b; 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 background on typhoons and wholesale vegetable markets. Section 3 shows the data in this study. Section 4 introduces this study's empirical strategy. Section 5 presents and discusses empirical results. Section 6 concludes this research.

2 | BACKGROUND

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[8] are expected to pass within 100 km of Taiwan during the next 24 h. 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 during the following 24 h. When the outer bands are predicted to be over the island in 18 h, 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 3 h, 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.

The daily wholesale market, as embodied in specific physical markets, starts in the very early morning (3:00 a.m.) 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 quantities are determined solely by the supply side.

3 | DATA

3.1 | Weather data

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 h.

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

[8]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 meters per second (m/s).

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 storms), 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.

3.2 | Daily wholesale vegetable market data

We use daily transaction data from the 1996–2014 period on Taiwan's wholesale vegetable market.[9] We then construct average prices and total quantity within each vegetable-market-day combination to proxy daily equilibrium prices and quantities for this study.

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.

Furthermore, we select 66 different vegetables for the following analysis.[10] 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 (six items). Detailed information is listed in Table A1. In addition, we further focus on four major wholesale markets:[11] 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 2200 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 6344 kg, which reduces to 5728 kg (5913 kg) during warning periods for NLS (LS), and yet smaller (5667 kg) during landfall periods. Average prices across the four markets varied substantially and average quantity for Taipei I is largest among these four markets.

4 | METHODOLOGY

To examine typhoon effects on market prices and quantities, we consider the following fixed effects model:

$$\log\left(Y_{\mathrm{jmdt}}\right) = \beta_0 + \beta_1 W_{\mathrm{dt}}^{\mathrm{NLS}} + \beta_2 W_{\mathrm{dt}}^{\mathrm{LS}} + \beta_3 L_{\mathrm{dt}} + X_{\mathrm{dt}}\gamma + f_{\mathrm{j}} + \theta_{\mathrm{m}} + g_{\mathrm{t}} + \epsilon_{\mathrm{jmdt}}, \tag{1}$$

where Y_{jmdt} is the price or quantity of vegetable j in market m on day d in month t. $W_{\mathrm{dt}}^{\mathrm{NLS}}$ and $W_{\mathrm{dt}}^{\mathrm{LS}}$ 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[12] 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

[10]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.

[11]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.

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

TABLE 2 Summary statistics on prices and quantities

Variables	Observations	Mean	SD	Min	Max
Prices (NTD/kg)	1,439,280	32.939	27.461	0.9	803.3
Quantities (kg)	1,439,280	6,320.623	14,950.655	1	471,475
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 (NTD/kg)					
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 (kg)					
Days without typhoons	1,381,491	6,343.571	14,989.980	1	471,475
Days in warning period for NLS	14,159	5,727.837	13,289.167	1.8	237,439
Days in warning period for LS	21,172	5,912.708	14,399.041	1.8	346,035
Days in landfall period for LS	22,458	5,667.241	13,968.765	2	298,894
Prices by market (NTD/kg)					
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 (kg)					
Taipei I	380,885	15,624.857	25,136.291	1	471,475
Taipei II	369,562	4,436.058	7,843.743	2	177,279
Taichung	324,884	1,323.546	2,279.596	1	54,804
Kaohsiung	363,949	2,957.762	5,272.258	1	96,342

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.
Source: The Agriculture and Food Agency Council of Agriculture (AFACA), Executive Yuan in Taiwan (https://amis.afa.gov.tw/main/Main.aspx).

overlapping events[13] 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).

[13]For instance, a 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.

Lastly, we specify a set of fixed effects, including the commodity fixed effects (f_j), market fixed effects (θ_m), day-of-week fixed effects (dummies in X_{dt}), and the 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 19) are correlated, the robust standard errors are clustered at the category-by-year level.[14]

We also further decompose the effects of typhoons on prices and quantities into effects based on supply or demand shifts. Since the supply curve is perfectly inelastic, the effect on quantities is mainly driven by supply shifts. If we 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.1 (Tables A2 and A3) and the overall price elasticity of demand for all vegetables is collectively −0.952.

5 | EMPIRICAL RESULTS

5.1 | Main results

The first two columns in Table 3 show estimation results from equation (1), and the last three columns in Table 3 present results of our decomposition.

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 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 1 and 2 present results for NLS and LS, respectively. First, prices rise significantly 1 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 3 days after warnings are issued

[14]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.

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 6 weeks[15] to return to normal levels, which affects both price and quantity in the market.

5.2 | 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.

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

TABLE 3 Estimation results and decomposition

	Estimates		Decomposition Price affected by	
Variables	**log(price)**	**log(quantity)**	**demand**	**supply**
NLS warning period	0.038*** (0.012)	−0.009 (0.012)	3.84%	–
LS warning period	0.118*** (0.016)	−0.020* (0.010)	9.67%	2.14%
LS landfall period	0.114*** (0.019)	−0.088*** (0.017)	2.09%	9.27%
Observations	1,439,280	1,439,280		
R^2	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. All regressions include the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, 5 days before warning periods, 3 days after warning periods for NLS and 6 weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. ***$p < .01$; **$p < .05$; *$p < .1$. The price elasticity of demand for decomposition is −0.952. The dash in the decomposition indicates an insignificant effect with p value greater than .1.

[15]Since plug seedlings can shorten the growth period of vegetables in the field, supply can be replenished within 6 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.

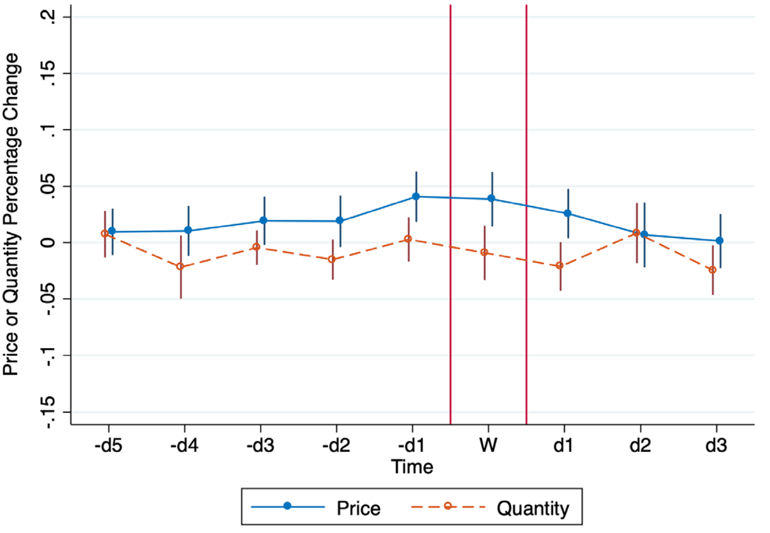

FIGURE 1 Market response for non-landfalling storms [Color figure can be viewed at wileyonlinelibrary.com]

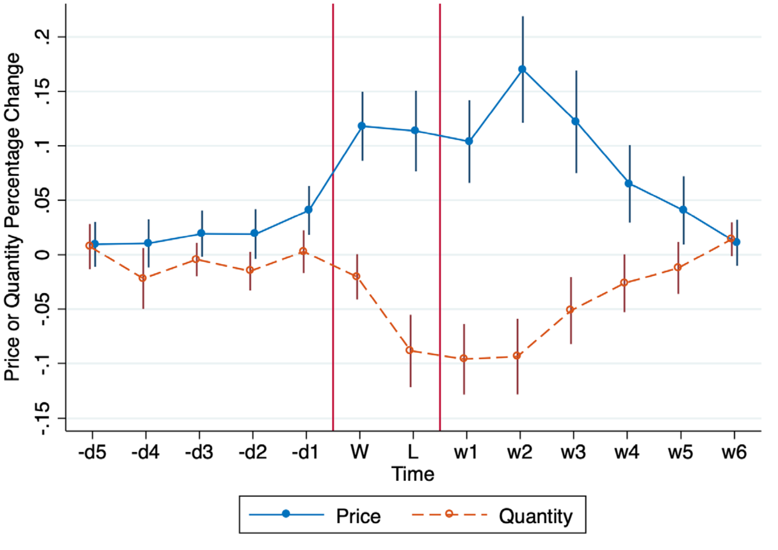

FIGURE 2 Market response for landfalling storms [Color figure can be viewed at wileyonlinelibrary.com]

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.[16] 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

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

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 1.8%, which might reflect the release of previous storage. In landfall periods, quantities decrease in these four categories and price effects are mainly driven by the supply side, except for the case of flower and fruit vegetables.

Figure 3 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 2 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[17]) and non-imported vegetables (others, with <5% imports). Figure A1 shows that the price and quantity patterns for those vegetables with a significant imported percentage are relatively more stable. In addition, we also apply the model in Equation (1) to each vegetable.[18] Figure A2 presents price effects during the warning and landfall periods for LS.[19] The results show that most estimates for green leafy vegetables (green circles) and flower and fruit vegetables (red square) are significantly above zero, consistent with previous results for these four groups. Similarly, estimates for partly imported vegetables are relatively smaller than those for non-imported vegetables.

5.3 | 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 2 weeks after landfall periods.

5.3.1 | 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

[17]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.

[18]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.

[19]The other four estimates are shown Figures A3 and A4 in the Appendix A.

TABLE 4 Estimation results for four categories

Variables	Estimates		Decomposition	
			Price affected by	
	log(price)	log(quantity)	demand	supply
Panel A: Green leafy vegetables				
NLS warning period	0.070*** (0.011)	−0.018 (0.013)	6.96%	-
LS warning period	0.198*** (0.012)	−0.049*** (0.012)	13.98%	5.82%
LS landfall period	0.194*** (0.013)	−0.134*** (0.014)	3.61%	15.75%
Observations	426,721	426,721		
R^2	0.642	0.846		
Panel B: Flower and fruit vegetables				
NLS warning period	0.040*** (0.010)	−0.006 (0.017)	4.03%	–
LS warning period	0.133*** (0.010)	−0.029** (0.012)	11.14%	2.15%
LS landfall period	0.122*** (0.011)	−0.068*** (0.016)	7.13%	5.06%
Observations	469,084	469,084		
R^2	0.654	0.740		
Panel C: root vegetables				
NLS warning period	0.015*** (0.005)	−0.003 (0.010)	1.46%	–
LS warning period	0.051*** (0.006)	0.018* (0.010)	6.58%	−1.47%
LS landfall period	0.053*** (0.006)	−0.073*** (0.010)	−0.73%	6.05%
Observations	427,708	427,708		
R^2	0.790	0.788		
Panel D: Mushrooms				
NLS warning period	0.002 (0.004)	−0.011 (0.016)	–	–
LS warning period	0.008* (0.005)	−0.018 (0.016)	0.79%	–
LS landfall period	0.010* (0.006)	−0.059*** (0.017)	−0.82%	1.86%
Observations	115,767	115,767		
R^2	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. All regressions include the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, 5 days before warning periods, 3 days after warning periods for NLS and 6 weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the commodity-by-year level. ***$p < .01$; **$p < .05$; *$p < .1$. 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). The dash in the decomposition indicates an insignificant effect with p value greater than .1.

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, the price effects for high-intensity LS are 12.3%, greater than 10.7% when LS is forecast to be of low intensity. Similarly, the price effects for high-intensity NLS are 4.5%, larger than 3.2% when NLS is forecast to be of low intensity.

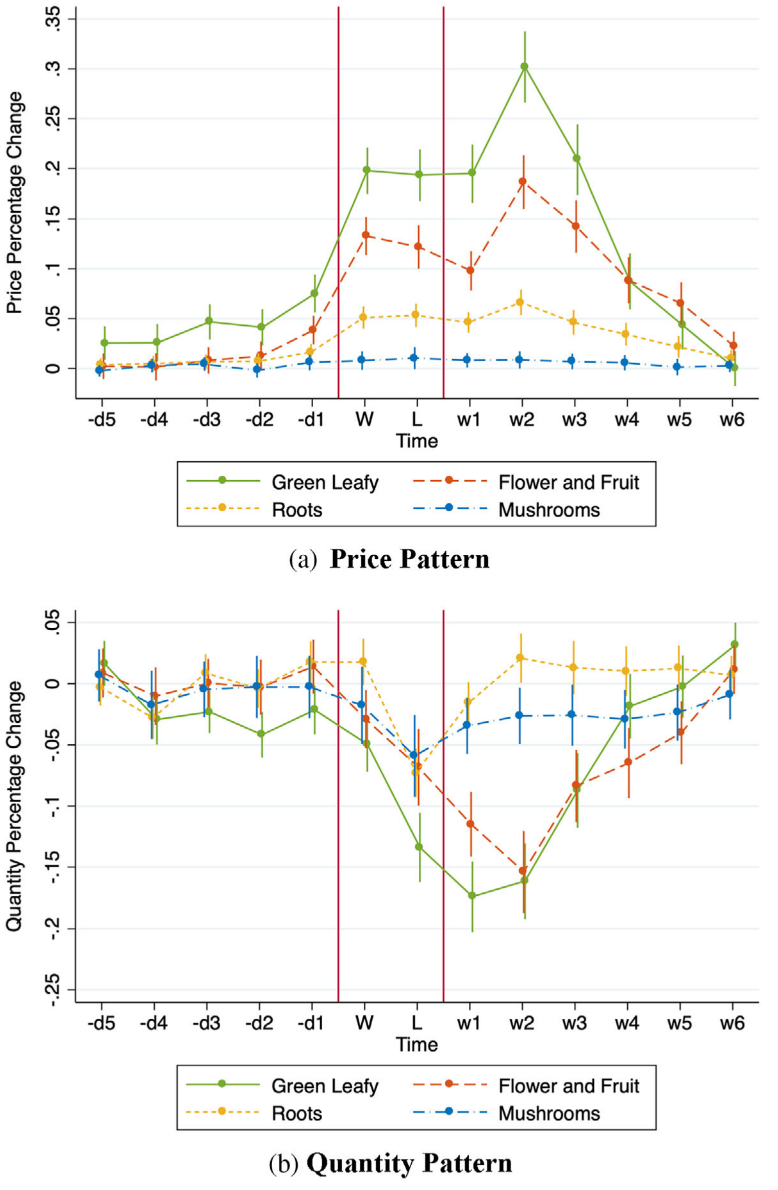

FIGURE 3 Four vegetable categories for landfalling storms [Color figure can be viewed at wileyonlinelibrary.com]

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.

TABLE 5 Estimation results by the intensity of typhoons

	Estimates		Decomposition Price affected by	
Variables	**log(price)**	**log(quantity)**	**demand**	**supply**
NLS warning period ×High intensity	0.045*** (0.016)	−0.002 (0.015)	4.46%	–
NLS warning period ×Low intensity	0.032* (0.019)	−0.017 (0.018)	3.25%	–
LS warning period ×High intensity	0.123*** (0.019)	−0.012 (0.012)	12.33%	–
LS warning period ×Low intensity	0.107*** (0.016)	−0.038** (0.015)	6.79%	3.95%
LS landfall period ×High intensity	0.119*** (0.017)	−0.042** (0.018)	7.58%	4.37%
LS landfall period ×Low intensity	0.108*** (0.026)	−0.132*** (0.024)	−2.97%	13.82%
Observations	1,439,280	1,439,280		
R^2	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. All regressions include the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, 5 days before warning periods, 3 days after warning periods for NLS and 6 weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. ***$p < .01$; **$p < .05$; *$p < .1$. The price elasticity of demand for decomposition is −0.952. The dash in the decomposition indicates an insignificant effect with p value greater than .1. Since we are not comparing the effect between high and low intensity, we directly interact the main interest variables with high/low intensity to test whether the effect under high/low intensity is significantly different from zero or not.

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 h—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 h can strengthen the consumer precautionary purchase effect. Similarly, information of impending landfall in 24 h 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 h, and we make 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.

TABLE 6 Estimation results by the information of landfall

Variables	Estimates		Decomposition Price affected by	
	log(price)	log(quantity)	demand	supply
NLS warning period	0.050***	−0.028*	2.12%	2.93%
×Typhoons will landfall in 24 h	(0.018)	(0.016)		
NLS warning period	0.033**	−0.001	3.34%	-
×Typhoons will not landfall in 24 h	(0.014)	(0.015)		
LS warning period	0.130***	−0.016	13.02%	-
×Typhoons will landfall in 24 h	(0.017)	(0.013)		
LS warning period	0.082***	−0.033**	4.71%	3.48%
×Typhoons will not landfall in 24 h	(0.023)	(0.014)		
LS landfall period	0.123***	−0.092***	2.67%	9.66%
×Prediction on the previous day: typhoons will landfall in 24 h	(0.020)	(0.018)		
LS landfall period	0.041*	−0.060***	−2.24%	6.30%
×Prediction on the previous day: typhoons will not landfall in 24 h	(0.022)	(0.023)		
Observations	1,439,280	1,439,280		
R^2	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. All regressions include the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, 5 days before warning periods, 3 days after warning periods for NLS and 6 weeks after landfall periods for LS. Robust standard errors in parentheses are clustered at the category-by-year level. ***$p < .01$; **$p < .05$; *$p < .1$. The price elasticity of demand for decomposition is −0.952. The dash in the decomposition indicates an insignificant effect with p value greater than .1. Since we are not comparing the effect under different scenarios, we directly interact the main interest variables with all of the scenarios to test whether the effect under that scenario is significantly different from zero or not.

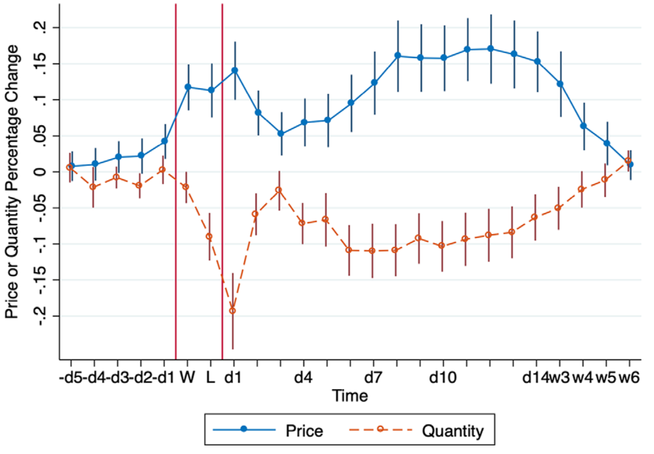

FIGURE 4 Two weeks after the landfall periods. (a) Price pattern. (b) Quantity pattern [Color figure can be viewed at wileyonlinelibrary.com]

5.3.2 | Recovery period after landfall

In Section 5.1, 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 2 weeks after landfall, we estimate equation (1) again but replace dummy variables for the first 2 weeks after landfall with 14 separate daily dummies, one for each day. Figure 4 summarizes results. First, vegetable quantities are lower on the first day after the storm leaves Taiwan, and then increase sharply on the next 2 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 3 days after storm departure, not only due to increased supply but also due to likely short-term decreased demand. Consumers may not immediately make purchase as they presumably stocked up during the prior warning period and may still have vegetables at home. However, once 6 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 10 through 12, prices and quantities start to return to normal but do not fully attain that until 6 weeks after storm departure as by then, new plantings and harvestings bring new supplies of most items to market.

5.4 | 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[20] to examine typhoons' effects on rice prices. We use the same framework as in

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

Equation (1), and bootstrapping robust standard errors are clustered at the year level. Figure A5 indicates that typhoon effects on rice for NLS and LS are very close to zero, relatively smaller than for vegetables.

6 | CONCLUSIONS

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 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 h, 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 et al., 2019); shifts in locations where typhoons reach peak wind intensity (Kossin et al., 2014; Kossin et al., 2017); more rainfall due to slowing typhoon movement (Kossin, 2018) and increasing abruptness of track direction changes (Hall & Kossin, 2019; Kossin et al., 2017) 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.

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APPENDIX A

A.1 | 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:

$$\log\left(\mathrm{Q_{jmdt}}\right) = \beta_0 + \beta_1 \log\left(\mathrm{P_{jmdt}}\right) + X_{\mathrm{dt}}\gamma + f_{\mathrm{j}} + \theta_{\mathrm{m}} + g_{\mathrm{t}} + \epsilon_{\mathrm{jmdt}},$$

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, 5 days before warning periods, 3 days after warning periods for NLS, 6 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 the 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[21]

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 (six 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*** (0.018)	−0.952*** (0.107)
NLS warning period	0.018 (0.011)	0.028** (0.013)
LS warning period	0.063*** (0.011)	0.092*** (0.019)
LS landfall period	−0.008 (0.013)	0.020 (0.019)
Observations	1,439,280	1,439,280
R^2	0.712	0.799
First stage F value		17.95
p value		<.001

Note: All regressions include the commodity fixed effects, market fixed effects, holiday effects, day of week fixed effects, month-by-year fixed effects, 5 days before warning periods, 3 days after warning periods for NLS and 6 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. ***$p < .01$; **$p < .05$; *$p < .1$.

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

TABLE A3 Demand estimation for four categories

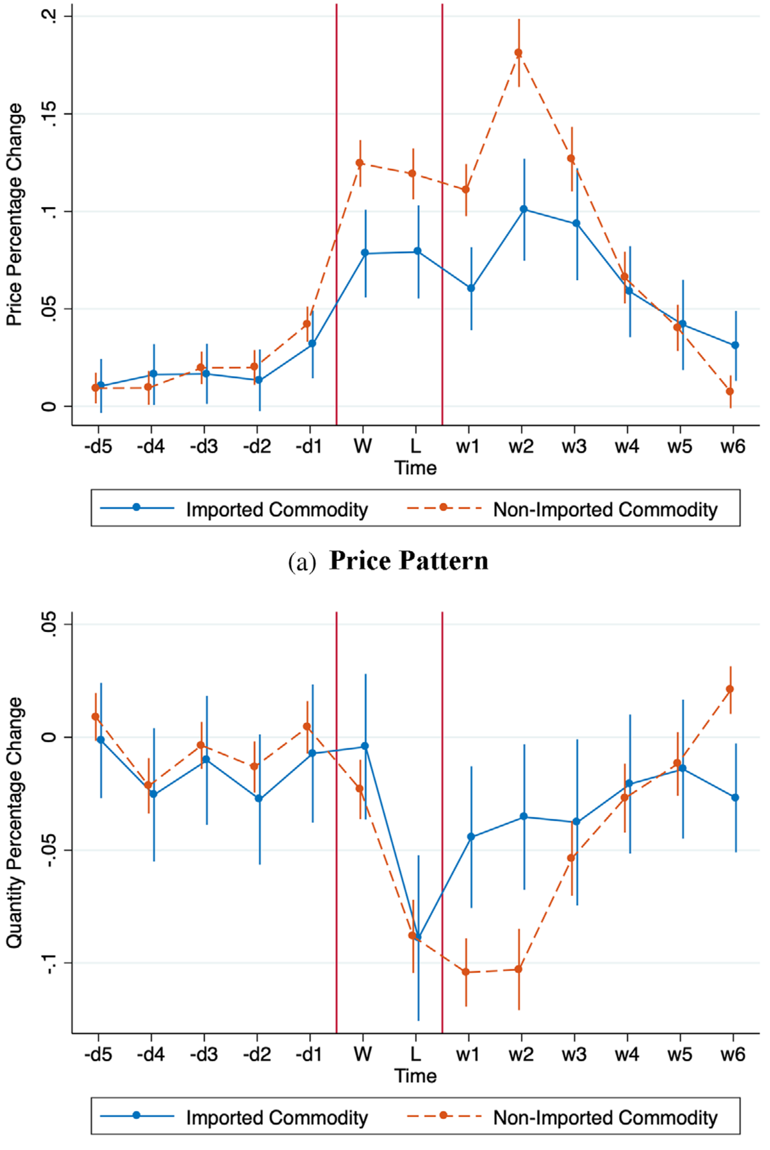
	Log(quantity)			
	2SLS Green leafy	2SLS Flower and fruit	2SLS Root	2SLS Mushrooms
log(price)	−0.850*** (0.053)	−1.354*** (0.121)	−1.204*** (0.195)	−3.173*** (1.220)
Observations	426,721	469,084	427,708	115,767
R^2	0.865	0.753	0.805	0.539
First stage F value	110.43	55.80	11.24	1.77
p value	<.001	<.001	<.001	.091

Note: All regressions include 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, 5 days before warning periods, 3 days after warning periods for NLS and 6 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. ***$p < .01$; **$p < .05$; *$p < .1$.

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 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.

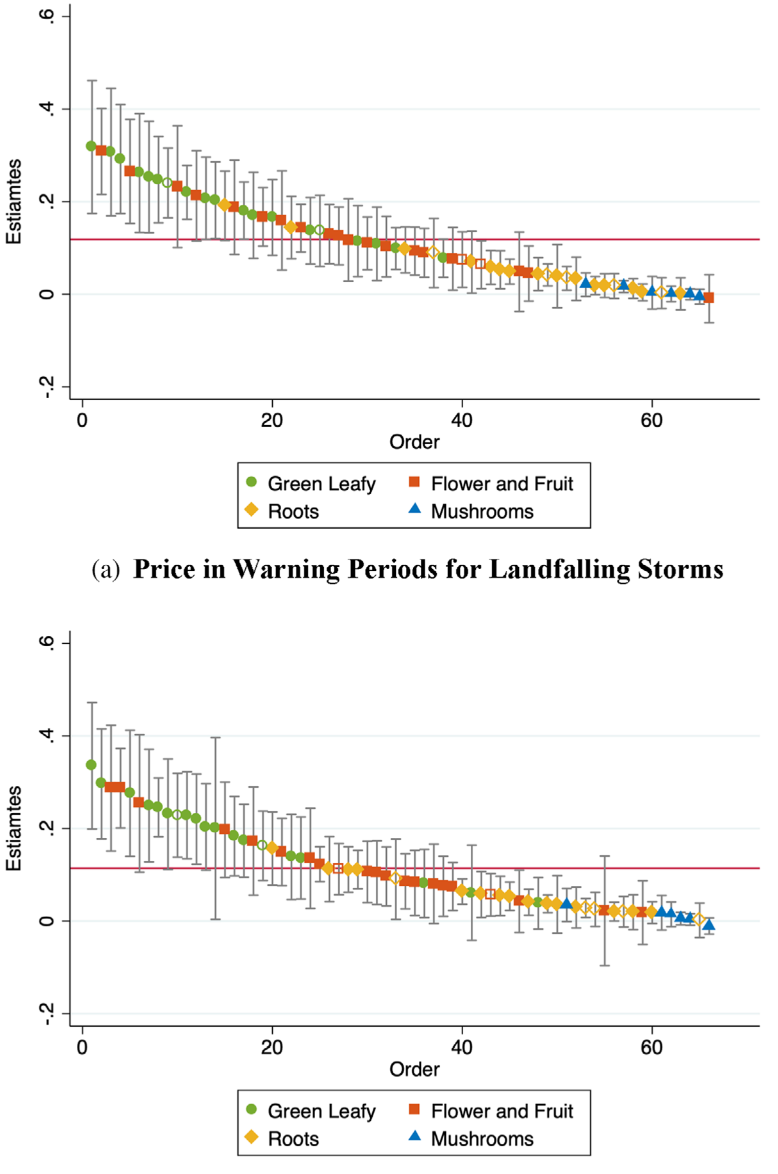
In addition, we use this same framework to estimate overall price elasticities of demand for our four vegetable categories and results are shown in Table A3. Since heavy rainfall would probably not have any effect on mushrooms (grown inside), the first-stage F statistics for mushrooms are very small, 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.



(a) **Price Pattern**

(b) **Quantity Pattern**

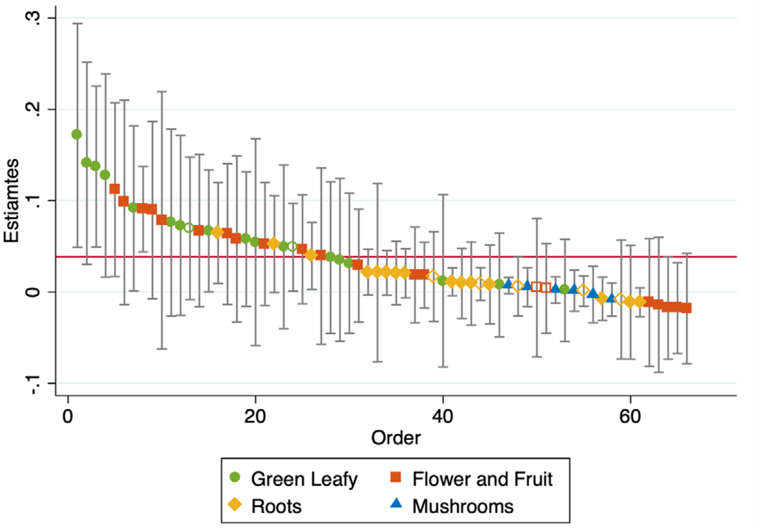
FIGURE A1 Imported and non-imported commodities for landfalling storms [Color figure can be viewed at wileyonlinelibrary.com]



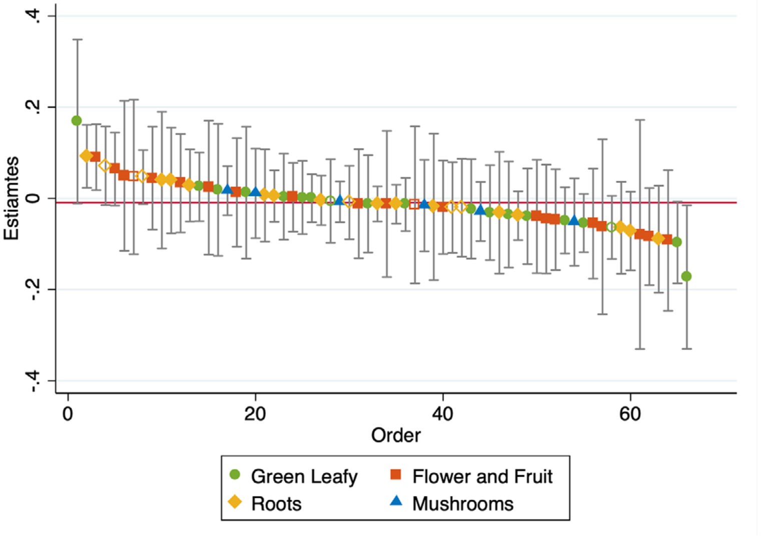
(a) **Price in Warning Periods for Landfalling Storms**

(b) **Price in Landfall Periods for Landfalling Storms**

FIGURE A2 Estimates by 66 vegetables for landfalling storms. 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. [Color figure can be viewed at wileyonlinelibrary.com]

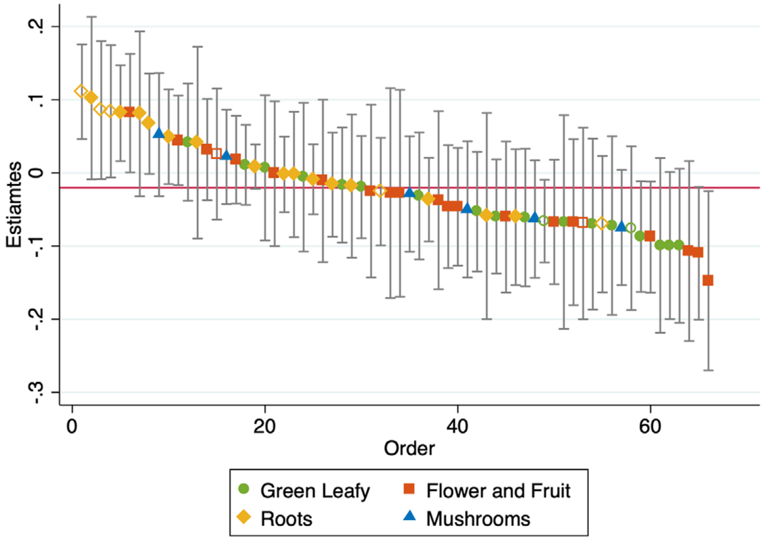


(a) **Price in Warning Periods for Non-Landfalling Storms**

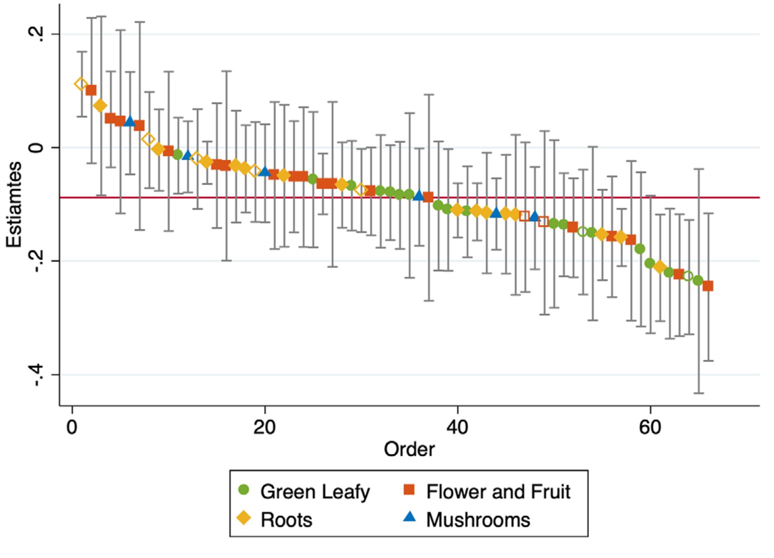


(b) **Quantity in Warning Periods for Non-Landfalling Storms**

FIGURE A3 Estimates by 66 vegetables for non-landfalling storms. 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. [Color figure can be viewed at wileyonlinelibrary.com]

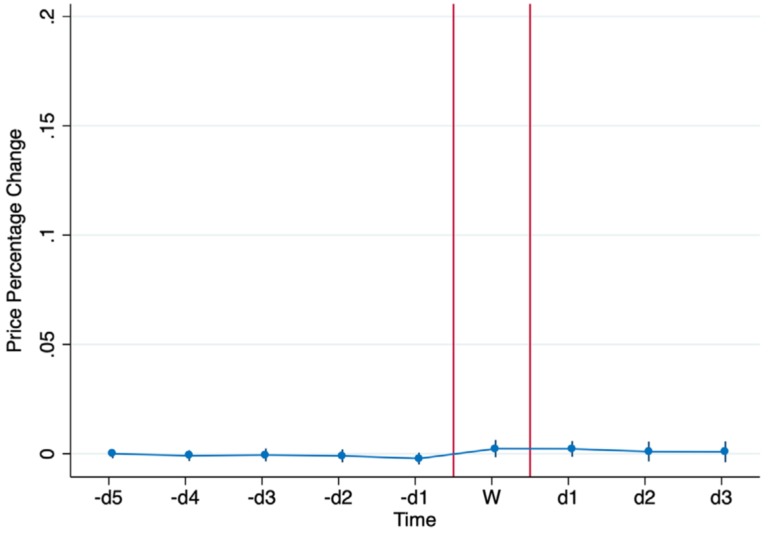


(a) **Quantity in Warning Periods for Landfalling Storms**

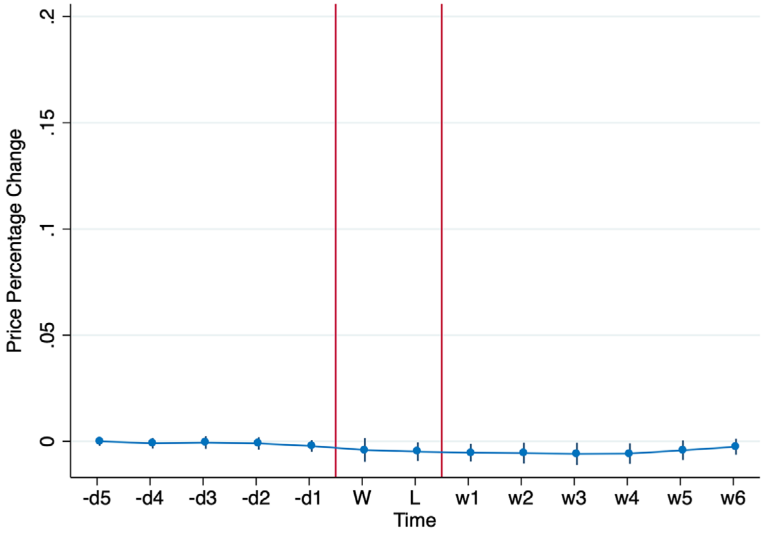


(b) **Quantity in Landfall Periods for Landfalling Storms**

FIGURE A4 Estimates by 66 vegetables for landfalling storms. 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. [Color figure can be viewed at wileyonlinelibrary.com]



(a) **Price Pattern of Rice for Non-Landfalling Storms**



(b) **Price Pattern of Rice for Landfalling Storms**

FIGURE A5 Placebo test [Color figure can be viewed at wileyonlinelibrary.com]