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Mitigation of temperature-induced vegetable price volatility in urban wholesale markets

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Content

Part A. Theoretical Framework: Spatial Supply-Demand Equilibrium and Distribution-related Explanations

A.1 Model Setting: Urban Demand

Consider a representative household whose utility derives from consuming two types of vegetables: a Storable good (*S*, e.g., root vegetables) with a low storage loss rate and a Perishable good (*N*, e.g., leafy greens) with high storage loss rate. The household's preferences are represented by a Constant Elasticity of Substitution (CES) utility function:

$$U(S, N) = (\phi N^{\rho} + (1-\phi) S^{\rho})^{1/\rho} \tag{1}$$

Where $\phi \in (0,1)$ represents the preference weight for perishable vegetables. ρ determines the substitutability between S and N. $\rho < 1 (\rho \neq 0)$ determines the elasticity of substitution between the two goods, defined as $\sigma = \frac{1}{1-\rho}$. As $\rho \to 1$, $\sigma \to \infty$ implying the goods are perfect substitutes. As $\rho \to -\infty$, $\sigma \to 0$ implying the goods are perfect complements.

A.2 Supply-side Mechanisms: The Distribution Wedge

Vegetables must be transported from production sites to the urban market. This process introduces a "price wedge" driven by transportation costs and physical losses.

A.2.1 Transportation Costs

Temperature deviations from an optimal level T_{opt} increase transportation costs (e.g., due to energy consumption for cooling or heat-induced delays), This effect is moderated by the density of the road network D. We model this as:

$$C_{trans}(N) = C_{N0}(\frac{T - T_{opt}}{D})^2 \tag{2}$$

$$C_{trans}(S) = C_{S0}(\frac{T - T_{opt}}{D})^2 \tag{3}$$

where C_{N0}, C_{S0} are baseline transportation costs. The quadratic form amplifies the cost penalty from temperature deviations, while a higher road density D dampens this penalty. Drawing on foundational spatial price analysis (Samuelson, 1952; Fackler & Goodwin, 2001), we define the difference between the production price and selling price as a transaction cost wedge (Eq. 2-3). Theoretically, this wedge comprises multiple factors including transportation costs (distance, fuel), labor/packaging inputs, and information frictions (Allen, 2014). In our framework, the overall distribution wedge depends on road network density, transport time and distance, and temperature-dependent losses ($\delta(T)$). (Donaldson, 2018). The short-term derivatives of structural factors—such as farm-gate prices ($\partial P_0/\partial t$), household income ($\partial I/\partial t$), and preferences ($\partial \phi/\partial t$)—are negligible (≈ 0) within the daily window.

A.2.2 Loss Due to Supply Chain

Goods deteriorate during transit and storage. The quantity arriving at the market is a function of the initial quantity and a temperature-dependent loss rate:

For storable goods:

$$Q_S = Q_{S0} * e^{-\delta_S(x)*t} \tag{4}$$

For perishable goods:

$$Q_N = Q_{N0} * e^{-\delta_N(x)*t} \tag{5}$$

where Q_{N0}, Q_{S0} are the initial quantities. t is the total time in transit and storage, which is inversely related to road density D (i.e., $t = L/v(D)$, where L is distance and v is speed). For simplicity, we define $x = |T - T_{opt}|$, representing the absolute deviation from the optimal temperature. $\delta_N(x)$ and $\delta_S(x)$ are temperature-dependent loss rates, defined as functions of the absolute deviation from the optimal temperature T_{opt}. These loss rates increase as temperature moves farther away from the optimum in either direction. We assume that $\delta_N(x) > \delta_S(x)$ and $\frac{\partial \delta_N(x)}{\partial x} \gg \frac{\partial \delta_S(x)}{\partial x} \geq 0$. Perishable goods are therefore significantly more vulnerable to non-optimal temperatures than storable goods.

Next, We define the loss-related distribution cost for good $i \in \{S, N\}$ as

$$C_{loss,i}(x) = \lambda_i \delta_i(x) \tag{6}$$

Where $\delta_i(x)$ is the temperature-dependent loss rate and $\lambda_i > 0$ converts physical loss into a unit cost borne in the urban wholesale market. A larger λ_i implies that a given loss rate translates into a greater increase in per-unit distribution cost.

A.3 Spatial Market Equilibrium and Pricing

A.3.1 Household Demand

The household faces the budget constraint $P_S S + P_N N = I$. Solving the utility maximization problem yields the Marshallian demand functions:
Demand for storable goods (*S*):

$$S = \frac{I(1-\phi)^\sigma}{P_S^\sigma[\phi^\sigma {P_N}^{1-\sigma} + (1-\phi)^\sigma {P_S}^{1-\sigma}]} \tag{7}$$

Demand for perishable goods (*N*):

$$N = \frac{I\phi^{\sigma}}{P_N^{\sigma}[\phi^{\sigma}{P_N}^{1-\sigma}+(1-\phi)^{\sigma}{P_S}^{1-\sigma}]} \tag{8}$$

Where σ represents the substitution elasticity. P_S and P_N are urban wholesale prices of storable and perishable goods, respectively.

A.3.2 Spatial Pricing Equilibrium

In a competitive spatial market, the urban wholesale price is determined by a no-arbitrage condition: the destination price equals the origin price plus distribution-related costs. We decompose these distribution costs into two components: transportation costs and loss-related distribution costs. The latter captures the market cost of spoilage, shrinkage, and quality deterioration during transit and storage.

Wholesale price of storable goods (P_S):

$$P_S(T) = P_{S0} + C_{trans}(S, x) + C_{loss,S}(x) \tag{9}$$

Wholesale price of perishable goods (P_N):

$$P_N(T) = P_{N0} + C_{trans}(N, x) + C_{loss,N}(x) \tag{10}$$

Where P_{S0} and P_{N0} denote the original (farm-gate) prices. Since both transportation costs and loss-related distribution costs rise with the absolute deviation from the optimal temperature, wholesale prices increase as thermal conditions become less favorable. Because perishable goods exhibit both higher loss rates and greater temperature sensitivity, P_N responds more strongly to non-optimal temperatures than P_S.

A.4 Comparative Statics: Short-Term Price Volatility

A.4.1 Deduction of Distribution-Driven Volatility

To analyze the impact of a temperature shock T on urban prices, we take the total derivative of the pricing equations (8) and (9):

$$\frac{dP_{urban}}{dT} = \underbrace{\frac{\partial P_{farm}}{\partial x}}_{\text{Production Channel}} + \underbrace{\frac{\partial C_{trans}}{\partial x} + \frac{\partial Loss}{\partial x}}_{\text{Distribution Channel}} + \underbrace{\frac{\partial P_{urban}}{\partial \phi} * \frac{\partial \phi}{\partial x}}_{\text{Demand Channel}} \tag{11}$$

For short-term (daily) price fluctuations, we make two key theoretical assumptions based on market characteristics. The first assumption is production rigidity: P_{farm} is determined by planting decisions, harvest cycles, and long-term supply contracts. In the daily window, the supply at the farm gate is fixed (supply is perfectly inelastic in the very short run). Thus, $\frac{\partial P_{farm}}{\partial x} \approx 0$. The second assumption is preference stability: As consumer preferences (ϕ) and sales channels across cities are unlikely to fluctuate significantly in the short term, demand-side parameter shifts are negligible. Consequently, short-term price volatility is strictly driven by distribution frictions (transportation and loss).

A.4.2 Direct Channel: Cost Pass-through

Based on the deduction above, the price sensitivity is driven by distribution costs. When temperature deviates from T_{opt}:

$$\frac{\partial P_S}{\partial x} = \frac{\partial C_{trans}(S,x)}{\partial x} + \frac{\partial C_{loss,S}(x)}{\partial x} \tag{12}$$

Assuming x is a fixed temperature deviation, the second term requires specifying $\frac{\partial^2 \delta_S(x)}{\partial x^2}$. For simplicity, we assume $\frac{\partial \delta_S(x)}{\partial x} \approx 0$. Therefore:

$$\frac{\partial P_S}{\partial x} \approx \frac{2C_{S0}(x)}{D^2} \tag{13}$$

For perishable goods,

$$\frac{\partial P_N}{\partial x} = \frac{\partial C_{trans}(N,x)}{\partial x} + \frac{\partial C_{loss,N}(x)}{\partial x} \tag{14}$$

Given that $\frac{\partial^2 \delta_N(T)}{\partial T^2} > 0$ and typically $C_{N0} > C_{S0}$ due to the need for specialized transport for perishables, it follows that:

$$\left|\frac{\partial P_N}{\partial x}\right| > \left|\frac{\partial\, P_S}{\partial x}\right| \tag{15}$$

Proposition 1 (Moderating Role of Infrastructure):

Higher road network density D attenuates the sensitivity of vegetable prices to temperature shocks.

Proof: This is directly observable from the derivatives $\frac{\partial P_S}{\partial x}$ and $\frac{\partial P_N}{\partial x}$, where D appears in the denominator. A higher D reduces the marginal cost increase from a temperature deviation.

Proposition 2 (Differential Price Sensitivity):

The wholesale price of perishable goods (P_N) is more sensitive to temperature shocks than that of storable goods (P_S).

Proof: This follows from the inequality $\left|\frac{\partial P_N}{\partial x}\right| > \left|\frac{\partial P_S}{\partial x}\right|$, which is driven by the significantly larger marginal loss term $\frac{\partial^2 \delta_N(T)}{\partial x^2}$ for perishable goods.

A.4.3 Indirect Channel: Substitution Effect

Temperature shocks alter the relative price $\frac{P_N}{P_S}$, inducing households to substitute between goods. The substitution elasticity determines the magnitude of this demand shift.

$$\frac{\partial ln(S/N)}{\partial x} = \sigma * \frac{\partial \ln{(P_N/P_S)}}{\partial x} \tag{16}$$

Where σ reflects the substitution elasticity. The relative price change (P_N/P_S) is captured by $\frac{\partial \ln{(P_N/P_S)}}{\partial x}$.

Proposition 3: *A higher elasticity of substitution σ mitigates the price increase of perishable goods during a temperature shock by enabling greater consumption switching towards storable goods.*

Proof: Consider a positive temperature shock that increases the relative price of perishables ($\frac{\partial \ln{(P_N/P_S)}}{\partial x} > 0$). From the demand functions, the resulting change in relative consumption is:

$$\frac{\partial ln(S/N)}{\partial x} = \sigma * \frac{\partial \ln{(P_N/P_S)}}{\partial x} \tag{17}$$

A higher σ leads to a larger increase in $\ln{(S^*/N^*)}$, meaning a stronger shift in demand from N to S. This shift in demand can partially offset the market pressure on perishable-goods prices in equilibrium (N).

Proof of Eq. (15):

$$\frac{\partial ln(S/N)}{\partial x} = (\frac{\partial lnS}{\partial lnP_S} * \frac{\partial lnP_S}{\partial x} + \frac{\partial lnS}{\partial lnP_N} * \frac{\partial lnP_N}{\partial x}) - (\frac{\partial lnN}{\partial lnP_S} * \frac{\partial lnP_S}{\partial x} + \frac{\partial lnN}{\partial lnP_N} * \frac{\partial lnP_N}{\partial x}) \tag{18}$$

Define substitution elasticity as:

$$\sigma = \frac{\partial \ln{(\frac{S}{N})}}{\partial \ln{(P_N/P_S)}} \tag{19}$$

Then, the Marshallian elasticity includes **Own-price elasticity of demand** and **cross-price elasticity of demand**:

For storable goods S: the **Own-price elasticity of demand** is $\eta_{SS}^M = \frac{\partial lnS}{\partial lnP_s} = -\sigma + (\sigma -$

$1)\pi_S$; while the cross-price elasticity of demand is $\eta_{SN}^M = \frac{\partial lnS}{\partial lnP_N} = (\sigma - 1)\pi_N$.

For perishable goods *N*: the **Own-price elasticity of demand** is $\eta_{NN}^M = \frac{\partial lnN}{\partial lnP_N} = -\sigma + (\sigma - 1)\pi_N$, while the cross-price elasticity of demand is $\eta_{NS}^M = \frac{\partial lnN}{\partial lnP_S} = (\sigma - 1)\pi_S$. The expenditure share $\pi_S = \frac{P_S S}{I}$, $\pi_N = \frac{P_N N}{I} = 1 - \pi_S$.

Equation 17 can be revised as:

$$\frac{\partial lnN}{\partial x} = \frac{\partial lnN}{\partial lnP_S} * \frac{\partial lnP_S}{\partial x} + \frac{\partial lnN}{\partial lnP_N} * \frac{\partial lnP_N}{\partial x} = \eta_{NS}^M \frac{\partial lnP_S}{\partial x} + \eta_{NN}^M \frac{\partial lnP_N}{\partial x} \quad (20)$$

$$\frac{\partial lnS}{\partial x} = \frac{\partial lnS}{\partial lnP_S} * \frac{\partial lnP_S}{\partial x} + \frac{\partial lnS}{\partial lnP_N} * \frac{\partial lnP_N}{\partial x} = \eta_{SS}^M \frac{\partial lnP_S}{\partial x} + \eta_{SN}^M \frac{\partial lnP_N}{\partial x} \quad (21)$$

Therefore,

$$\begin{aligned} \frac{\partial ln(S/N)}{\partial x} &= \left(\eta_{SS}^M \frac{\partial lnP_S}{\partial x} + \eta_{SN}^M \frac{\partial lnP_N}{\partial x}\right) - \left(\eta_{NS}^M \frac{\partial lnP_S}{\partial x} + \eta_{NN}^M \frac{\partial lnP_N}{\partial x}\right) = \\ &(\eta_{SS}^M - \eta_{NS}^M)\frac{\partial lnP_S}{\partial T} + (\eta_{SN}^M - \eta_{NN}^M)\frac{\partial lnP_N}{\partial T} \end{aligned} \quad (22)$$

As $\eta_{SS}^M - \eta_{NS}^M = [-\sigma + (\sigma - 1)\pi_S] - [(\sigma - 1)\pi_S] = -\sigma$; $\eta_{SN}^M - \eta_{NN}^M = (\sigma - 1)\pi_N + \sigma - (\sigma - 1)\pi_N = \sigma$

Finally, we have

$$\frac{\partial ln(S/N)}{\partial x} = \sigma\left[\frac{\partial lnP_N}{\partial x} - \frac{\partial lnP_S}{\partial x}\right] = \sigma \frac{\partial \ln (P_N/P_S)}{\partial x} \quad (23)$$

Theoretical Remark 1: Welfare Implications

Our CES framework (Eq. 1) explicitly models consumers as utility maximizers, distinguishing our approach from the classic "Stigler Diet" problem which assumes consumers solely seek to minimize the cost of nutritional requirements (Stigler, 1945).
Cost vs. Utility: Under a strict Stiglerian framework, if climate shocks spike the price of perishable greens (P_N), consumers could costlessly substitute to storable root vegetables (P_S) to maintain vitamin intake, implying a negligible "cost" of climate change.
Utility Loss: However, our model captures the welfare loss inherent in this substitution. As long as fresh vegetables are not perfect substitutes for storable ones ($\sigma < \infty$) and consumers prefer freshness ($\phi > 0$), forced substitution to cheaper storables—while calorically sufficient—results in a lower total utility level (U).
Systemic Risk: Furthermore, unlike idiosyncratic shocks to a single crop (e.g., carrots),

heatwaves often cause systemic supply contractions across the entire "Perishable" category. This limits the efficacy of within-category substitution, forcing a shift to less preferred "Storable" goods, thereby validating the significant welfare costs reflected in the observed price volatility.

Theoretical Remark 2: Political Implications

Finally, the political economy of adaptation plays a decisive role in determining whether policy acts as a 'friend' or 'foe' of resilience. As documented by Hsiao, Moscona, and Sastry (2025), governments globally face strong political incentives to intervene in agricultural markets to shield consumers from domestic supply shocks. In China, this is institutionalized through the 'Vegetable Basket Program,' which holds city mayors politically accountable for food availability.

This political motivation can drive adaptation when it channels investment into public goods—acting as a friend by subsidizing cold chain logistics and establishing Green Lanes that reduce transaction costs. Our empirical findings strongly support the efficacy of this pathway: cities with superior logistics infrastructure exhibited significantly lower price volatility under temperature shocks, validating that state capacity serves as a complement to market mechanisms.

However, policy risks becoming a foe if it reverts to the rigid price ceilings during climate extremes. While price controls may offer short-term relief to consumers (aligning with the redistributive motives highlighted by Hsiao et al., 2025), they suppress the scarcity signals required to trigger the inter-regional arbitrage described in our model. Therefore, effective policy must navigate this trade-off: prioritizing market-facilitating investments (infrastructure) over market-distorting interventions (price caps) to ensure that supply chains can freely adapt to future climate volatility.

Part B. Background

B.1 Vegetable Supply Chain and Wholesale Prices in Urban Contexts

The fresh agricultural product supply chain in China comprises three key segments: **upstream**, **midstream**, and **downstream**, with cities serving as pivotal nodes for distribution and consumption. Upstream connects to production sources including farmers, breeding enterprises, and other agricultural producers (information on China's vegetable production is provided in Section B.3 below). Midstream focuses on circulation, processing, and distribution through business-to-business supply chain platforms, logistics providers, urban wholesale markets, and primary processing facilities. Downstream links to retail and consumption channels such as fresh e-commerce platforms, supermarkets, farmers' markets, specialty fruit retailers, and catering businesses in metropolitan areas. This long and complex agri-food supply chain, often concentrated in urban and peri-urban zones, may exacerbate heat/cold wave risks due to dense infrastructure and high-volume throughput (Pankratz and Schiller, 2024; Sun et al. 2024). For developing countries, postharvest losses of vegetables could range from 32.93% to 60.78% (FAO, 2015), highlighting the need for urban-centered interventions to reduce waste and enhance food security.

China's cold storage and preservation capacity, totaling approximately 307 million cubic meters as of 2024, remains insufficient relative to vegetable production volume, covering less than 30% of the total output (Mordor Intelligence, 2025; Ministry of Agriculture and Rural Affairs, 2024). This shortfall exacerbates urban wholesale price volatility in city-based distribution networks, a challenge also prevalent in Global South cities, where limited urban storage infrastructure similarly constrains food system resilience (FAO, 2024). This creates systemic pressure on upstream wholesalers to absorb losses from rapid spoilage, particularly in cities lacking adequate infrastructure. Wholesale markets must dynamically adjust pricing to account for daily degradation (12–15% for leafy greens), which worsens exponentially with ambient heat (Moretti et al., 2010; Batziakas et al., 2020). Furthermore, while refrigerated transport is growing, a significant portion of vegetables, estimated at over 60% based on chilled logistics penetration, are still transported via non-refrigerated or partially refrigerated vehicles (CLPA, 2023; Mordor Intelligence, 2025), forcing urban wholesalers to price in the risk of thermal damage during long-haul transit to city hubs. Unlike retail prices, which pass logistical costs directly to urban consumers, wholesale prices internalize these inefficiencies, compressing margins for producers and amplifying volatility in city-based markets. Moreover, while consumers substitute non-perishable vegetables during heatwaves and cold waves (Dercon et al., 2005; Kroeger, 2023), wholesale markets bear the brunt of demand volatility through inventory mismatches, as sudden order cancellations or surges undermine price stability. In China's context, wholesale prices act as a critical buffer with cascading societal impacts for two reasons. First, wholesale volatility indirectly strains household welfare, as 20%-60% of low-income budgets are spent on food (USDA, 2023). When wholesalers fail to mitigate temperature-driven losses, downstream retail inflation becomes inevitable, disproportionately harming the poor, who lack refrigeration to hedge against scarcity. Second, they serve as supply chain diagnostics. Wholesale price trends reveal systemic vulnerabilities (e.g., fragmented cold-chain infrastructure) that retail fluctuations often obscure, as daily wholesale data captures upstream post-harvest bottlenecks rather than transient retail shocks.

Price dynamics in agricultural markets reflect both production costs and supply chain disruptions (Mankiw et al., 1998). Existing literature has predominantly focused on **retail prices**, which aggregate production and distribution effects, factors that are undeniably vital to understanding food price dynamics but often neglect midstream segments and supply chains (Gonzalez et al. 2023). However, **wholesale prices** in urban markets serve as a more direct proxy for **midstream logistics vulnerabilities**, such as transportation bottlenecks or refrigeration failures during heatwaves in urban disruption networks (Lobell et al., 2011; Wang et al., 2018). Conversely, retail prices may lag behind wholesale trends due to inventory buffers and markup strategies, masking acute supply chain stressors. Extended Fig. 3 plots the vegetable supply chain.

B.2 Generalizability of Climate Change Effects on Vegetable Wholesale Prices in Global South

While our empirical base is Chinese cities, the core mechanisms we identify—*temperature disruptions to urban wholesale distribution, and urban-specific adaptations to mitigate volatility*—are transferable to cities globally, with particular relevance for the Global South (more details are provided in Supplementary part I). These challenges are not unique to China; they are generalizable to other urban contexts, particularly in the Global South, where cities like eThekwini Metropolitan Municipality (in South Africa) face similar postharvest losses (up to 44% for vegetables) due to inadequate cold storage and informal urban markets (Qange et al. 2024). Urban policy implications include investing in city-specific adaptations, such as peri-urban cold chain hubs and integrated transport planning, to reduce volatility and enhance nutritional access for growing urban populations across developing economies (von Braun et al., 2023; Resnick et al., 2024). Three traits of Global South urban food systems align with our findings, supporting generalizability: dependence on urban wholesale hubs, vulnerable urban distribution networks and high stakes for urban food security.

B.3 Vegetables in China

Abundant in vitamins and beneficial compounds, vegetables are renowned for their wide-ranging health advantages across all age groups. They contribute significantly to childhood growth, adults' physical and mental well-being, and the social prosperity of communities (Salvin and Lloyd, 2012; FAO, 2020; Miller, 2017). Moreover, vegetables effectively prevent various nutritional deficiencies and mitigate the risk of chronic diseases (Afshin et al., 2019; World Bank, 2019). Despite their known health benefits, many individuals do not consume enough fruit and vegetables. The World Health Organization (WHO) recommends a minimum daily intake of 400 grams to reap significant health and nutritional benefits. In 2017 alone, inadequate consumption contributed to an estimated 3.9 million deaths globally (WHO, 2019). Specifically, insufficient intake is linked to 14% of gastrointestinal cancer deaths, 11% of ischemic heart disease deaths, and 9% of stroke deaths worldwide (WHO, 2019). In England, 66% of adults and 80% of children do not meet the recommended daily fruit and vegetable intake (Scheelbeek et al., 2020). Affordability issues significantly influence this dietary gap (Miller et al., 2016; Scheelbeek et al., 2020). Furthermore, transitioning to plant-rich diets, which benefit both human health and environmental sustainability and incorporate 400 to 500 grams of fruits and vegetables daily, presents challenges due to rising food costs (Miller et al., 2016; Scheelbeek et al., 2020). Therefore, this article aims to investigate China's vegetable price change response to temperature shocks, which is representative of other regions globally. In estimating price changes in response to temperature shocks, it is essential to consider farmers' compensatory responses, or adaptations, to climate change, such as investments in heat-resistant seed innovations and air-conditioned agricultural greenhouses. These adaptations help mitigate the risks associated with extreme temperatures and reduce costs related to forgone production and non-productive coordination. Consequently, the total price deviation from the optimal level due to temperature shock risks is the sum of changes in vegetable prices after accounting for these adaptations and their associated costs. In this article, we define key concepts to be estimated, including the overall changes in vegetable prices resulting from temperature extremes.

The UN General Assembly designated 2021 as the International Year of Fruits and Vegetables (IYFV) to highlight their critical role in human nutrition and food security (FAO, 2020). Vegetables are typically considered high-priced cash crops, thus generating significant income rather than serving as subsistence food (Priyadarshan and Jain, 2022). While distributional disparities contribute to insufficient vegetable consumption for a substantial portion of the population, vegetable production itself is also vulnerable to climatic fluctuations (Coolong and Randle, 2003). Furthermore, vegetable prices are more susceptible to extreme weather events like earthquakes and tropical storms than other food commodities, resulting in heightened price volatility (Abe et al., 2014; Cavallo et al., 2014). China stands as the largest vegetable producer in the world, accounting for over 50% of global production (Wang et al., 2020). On the production front, from 2012 to 2021, vegetable production in China surged by 26%, markedly overtaking the production of animal-sourced foods by 7% and cereal grains by 12% (Wang et al., 2020; NBS, 2022). In contrast, during the same period and excluding China, global vegetable production witnessed a more modest increase of less than 10% (Wang et al., 2020; FAO, 2023). Furthermore, China's vegetable exports experienced a dramatic rise, soaring from 2.5 million tons in 2000 to 10.2 million tons in 2020, an increase of 308% (NBS, 2023). In 2015, the per capita daily available supply of vegetables at the Chinese household level stood at 585 grams (reflecting domestic production of 535 million tons, minus exports of 13.4 million tons, plus imports of 1.8 million tons), which is approximately 2.83 times higher than the global average. Therefore, conducting research on China's vegetable market is highly indicative and representative of global vegetable production and consumption patterns.

Part C: Vegetable Subcategories[1]

Vegetable subcategories: Leaf, Eggplant, Scallions and garlic, Cabbage, Potato and taro, Root vegetables, Melons and vegetables, Beans

Vegetables typically exhibit heterogeneous vulnerabilities to temperature extremes. For instance, leafy vegetables (e.g., spinach, lettuce) are highly sensitive to temperature fluctuations and humidity changes, making them more perishable. In contrast, root vegetables (e.g., potatoes, carrots) are naturally protected by their underground growth environment and thick epidermal structures, which enhance their storability under proper dry and ventilated conditions.

To assess the resilience of certain vegetables to extreme heat and cold, we categorize our sample into the following subcategories: leaf vegetables; eggplant; scallions and garlic; cabbage; potato and taro; root vegetables; melons and beans. Supplementary Fig. 1a-h present the price responses of these vegetables to temperature extremes. The results depicted in Supplementary Fig. 1a indicate that leaf vegetables are particularly susceptible to temperature extremes. Potato and taro show resistance to both hot and cold temperatures – their coefficients (Supplementary Fig. 1e) are statistically insignificant for temperature ranges exceeding 27°C and below -6°C, in comparison to the reference bin. Root vegetables (Supplementary Fig. 1f) and beans (Supplementary Fig. 1h) exhibit resistance to extremely cold temperatures, including the [-18°C, -15°C) range and temperatures below -18°C. Other vegetables respond to temperature shocks in a manner like the overall effects, albeit with some variations.

These phenomena align with our expectations through two interconnected mechanisms: labor-productivity constraints and perishability gradients, **with distribution-phase losses amplifying both effects**. First, temperature extremes disrupt agricultural workflows through heat-induced fatigue and cold-related operational delays, **particularly impactful for leafy vegetables that require immediate post-harvest cooling** (Colmer, 2021; FAO, 2021; Venkat et al. 2022). Second, **biological durability creates natural buffers that mitigate distribution risks** — root vegetables' waxy cuticles and underground development enable extended field storage during temperature shocks, whereas leafy vegetables' high surface-area-to-mass ratio accelerates moisture loss and quality degradation when exposed to thermal stress (Mulaosmanovic, et al. 2021). Thus, the observed temperature-price relationship in our study is primarily influenced by leaf vegetables.

Our analysis reveals a seemingly paradoxical pattern: hotter days are associated with lower wholesale vegetable prices. In the short run, this pattern is more plausibly explained by market-side adjustments than by changes in underlying production capacity. Extreme

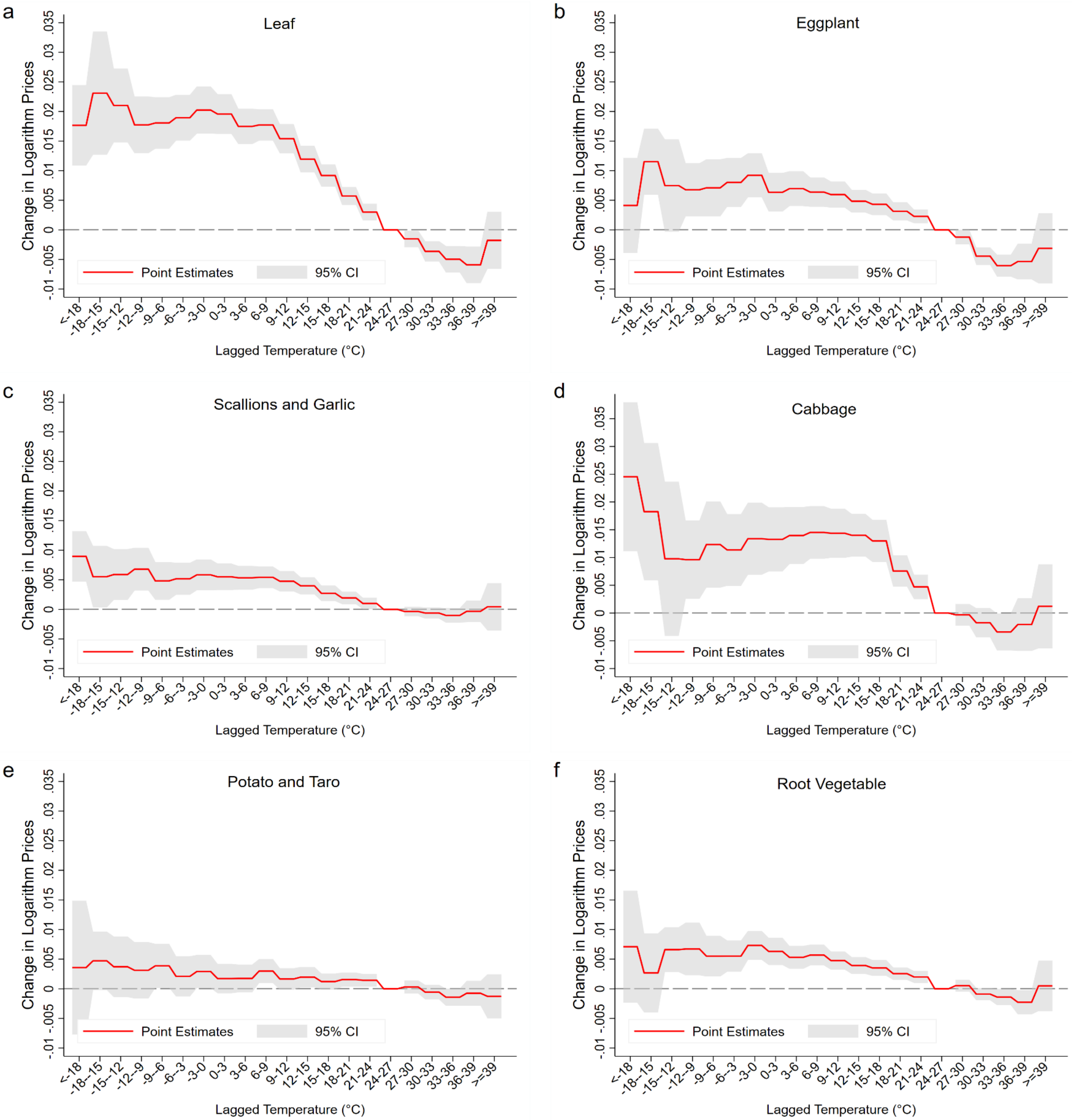
[1] The nine categories of vegetables in Figure 1 include: Leafy Greens (*N*=2,990,900), Eggplants (*N*=1,423,007), Scallions and Garlic (*N*=1,748,013), Cabbage (*N*=443,456), Potatoes and Taro (*N*=605,702), Root Vegetables (*N*=1,236,303), Melons (*N*=1,621,972), Beans (*N*=709,547), and Others (e.g., edible fungi and asparagus) (*N*=780,958).

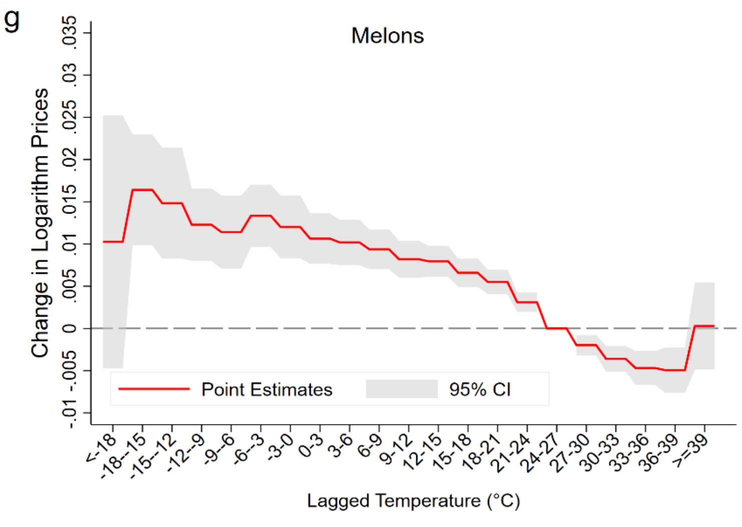
heat can weaken consumer demand for fresh produce (Lai et al. 2022; Long et al. 2024) and simultaneously increase the urgency of clearing highly perishable inventories before quality deteriorates further (Gu et al. 2020). At the wholesale stage, this combination can place downward pressure on clearing prices, especially for temperature-sensitive vegetables. Because our empirical design identifies short-run responses to daily temperature shocks, we interpret the negative heat effect primarily as a post-harvest distribution and market-adjustment mechanism rather than a long-run production response.

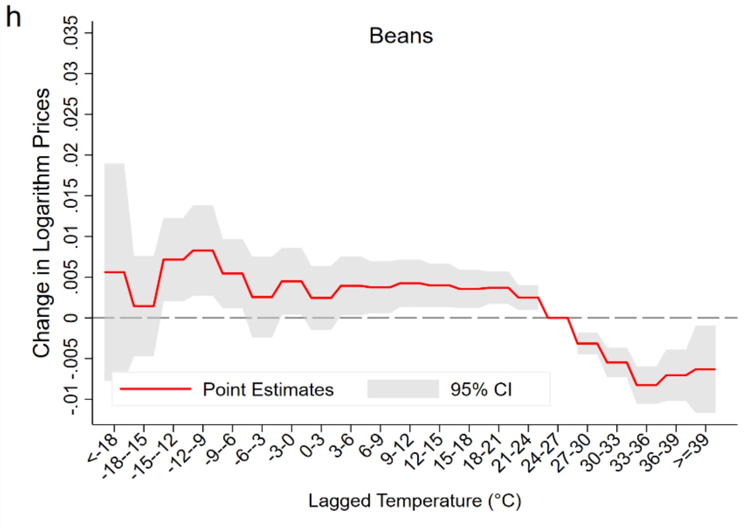
Our findings should not be interpreted as climate change simply benefiting one group at the expense of another. Instead, they reveal a more profound risk: climate change acts as a major destabilizing force for the entire food system. The core objective of a resilient food policy is not to push prices permanently higher or lower, but to maintain price stability. Both extreme scenarios projected by our model, a sharp price collapse of 25.1% under RCP 8.5 and significant price increases in other contexts, are harmful in the long run. A sudden, deep price collapse (as under RCP 8.5), often stemming from climate-driven supply destruction, bankrupts producers and forces them to exit the industry. This erodes the long-term production capacity of the domestic food system. Sustained high and volatile prices undermine food affordability for consumers, particularly the most vulnerable, and threaten nutritional security.

Both extremes disrupt the delicate balance between producer livelihoods and consumer access. Therefore, the central policy challenge illuminated by our research is not to manage a transfer between groups, but to implement adaptations that enhance systemic resilience against climate shocks. Our proposed investments are designed precisely to buffer these extremes and maintain stability, thereby safeguarding the interests of both producers and consumers while ensuring the long-term equilibrium of the urban food system.

Supplementary Fig. 1: Temperature effects on price change, sub-categories including leaf, eggplant, scallions and garlic, cabbage, potato and taro, root vegetables, melons and beans.







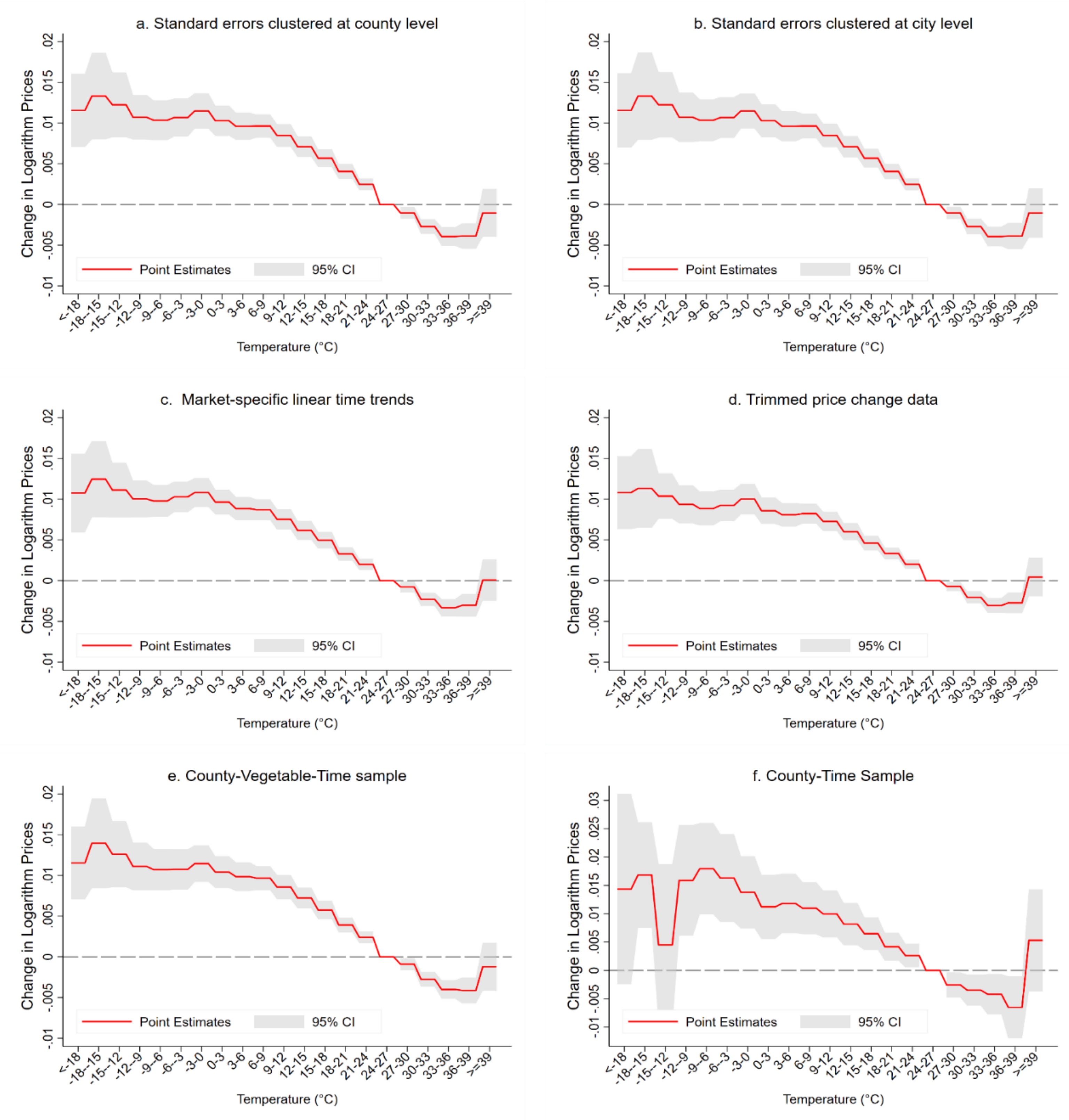
a, the effects of temperature on leafy vegetable wholesale price changes. **b,** the effects of temperature on eggplant wholesale price changes are presented. **c,** the effects of temperature on scallions and garlic wholesale price changes are presented. **d,** the effects of temperature on cabbage wholesale price changes are presented. **e,** the effects of temperature on the prices of potatoes and taro are presented. **f,** the effects of temperature on root vegetable price changes are presented. **g,** the effects of temperature on Melon wholesale price changes are presented. **h,** the effects of temperature on beans wholesale price changes are presented. The number of observations for a, b, c, d, e, f, h, and g are 2,107,572; 967,556; 1,210,550; 305,911; 423,820; 860,612; 1,087,791; and 482,683 respectively (refer to the Extended Data Table for additional information). Equation (1) outlines the statistical model used in our analysis. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. The accompanying figure visually represents the results, with shaded regions indicating the 95% confidence intervals around our estimates. The depicted lines illustrate the estimated relationship between independent variables and vegetable wholesale price patterns. We addressed potential within-market correlation by clustering standard errors at the market level.

Part D. Robustness

D.1 Econometric Model Setting

Our findings demonstrate robustness across various alternative models and data specifications, as shown in Supplementary part D. Specifically, (1) **Spatial Autocorrelation:** Since some explanatory variables are measured at the market level, unobserved yet persistent supply-side factors might influence local vegetable wholesale prices. Similarly, county-level or province-level vegetable subsidies could downwardly bias standard errors (SEs) (Moulton, 1986; Fu et al., 2021). To account for these possibilities, we adjusted the SEs for county- and city-level spatial autocorrelation, with results presented in Supplementary Fig. 2a, b. (2) **Time-Varying Trends and Agricultural Shocks:** The daily structure of our dataset presents challenges in controlling for time-varying trends. Additionally, agricultural shocks within our sample period—such as the Land Contracting Right Reform—may influence vegetable production. To address these concerns, we incorporated county-specific temporal trends to mitigate potential biases, with results presented in Supplementary Fig. 2c. (3) **Outlier Data Points:** Analyzing data at the individual vegetable level introduces the potential for outlier data points to skew our findings. To mitigate this, we applied winsorization to the extreme 0.5% of data points (top and bottom 0.25%) to trim potentially unreliable observations, with results presented in Supplementary Fig. 2d. (4) **Data Structure:** To ensure our estimates are not overly sensitive to the data structure, we implemented two alternative specifications. First, we averaged vegetable wholesale prices at the county level, resulting in a single daily price for all vegetables within a county, with results presented in Supplementary Fig. 2e. Second, we calculated the average price for vegetable subcategories when multiple markets exist within a county, producing one daily price per subcategory, with results presented in Supplementary Fig. 2f. Notably, our core conclusions remain consistent across these robustness checks.

Supplementary Fig. 2: Robustness Checks for Equation (1).

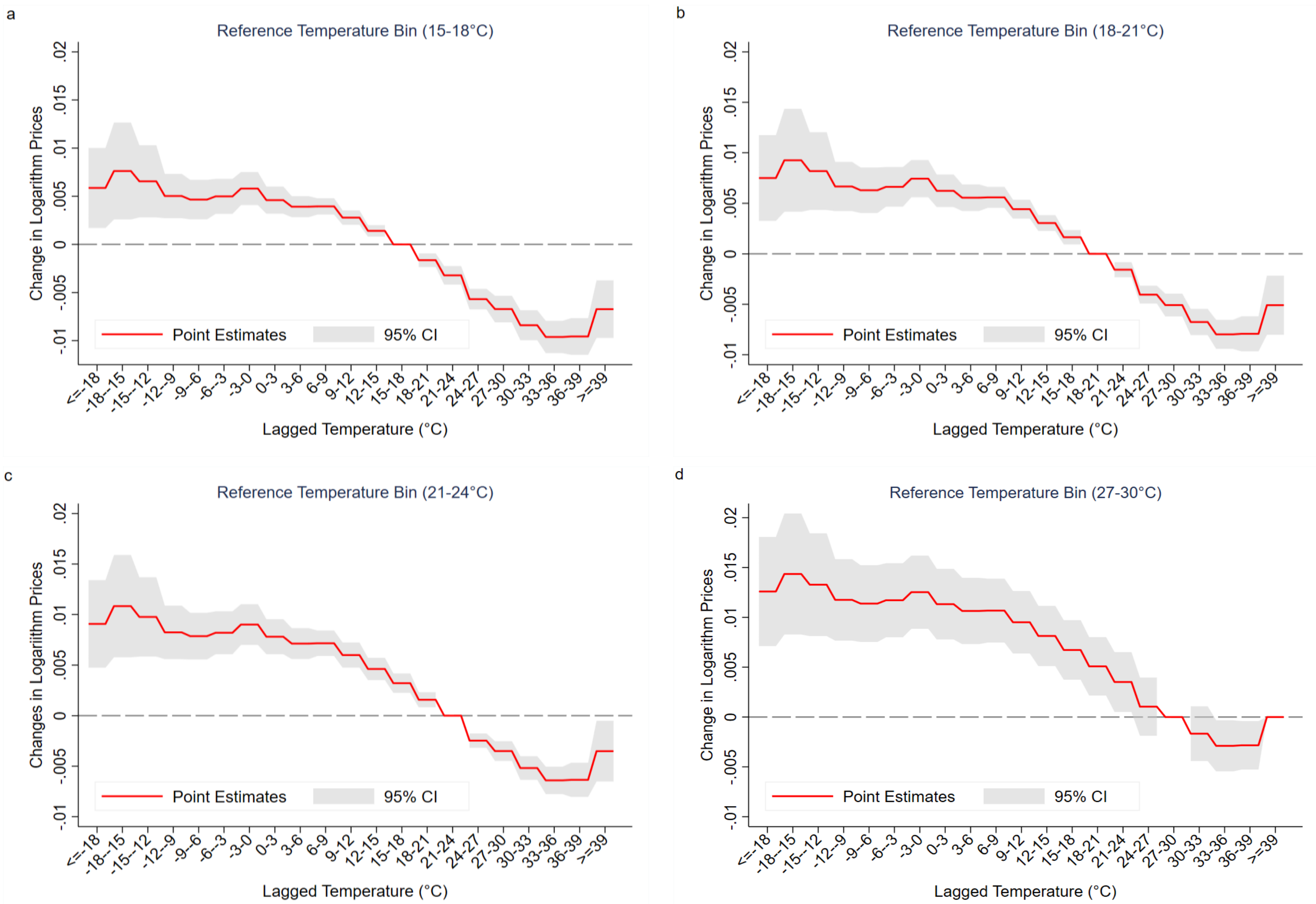


a-f, the analysis examines how a shift in temperature from the reference range (24°C - 27°C) to other temperature bins in various climate zones impacts the six-day cumulative change in daily logarithmic prices. To account for spatial autocorrelation, standard errors are adjusted at both the county (in panel a) and city (in panel b) levels. In panel **c**, city-specific linear time trends replace the year-quarter fixed effects. Robustness checks (**d**) involve trimming extreme values from the sample distribution by 0.25% at both ends (a total of 0.5%), focusing on mitigating the influence of extreme vegetable price fluctuations. e, the vegetable price change is averaged to county-vegetable-time level. f, the vegetable price change is averaged to county-time level. Observations for **a**, **b**, and **c**, are 7,982,688, for **d**, are 7,942,845, for **e**, are 7,779,712, for f, are 247,861. The regression formula adjusts for several fixed effects – specifically, those related to individual vegetables, the specific day within our sample period, each vegetable market's seasonal quarter, and holidays. Our controls include air pollution, rainfall, relative humidity, sunshine duration, temperature, along with their squared terms to capture any non-linear effects these factors may have on the vegetable price changes. We apply market-level clustering in **a-f** to the standard errors to account for spatial inter-market variability.

D.2 Alternative Reference Category

Specifically, our temperature bins include <-18°C, [-18, -15), [-15, -12), [-12, -9), [-9, -6), [-6, -3), [-3, 0), [0, 3), [3, 6), [6, 9), [9, 12), [12, 15), [15, 18), [18, 21), [21, 24), [24, 27), [27, 30), [30, 33), [33, 36), [36, 39) and >=39°C. In our investigation, we have identified the optimal range for vegetable comfort temperature to be between 24°C and 27°C, which we use as a baseline for comparison (Bisbis et al. 2018). For robustness, we also tested alternative omitted variable ranges, [15, 18°C), [18, 21°C), [21, 24°C), and [27, 30°C) (as displayed in Panels **a**, **b**, **c** and **d** of Supplementary Fig. 3 respectively)—and found that these changes do not bias our conclusions.

Supplementary Fig. 3: Robustness using alternative temperature bins.

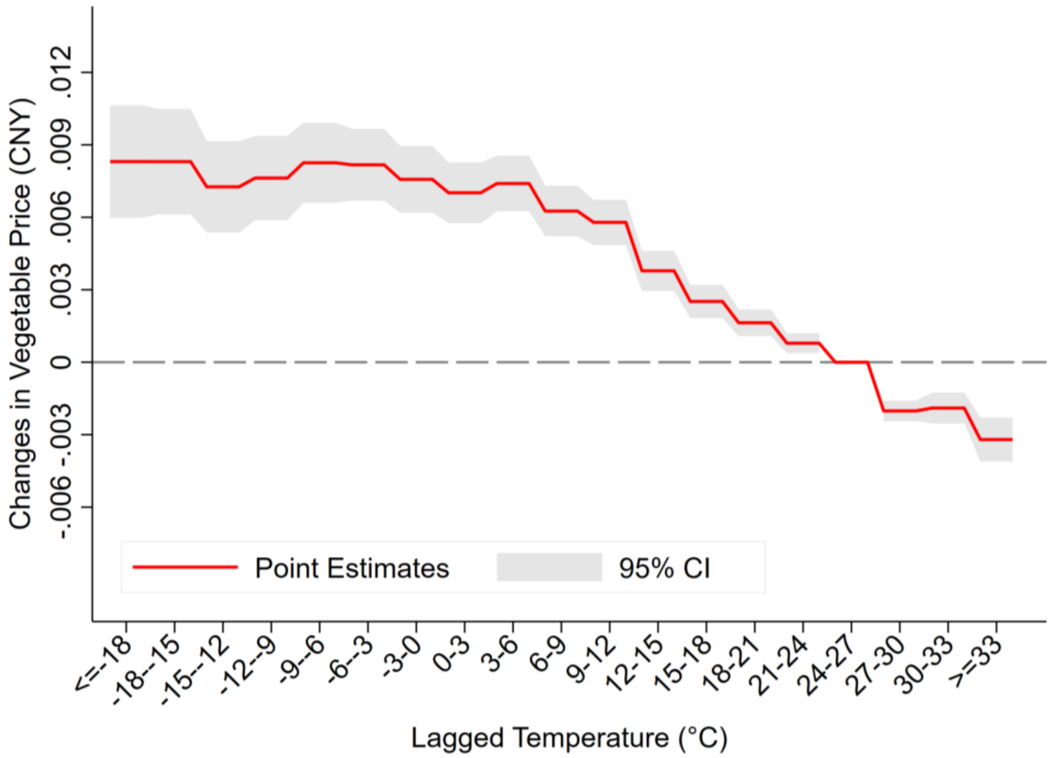


a, we consider [15, 18°C) as the reference category; b, we consider [18, 21°C) as the reference category; c, we consider [21, 24°C) as the reference category; d, we consider [27, 30°C) as the reference category. Observations for all Panels are 7,982,688. Equation (1) outlines the statistical model used in our analysis. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year -quarter fixed effects), city-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. The accompanying figure visually represents the results, with shaded regions indicating the 95% confidence intervals around our estimates. The depicted lines illustrate the estimated relationship between the independent variables and vegetable wholesale price patterns. We addressed potential within-market correlation by clustering standard errors at the market level.

D.3 Alternative Temperature Measure: Satellite Data

To complement station-level meteorological measurements, we employ satellite-derived temperature data for cross-validation using the ERA-Interim atmospheric reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), which has been widely employed (Lai et al. 2022). This global climate reanalysis system integrates satellite observations with conventional meteorological measurements through a 4D-Var assimilation framework, generating comprehensive atmospheric parameters, including surface temperature (2m elevation), total precipitation flux, wind vectors (10m elevation), and relative humidity fields. Operational since 1979, ERA-Interim provides gridded outputs at 0.75°×0.75° spatial resolution (~79 km grid spacing) and 6-hourly temporal resolution. This satellite-based validation framework addresses potential biases in ground monitoring networks while leveraging satellite data's spatial coverage advantages, with spatial correspondence protocols (50 km buffer zones) and temporal synchronization mechanisms ensuring robust comparison between measurement modalities. Supplementary Fig. 4 further validates our baseline station-based temperature measures by estimating satellite-based temperature effects on vegetable price fluctuations through market-gridded weather data matching.

Supplementary Fig. 4: Temperature effects on Changes of Vegetable Prices, Measured by Satellite Data.



Note: the effects of temperature on vegetable wholesale price changes. The marginal effects are measured as the temperature effects on vegetable wholesale price change, in the logarithm form, defined as $lnp_{ict} - lnp_{ic(t-1)}$. Observations for this regression are 7,982,688. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. The accompanying figure visually represents the results, with shaded regions indicating the 95% confidence intervals around our estimates. The depicted lines illustrate the estimated relationship between the independent variables and vegetable wholesale prices patterns. We addressed potential within-market correlation by clustering standard errors at the market level.

D.4 Price Reporting Issues

Our market-level daily vegetable prices have shown imbalances across different markets over time, raising concerns that our baseline results may be biased due to missing price reports. We address how this missing data could influence our findings, as well as the potential sources of price changes related to heatwave-induced shocks. Specifically, we have concerns in two areas: first, that vegetable markets may experience direct disruptions; and second, that temperature shocks could lead to increased prices. If the missing price data for one vegetable market is driven by the local temperature shocks, then our estimates may be underestimated. The second concern is about the sources of price increases after temperature shocks. Even though we find that market prices were generally higher after temperature hits, prices might increase or decrease because of shifts in demand or supply.

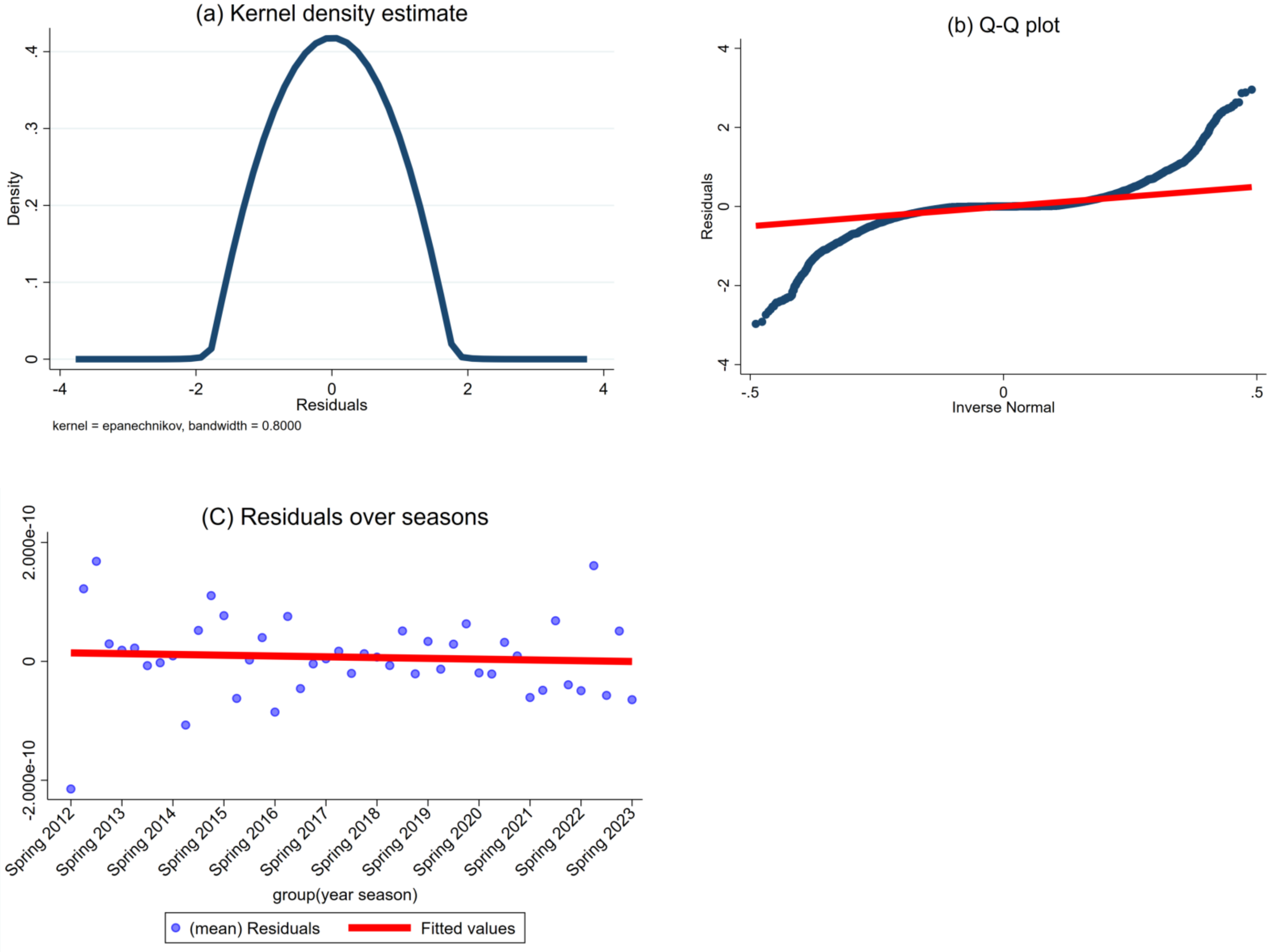
To ensure our estimates are not overly sensitive to the data structure, we implemented two alternative specifications. First, we averaged vegetable prices at the county level, resulting in a single daily price for all vegetables within a county. Second, we calculated the average price for vegetable subcategories when multiple markets exist within a county, producing one daily price per subcategory. The results from these alternative specifications are presented in Supplementary Figs. 2e, f. Notably, our core conclusions remain consistent across these robustness checks.

D.5 Serial Correlation

As we employ long-term daily temperature data, there may be serial correlation of temperature across time, such as during heatwaves spanning several days. To examine this, we plot the trend of residuals. We conducted a systematic residual analysis to detect autocorrelation, as shown in Supplementary Fig. 5. These checks confirm that our inferences are not qualitatively changed.

First, we plotted residuals over time to visually inspect for non-random patterns. Panel (a) presents the kernel density estimate (using the Epanechnikov kernel with a bandwidth of 0.8), superimposed with a normal density curve for comparison. In Panel (b), we plot the Q-Q plot, where the red line represents the 45-degree reference line for perfect normality. Panel (c) plots residuals from the baseline model in Equation (1), aggregated seasonally into spring (March-May), summer (June-August), autumn (September-November), and winter (December-February). The residuals exhibit no discernible seasonal patterns, suggesting that Equation (1) effectively accounts for seasonality in the data.

Supplementary Fig. 5: Residuals.



Note: Panel (a) displays the kernel density estimate (using the Epanechnikov kernel with a bandwidth of 0.8), superimposed with a normal density curve for comparison. Panel (b) presents the Q-Q plot, where the red line represents the 45-degree reference line for perfect normality. Panel (c) illustrates residuals from the baseline model in Equation (1), aggregated seasonally into spring (March-May), summer (June-August), autumn (September-November), and winter (December-February). The residuals exhibit no discernible seasonal patterns, suggesting that Equation (1) effectively accounts for seasonality in the data.

D.6 Spatial Correlation - Conley Standard Errors

As inter-market vegetable trades are possible, spatial correlation in vegetable price changes may also exist, depending on the distance. To address this, we compute Conley standard errors to account for spatial correlation in the error term (Conley, 1999; Hsiang, 2010; Lai et al., 2022). Columns (6)-(9) in Supplementary Table 1 report Conley standard errors to account for spatial correlation among markets within 300 km and 500 km radii, respectively. Columns (1)-(5) provide baseline statistics for comparison (including Coef., Std. Error, P-value, 95% CI-Upper, and 95% CI-Lower).

The uniform kernel assigns equal weights to all observations within the chosen radius and sets the weight for all observations farther away to zero. The Bartlett kernel applies linearly decaying weights to observations inside the radius and assigns zero weight to observations outside the radius. These results of the Conley Standard Errors confirm that our baseline estimates are robust to potential spatial correlation.

Supplementary Table 1. Conley Standard Errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
						Conley Standard Errors			
						150 km		300km	
Temperature bin	Coef.	Stan. Error.	P-value	95% CI-Upper	95% CI-Lower	Uniform	Bartlett	Uniform	Bartlett
<-18	0.0147087	0.003398	0.000	0.0080114	0.021406	0.003422	0.003326	0.0035253	0.002977
[-18, -15)	0.0140459	0.0039831	0.001	0.0061954	0.0218965	0.004095	0.004018	0.0044884	0.004252
[-15, -12)	0.0129159	0.0025118	0.000	0.0079653	0.0178666	0.002544	0.002162	0.0017122	0.001842
[-12, -9)	0.011581	0.0017007	0.000	0.0082289	0.0149331	0.001936	0.001658	0.0018102	0.001785
[-9, -6)	0.0108058	0.0014697	0.000	0.0079091	0.0137026	0.001539	0.001543	0.0016386	0.001472
[-6, -3)	0.0117015	0.0012481	0.000	0.0092417	0.0141614	0.001368	0.001132	0.0014621	0.001167
[-3, 0)	0.0123643	0.0011896	0.000	0.0100198	0.0147089	0.001199	0.001007	0.001157	0.001039
[0, 3)	0.0109064	0.0010426	0.000	0.0088515	0.0129614	0.001147	0.000943	0.0013107	0.001007
[3, 6)	0.0099697	0.0009131	0.000	0.0081701	0.0117693	0.001096	0.000842	0.0011709	0.000871
[6, 9)	0.009908	0.0007939	0.000	0.0083432	0.0114729	0.000881	0.000756	0.0008943	0.000804
[9, 12)	0.0086809	0.0007709	0.000	0.0071615	0.0102003	0.000844	0.000676	0.0008494	0.000698
[12, 15)	0.0072754	0.0006917	0.000	0.005912	0.0086388	0.000774	0.000619	0.0007776	0.000668
[15, 18)	0.0057607	0.0006049	0.000	0.0045684	0.006953	0.000681	0.000554	0.0006199	0.000594
[18, 21)	0.0041676	0.0004881	0.000	0.0032056	0.0051297	0.000532	0.000456	0.0004626	0.000453
[21, 24)	0.0027695	0.0003819	0.000	0.0020168	0.0035222	0.000406	0.000359	0.0003601	0.00037
[24, 27)		Reference Category							
[27, 30)	-0.0011036	0.0004088	0.007	-0.0019094	-0.0002979	0.000434	0.000341	0.0003737	0.000333
[30, 33)	-0.0028482	0.0005038	0.000	-0.0038411	-0.0018552	0.00053	0.000415	0.0006123	0.000425
[33, 36)	-0.0040791	0.0006218	0.000	-0.0053048	-0.0028535	0.000648	0.00056	0.0006217	0.000565
[36, 39)	-0.0039879	0.0008614	0.000	-0.0056858	-0.0022901	0.000877	0.000743	0.0009384	0.000709

>=39	-0.0015444	0.0015829	0.330	-0.0046643	0.0015755	0.001689	0.001575	0.0018137
Observations	6,867,262							

Note: this table presents the impact of temperature fluctuations on daily vegetable prices, utilizing Equation (1) as the foundation. Dependent Variable: Daily change in vegetable price per Chinese catty. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetable, day-of-the-sample, market by year-quarter, and market by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms) are included. Columns (1)-(5): Display standard coefficients, cluster-robust standard errors (clustered at the market level), P-values, and 95% confidence intervals. Columns (6)-(9) report Conley standard errors to account for spatial correlation among markets within the 150 km and 300 km radii, respectively. The uniform kernel weighs all observations within the chosen radius equally and sets the weight for all observations farther as zero. The Bartlett kernel gives linear decaying weights for observations inside the radius and zero weight for observations outside the radius.

D.7 Results Using Three Temperature Bins for Comparison

The main analysis (Figs. 3-5) employs 21 temperature bins spanning <-18°C to ≥39°C with 3°C intervals ([−18,−15), [−15,−12), ..., [36,39)) to analyze vegetable price fluctuations, while projection estimates (Fig. 6) utilize three aggregated bins (<10°C, 10-30°C, >30°C). For comparison, Supplementary Tables 2-5 provide estimates using three temperature bins, including <10°C, 10-30°C, >30°C. Specifically, Supplementary Table 2 presents temperature effects on vegetable price changes using these three bins; Supplementary Table 3 extends this analysis to vegetable subcategories; Supplementary Table 4 conducts heterogeneity assessments across storability tiers, price segments, self-sufficiency levels and transport networks. Supplementary Table 5 reports heterogeneity results by different climate zones.

Supplementary Table 2. Temperature Effects on Price Change of Vegetable, Using Three Temperature Bins.

	(1)	(2)	(3)	(4)
	Price	Changes in logged Price	Price	Changes in logged Price
Max Temp Below 10 (current day)	0.0622***	0.0845***		
	(0.0070)	(0.0086)		
Max Temp Above 30 (current day)	-0.0008	-0.0082		
	(0.0038)	(0.0055)		
Max Temp Below 10 (six-day average)			0.0021***	0.0010***
			(0.0003)	(0.0003)
Max Temp Above 30 (six-day)			-0.0016***	-0.0018***
			(0.0003)	(0.0003)
Day-of-the-sample fixed effects	Yes	Yes	Yes	Yes
Vegetable (386) by market (265) fixed effects	Yes	Yes	Yes	Yes
Vegetable market-by-year-quarter	Yes	Yes	Yes	Yes
Vegetable market-by-holiday	Yes	Yes	Yes	Yes
Cluster	Market	Market	Market	Market
Observation	11,559,858	7,982,690	11,559,858	7,982,690

Note: Column (1) reports results of temperature effects on vegetable wholesale prices, using three temperature bins; Column (2) reports estimate of temperature on changes of logarithm prices; Column (3) reports lagged temperature effects on vegetable wholesale prices; Column (4) reports results of lagged temperature on changes of logarithm prices. Each column represents a separate regression. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. We addressed potential within-market correlation by clustering standard errors at the market level. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Supplementary Table 3. Vegetable Subcategories Using Three Temperature Bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Leaf	**Eggplant**	**Scallions and garlic**	**Cabbage**	**Potato and taro**	**Root vegetables**	**Melons and vegetables**	**Beans**
Max Temp Below 10 (six-day average)	0.0034***	0.0006	0.0003	-0.0013*	-3.47e-07	0.0008**	-0.0002	-0.0008
	(0.0005)	(0.0005)	(0.0004)	(0.0009)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Max Temp Above 30 (six-day average)	-0.0021***	-0.0035***	-0.0002	-0.0012	-0.0009*	-0.0012***	-0.0019***	-0.0034***
	(0.0006)	(0.0006)	(0.0003)	(0.0010)	(0.0005)	(0.0004)	(0.0006)	(0.0006)
Day-of-the-sample fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable (386) by market (265) fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable market-by-year-quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable market-by-holiday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Market	Market	Market	Market	Market	Market	Market	Market
Observation	2,107,572	967,557	1,210,555	305,944	423,841	860,616	1,087,800	482,711

Note: Each column represents a separate regression, using three temperature bins. Columns (1) – (9) report results for Leaf, Eggplant, Scallions and garlic, Cabbage, Potato and taro, Root vegetables, Melons and vegetables and Beans, respectively. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. We addressed potential within-market correlation by clustering standard errors at the market level. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Supplementary Table 4. Heterogeneity Analysis by Storability, Price Tiers, Self-sufficiency and Transport Network: Using Three Temperature Bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)
	Perishable	Non-perishable	Cheap	Expensive	Self-sufficiency	Non- self-sufficiency	Underdevelo ped transport Network	Developed transport Network
Max Temp Below 10 (six-day average)	0.0025***	0.00004	0.0037***	-0.0007	0.0007**	0.0013**	-0.0012***	0.0009**
	(0.0004)	(0.0002)	(0.0008)	(0.0007)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Max Temp Above 30 (six-day average)	-0.0026***	-0.0013***	-0.0016**	-0.0029***	-0.0009***	-0.0032***	-0.0017***	-0.0018***
	(0.0005)	(0.0003)	(0.0007)	(0.0007)	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Day-of-the-sample fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable (386) by market (265) fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable market-by-year-quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vegetable market-by-holiday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Market	Market	Market	Market	Market	Market	Market	Market
Observation	3,075,133	4,907,537	1,869,076	2,014,094	4,575,972	1,816,675	3,199,324	4,783,232

Note: Each column represents a separate regression, using three temperature bins. Columns (1) and (2) report results for perishable and storable vegetables, respectively. Columns (3) and (4) report estimates for cheap and expensive vegetables, respectively. Columns (5) and (6) introduce results for regions with self-sufficiency and non-self-sufficiency abilities, while Columns (7) and (8) report results for regions with undeveloped and developed transport network. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. We addressed potential within-market correlation by clustering standard errors at the market level. City-level highway data is obtained from the China Statistical Yearbook, while the classification of non-perishable vegetable is based on Zheng et al. (2009) and Bao et al. (2023). *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Supplementary Table 5. **Heterogeneity Analysis by Climate Zones: Using Three Temperature Bins.**

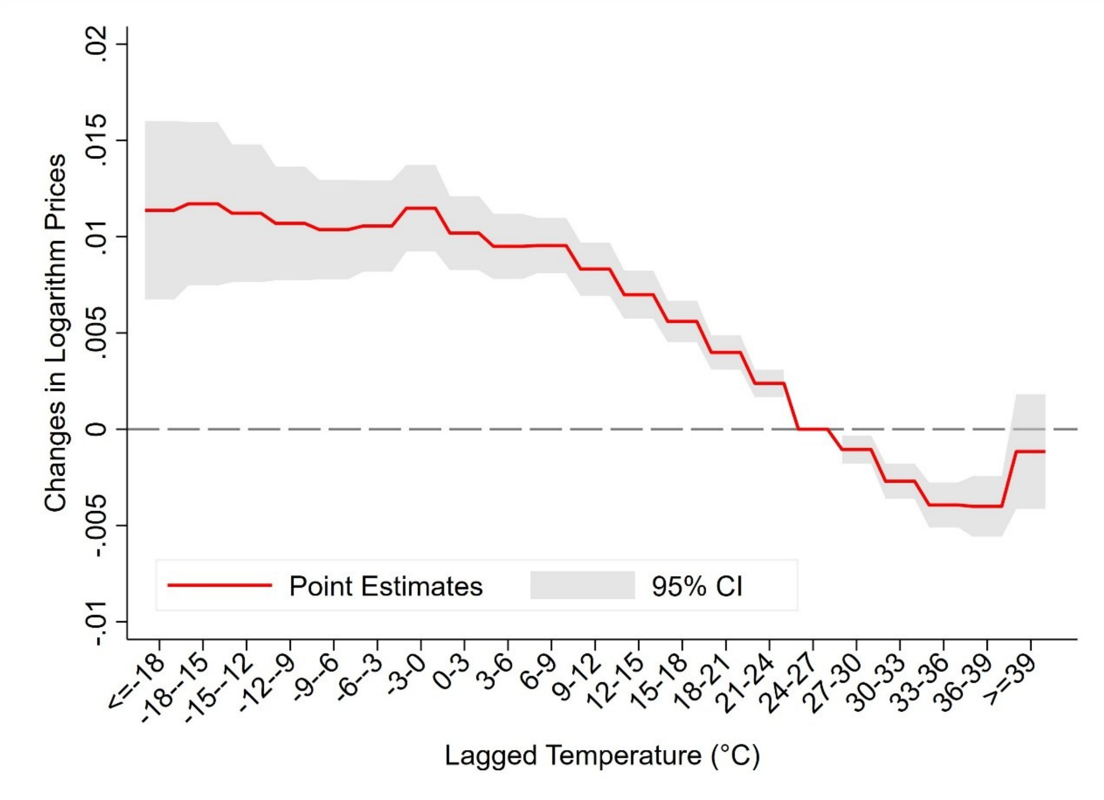
	(1)	(2)	(3)
	Changes in Price (log)	Changes in Price (log)	Changes in Price (log)
	Cold	Mild	Hot
Max Temp Below 10 (six-day average)	0.0007	0.0010**	0.0012**
	(0.0005)	(0.0004)	(0.0005)
Max Temp Above 30 (six-day average)	-0.0028***	-0.0015***	0.0012*
	(0.0005)	(0.0005)	(0.0007)
Day-of-the-sample fixed effects	Yes	Yes	Yes
Vegetable (386) by market (265) fixed effects	Yes	Yes	Yes
Vegetable market-by-year-quarter	Yes	Yes	Yes
Vegetable market-by-holiday	Yes	Yes	Yes
Cluster	Market	Market	Market
Observation	2,576,811	3,262,376	2,143,293

Note: Each column represents a separate regression. Columns (1)–(3) report results for Cold, Mild and Hot regions in China. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). **Markets** are categorized into three regions or climate zones based on the 30-year average temperature from 1981 to 2010. The hot, mild, and cold regions include counties with average temperatures in the highest 30%, middle 40%, and lowest 30% of the distribution, respectively. The sample size for the cold, mild, and hot regions are 2,576,291; 3,262,375; and 2,143,291, respectively. To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. We addressed potential within-market correlation by clustering standard errors at the market level. *** significant at 1% level; ** significant at 5% level; * significant at

10% level.

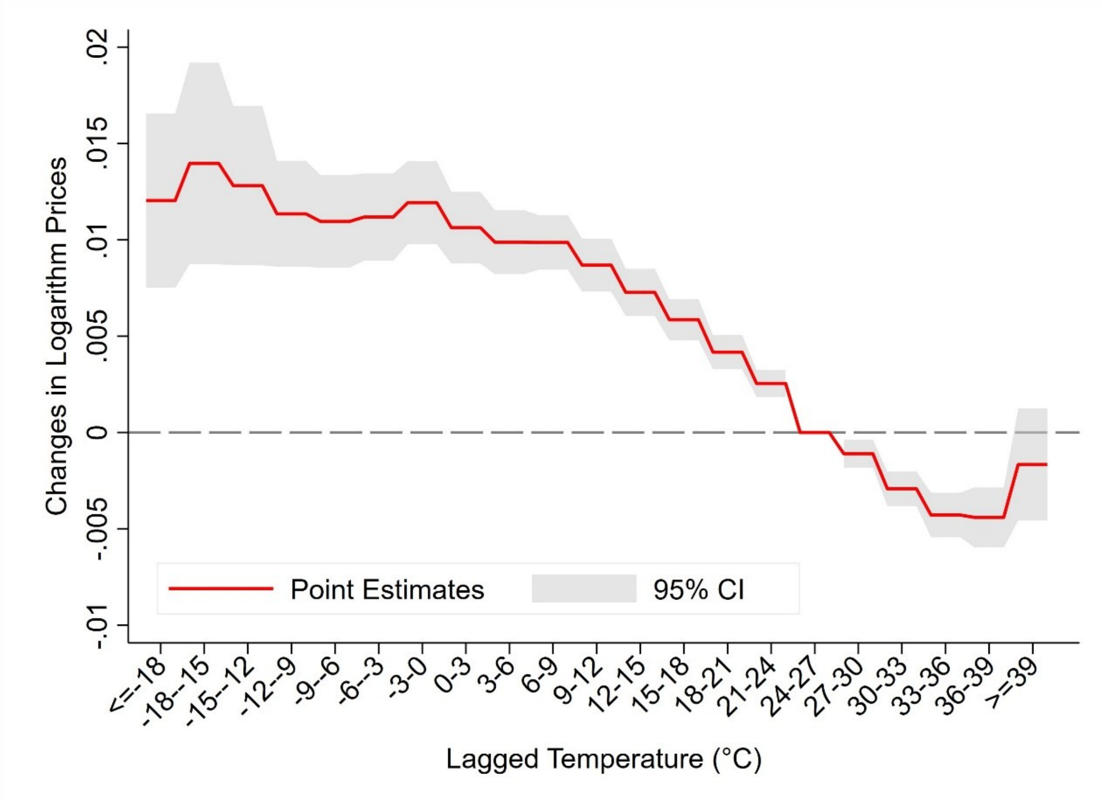
D.8 Results Controlling Weather, Soil, and Other Conditions During the Growing Season

Supplementary Fig. 6: Temperature Effects on Changes in Logarithm Vegetable Wholesale Price.



Note: the marginal effects are measured as the lagged temperature effects on changes of logarithm prices. Observations for the regression are 7,982,688. Equation (1) outlines the statistical model used in our analysis. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year -quarter fixed effects), city-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. Additionally, we have added controls including weather, soil and water availability. Weather conditions are collected during the vegetable growing season. Vegetable growing season information is based on the monitoring calendar (see http://www.moa.gov.cn/gk/tzgg_1/tfw/201105/t20110519_1995188.htm?keywords=). Soil quality data are derived from the Chinese Survey of Soil and Water Conservation (2010), which provides 1 km × 1 km grid-level data. These grid-level data are converted into county-level soil erosion severity (Li and Zhu, 2023) and interacted with year fixed effects. Water availability is measured using irrigation data from Zhang et al. (2022). The accompanying figure visually represents the results, with shaded regions indicating the 95% confidence intervals around our estimates. The depicted lines illustrate the estimated relationship between the independent variables and vegetable wholesale price patterns. We addressed potential within-market correlation by clustering standard errors at the market level.

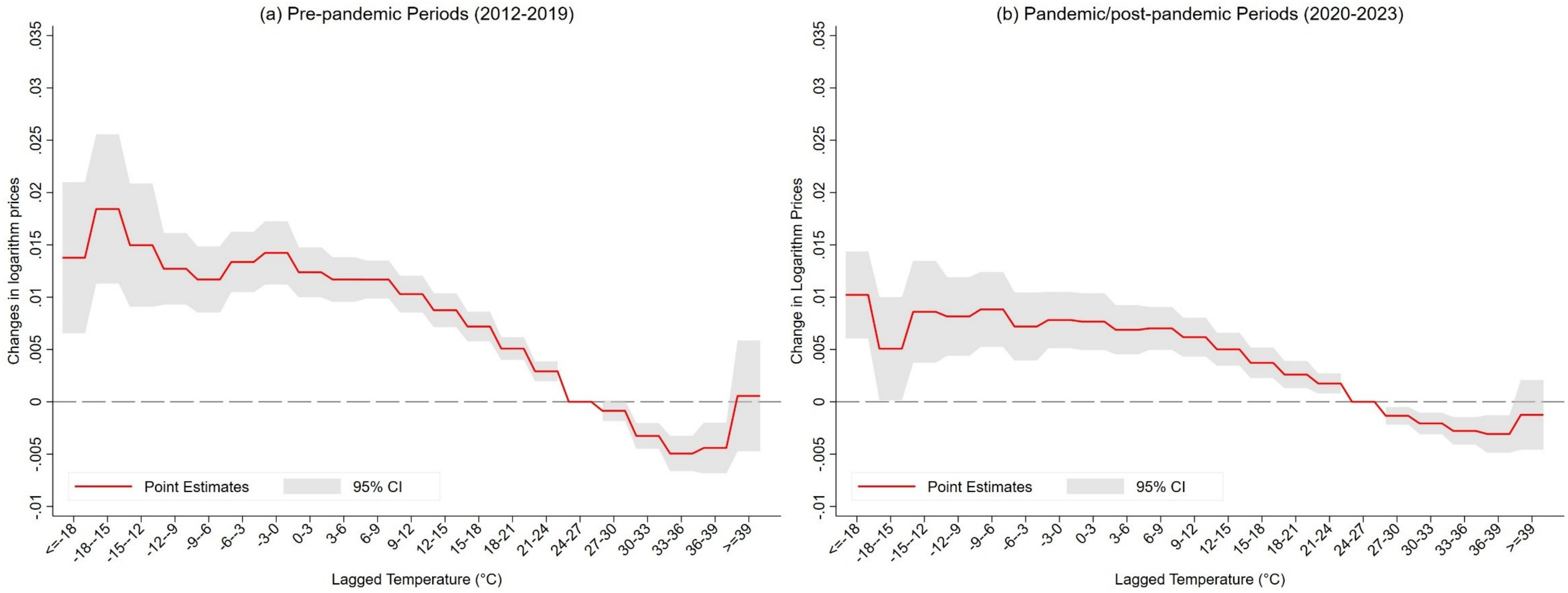
Supplementary Fig. 7: Temperature Effects on Changes in Logarithm Vegetable Wholesale Price, Controlling for Demand-side Confounders.



Note: the marginal effects are measured as the lagged temperature effects on changes of logarithm prices. Observations for the regression are 7,982,688. Equation (1) outlines the statistical model used in our analysis. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), city-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. We have added the consumer price index, income, population density and holiday consumption surges as demand-side control. Specifically, we have added city-level income and population density as controls, and consumption surge in holiday is absorbed by the market-by-holiday fixed effect. The accompanying figure visually represents the results, with shaded regions indicating the 95% confidence intervals around our estimates. The depicted lines illustrate the estimated relationship between the independent variables and vegetable wholesale price patterns. We addressed potential within-market correlation by clustering standard errors at the market level.

D.9 The COVID-19 Confounding Effect

Supplementary Fig. 8: Temperature Effects on Changes in Logarithm Vegetable Wholesale Price: Examining the COVID-19 Confounding Effect.



Note: The regression coefficients represent the lagged daily temperature effects on changes of logarithm vegetable wholesale prices. There are 4,454,070 observations for Panel a (the pre-pandemic sub-sample) and 3,528,486 observations for Panel b (the pandemic and post-pandemic sub-sample). Equation (1) outlines the baseline statistical model used in our analysis. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional daily weather variables in the model. These variables capture the impact of precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. The coefficients and standard errors are depicted in the figure with market-level clustering applied to standard errors.

Part E: Post-harvest Explanations: Transportation and Storage

$$dln(Y_{v,m,t}) = \alpha_1 T^{10}_{v,m,t} + \alpha_2 T^{10}_{v,m,t} * highway_c + \beta_1 T^{30}_{v,m,t} + \beta_2 T^{30}_{v,m,t} * highway_c + \rho X_{v,m,t} + \theta_t + \varphi_{v,m} + \tau_{v,m,s} + \omega_{m,h} + \varepsilon_{v,m,t} \tag{24}$$

Where $T^{10}_{v,m,t}$ is a categorical vector for temperature, equals to 1 if the average temperature over the preceding 6 days (*t*-5 to *t*) for vegetable *v* in market *c* falls below 10 degrees, and is 0 otherwise. $T^{30}_{v,m,t}$ represents the day falls above 30 degrees. $highway_c$ indicates a dummy variable of city *c*, equals 1 if cities have above-median highway density and 0 otherwise. Other symbols have the same definition as equation (1).

$$dln(Y_{v,m,t}) = \alpha_1 T^{10}_{v,m,t} + \alpha_2 T^{10}_{v,m,t} * D_v + \beta_1 T^{30}_{v,m,t} + \beta_2 T^{30}_{v,m,t} * D_v + \rho X_{v,m,t} + \theta_t + \varphi_{v,m} + \tau_{v,m,s} + \omega_{m,h} + \varepsilon_{v,m,t} \tag{23}$$

Where $T^{10}_{v,m,t}$ is a categorical vector for temperature, equals to 1 if the average temperature over the preceding 6 days (*t*-5 to *t*) for vegetable *v* in market *c* falls below 10 degrees, and is 0 otherwise. $T^{30}_{v,m,t}$ represents the day falls above 30 degrees. D_v indicates the storability of vegetable *v*, equals 1 if vegetable *v* is storable and 0 otherwise. Other symbols have the same definition as equation (1).

The price of agricultural products reflects an equilibrium outcome shaped by underlying demand and production dynamics (Bao et al., 2023). The relationship between temperature shocks and agricultural commodity pricing operates through three key channels: (1) production-side yield disruptions, (2) post-harvest preservation efficacy, and (3) logistics network resilience (Bao et al., 2023; FAO, 2022). While prior research often focuses on production impacts, our analysis of wholesale prices emphasizes post-harvest temperature effects, specifically those tied to storage, transportation, and demand-side factors. We argue that the observed temperature-price relationship is primarily driven by transportation logistics and product durability, both of which can significantly affect food quality and availability (FAO, 2022). Consequently, our study isolates the moderating roles of distributional capacity and product durability in mitigating price volatility.

Given that China's vegetable distribution system relies heavily on highways (Song et al., 2024), we use prefecture-level highway density (km/km²) as a proxy for transportation accessibility and distribution capacity. By incorporating an interaction term with highway density, our regression results in Column (1) of Supplementary Table 6 reveal a statistically significant effect: a 10% increase in highway density reduces temperature-induced price volatility by 0.18% (*P*=0.002, 95% CI: 0.05% to 0.23%). This suggests that improved transportation infrastructure can buffer the economic impacts of temperature shocks by enhancing the efficiency of vegetable distribution.

Additionally, vegetables are typically stored and traded through wholesale markets, where their durability influences price responses to temperature fluctuations. In our theoretical framework, we hypothesize that price fluctuations for non-perishable vegetables are less pronounced than those for perishable ones due to differences in spoilage rates. To test this, we construct a dummy variable classifying vegetables as non-perishable based on technical standards from Bao et al. (2023). By interacting temperature bins with this durability indicator, we assess whether price sensitivity varies by vegetable type. The results in Column (2) show that, relative to perishable vegetables, an additional day in the below-10°C or above-30°C temperature ranges reduce price changes for non-perishable vegetables by 0.41% (P<0.001, 95% CI: 0.37% to 0.46%) and 0.28% (P<0.001, 95% CI: 0.25% to 0.33%), respectively. These findings highlight how durability moderates the economic consequences of extreme temperatures, likely by reducing spoilage and waste during storage and transport.

Supplementary Table 6. Distribution-related Explanation on Observed Vegetable Price Change.

	(1)	(2)
	Changes in Price (log)	Changes in Price (log)
(a) Interaction term with highway density		
Below 10*Highway	-0.0018***	-
	(0.0004)	-
Above 30*Highway	0.0006	-
	(0.0005)	-
(b) Interaction term with Non-perishable vegetable		
Below 10*Non-perishable vegetable	-	-0.0041***
	-	(0.0002)
Above 30*Non-perishable vegetable	-	-0.0028***
	-	(0.0002)
		(0.0009)
Day-of-the-sample fixed effects	Yes	Yes
Vegetable (386) by market (265) fixed effects	Yes	Yes
Vegetable market-by-year-quarter	Yes	Yes
Vegetable market-by-holiday	Yes	Yes
Cluster	Market	Market
Observation	5,044,932	7,982,688

Note: Each column represents a separate regression. We accounted for potential confounding factors by incorporating a series of fixed effects. These include controls for day-to-day variations (day-of-the-sample fixed effects), market-specific seasonality (market-by-year-quarter fixed effects), market-specific holiday effects (market-by-holiday fixed effects), and vegetable-specific characteristics (vegetable-specific fixed effects). To further enhance the robustness of our findings, we included several additional variables in the model. These variables capture the impact of air pollution, precipitation levels, relative humidity, and sunshine duration, along with their respective squared terms. Column (1) reports whether highway effects in mitigating temperature extremes, while effects of storability are reported in Column (2). We addressed potential within-market correlation by clustering standard errors at the market level. City-level highway data is obtained from the China Statistical Yearbook, while the classification of non-perishable vegetable is based on classification in Bao et al. (2023). *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Part F. Comparing Cold Regions and Hot Regions

Supplementary Table 7. Comparing cold regions with hot regions (cold-hot), interaction term strategy.

	(1)	(2)
Temperature bin	Coef. Diff. (b0-b1, cold-hot)	P-value
<-18	-0.005	*P*<0.1
[-18, -15)	-0.001	*P*<0.1
[-15, -12)	-0.001	*P*>0.1
[-12, -9)	-0.002	*P*<0.1
[-9, -6)	0.000	*P*>0.1
[-6, -3)	-0.000	*P*>0.1
[-3, 0)	-0.000	*P*>0.1
[0, 3)	-0.000	*P*>0.1
[3, 6)	-0.000	*P*>0.1
[6, 9)	-0.000	*P*>0.1
[9, 12)	-0.000	*P*>0.1
[12, 15)	-0.000	*P*>0.1
[15, 18)	0.000	*P*>0.1
[18, 21)	-0.001	*P*>0.1
[21, 24)	-0.000	*P*>0.1
[24, 27)	Reference bin	
[27, 30)	0.001	*P*<0.1
[30, 33)	-0.001	*P*<0.1
[33, 36)	-0.002	*P*<0.1
[36, 39)	-0.001	*P*<0.1
>=39	-0.008	*P*<0.1
Observed difference	-0.005	-
Empirical *P*-value	-	*P*<0.1
Day-of-the-sample fixed effects	Yes	-
Vegetable (386) by market (265) fixed effects	Yes	-
Vegetable market-by-year-quarter	Yes	-
Vegetable market-by-holiday	Yes	-
Cluster	Market	-
Observations	4,719,582	-

Note: The 'Observed difference' represents the average coefficient difference across all temperature bins. The corresponding P-value is derived from a cluster-robust joint F-test, testing the null hypothesis that the temperature effects are strictly equal between the cold and hot regions. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetables, day-of-the-sample, market by year-quarter, and market by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms). The hot and cold regions include counties with average temperatures in the highest 30% and lowest 30% of the distribution, respectively.

Part G. Coefficients for Projection

Supplementary Table 8. Vegetable Price Response Accounting for Adaptation, All Regions.

	(1)	(2)	(3)	(4)	(5)
	Coef.	Stan. Error.	P-value	95% CI-Upper	95% CI-Lower
	All regions				
TP	0.000182	0.000307	0.555	-0.00042	0.000786
$TP * CMc$	-2.55E-05	5.27E-06	0.000	-3.6E-05	-1.5E-05
$TP * log(GDP\ per\ capita)_c$	-2.2E-05	2.74E-05	0.416	-7.62E-05	3.16E-05
$TP * \mathbb{I}(TP \in 24{,}27)$	0.000272	0.000174	0.119	-7.1E-05	0.000614
$TP * \mathbb{I}(TP \in 24{,}27) * CMc$	-7.53E-06	3.67E-06	0.041	-1.48E-05	-3.14E-07
$TP * \mathbb{I}(TP \in 24{,}27) * \log$ (GDP per capita) c	-6.57E-06	1.57E-05	0.676	-3.8E-05	2.44E-05
$TP * \mathbb{I}(TP \geq 27)$	-7.6E-05	0.000178	0.668	-0.00043	0.000274
$TP * \mathbb{I}(TP \geq 27) * CMc$	-1.58E-06	3.13E-06	6.14E-01	-7.74E-06	4.58E-06
$TP * \mathbb{I}(TP \geq 27) * \log$ (GDP per capita) c	1.12E-05	1.59E-05	4.82E-01	-2E-05	4.25E-05
Cluster	Market				
Observation	7,520,901				

Note: The table summarizes the estimated results derived from the semi-parametric version of Equation (2b). It focuses on the daily changes in logarithmic vegetable wholesale prices as the dependent variable. Each data point represents the price of vegetables in each market on a particular day. 'CMc' denotes the historical mean temperature of market 'c,' calculated over the period from 1980 to 2010. Meanwhile, the GDP per capita for market 'c,' expressed in its natural logarithmic form, is denoted as 'log (GDP per capita) c.' The regression formula adjusts for several fixed effects – specifically, those related to individual vegetables, the specific day within our sample period, each vegetable market's seasonal quarter, and holidays. In our model, we account for variables such as air pollution, rainfall, relative humidity, sunshine duration, along with their squared terms to capture any non-linear effects these factors may have on the vegetable price change. We apply market-level clustering to the standard errors to account for inter-market variability.

Supplementary Table 9. Vegetable Price Response Accounting for Adaptation, by Hot, Mild, and Cold Regions.

	(1)	(2)	(3)	(4)	(5)
	Coef.	Stan. Error.	*P*-value	95% CI-Upper	95% CI-Lower
Panel A: Hot regions					
TP	-0.00025	0.000465	0.589	-0.00118	0.000673
$TP * CM_c$	-2.6E-05	8.32E-06	0.003	-4.3E-05	-9.33E-06
$TP * log(GDP\ per\ capita)_c$	2.07E-05	4.64E-05	0.657	-7.2E-05	0.000113
$TP * \mathbb{I}(TP \in [24{,}27))$	5.37E-05	0.000326	0.87	-0.0006	0.000702
$TP * \mathbb{I}(TP \in [24{,}27)) * CM_c$	-8.28E-07	8.61E-06	0.924	-1.8E-05	1.63E-05
$TP * \mathbb{I}(TP \in 24{,}27) * \log$ (GDP per capita) c	1.81E-06	3.05E-05	0.953	-5.9E-05	6.24E-05
$TP * \mathbb{I}(TP \geq 27)$	0.000503	0.000254	0.051	-3.15E-06	0.001009
$TP * \mathbb{I}(TP \geq 27) * CM_c$	-5.16E-06	5.87E-06	0.382	-1.7E-05	6.52E-06
$TP * \mathbb{I}(TP \geq 27) * \log\ (GDP\ per\ capita)_c$	-3.9E-05	2.35E-05	0.1	-8.6E-05	7.62E-06
Observation	2,576,291				
Panel B: Mild Regions					
TP	0.000601	0.000712	0.401	-0.00082	0.002019
$TP * CM_c$	-3.1E-05	1.35E-05	0.024	-5.8E-05	-4.15E-06
$TP * log(GDP\ per\ capita)_c$	-5.8E-05	5.93E-05	0.33	-0.00018	5.99E-05
$TP * \mathbb{I}(TP \in [24{,}27))$	0.000442	0.000312	0.161	-0.00018	0.001063
$TP * \mathbb{I}(TP \in [24{,}27)) * CM_c$	7.23E-07	6.23E-06	0.908	-1.2E-05	1.31E-05
$TP * \mathbb{I}(TP \in 24{,}27) * \log\ (GDP\ per\ capita)_c$	-3.9E-05	3.05E-05	0.207	-9.9E-05	2.19E-05
$TP * \mathbb{I}(TP \geq 27)$	-0.0006	0.000369	0.111	-0.00133	0.000139
$TP * \mathbb{I}(TP \geq 27) * CM_c$	4.83E-06	6.43E-06	0.456	-7.99E-06	1.76E-05
$TP * \mathbb{I}(TP \geq 27) * \log\ (GDP\ per\ capita)_c$	5.43E-05	0.000032	0.094	-9.45E-06	0.000118
Observation	3,262,375				

Panel C: Cold Regions					
TP	0.000226	0.00044	0.609	-0.00065	0.001097
$TP * CM_c$	-2.4E-05	8.20E-06	0.004	-4E-05	-7.54E-06
$TP * log(GDP\ per\ capita)_c$	-2.6E-05	3.83E-05	0.501	-0.0001	0.00005
$TP * \mathbb{I}(TP \in [24,27))$	0.000431	0.000272	0.116	-0.00011	0.00097
$TP * \mathbb{I}(TP \in 24,27) * CM_c$	-1.8E-05	4.61E-06	0.000	-2.7E-05	-8.85E-06
$TP * \mathbb{I}(TP \in [24,27)) * \log(GDP\ per\ capita)_c$	-1.62E-06	2.43E-05	0.947	-5E-05	4.66E-05
$TP * \mathbb{I}(TP \geq 27)$	-0.00011	0.00026	0.686	-0.00062	0.00041
$TP * \mathbb{I}(TP \geq 27) * CM_c$	-3.46E-06	3.55E-06	0.332	-1.1E-05	3.58E-06
$TP * \mathbb{I}(TP \geq 27) * \log(GDP\ per\ capita)_c$	1.45E-05	2.42E-05	0.549	-3.3E-05	6.24E-05
Observation	2,143,291				
Cluster	Market				

Note: The table provided summarizes the estimated results derived from the semi-parametric version of Equation (2b). It focuses on the daily changes in logarithmic vegetable wholesale prices as the dependent variable. Regions are categorized based on their 30-year average temperatures: 'hot' regions are those in the top 30% of temperature values, 'mild' regions fall within the middle 40%, and 'cold' regions are in the bottom 30% of the temperature distribution. Each data point represents the price of vegetables in a given market on a particular day. 'CMc' denotes the historical mean temperature of market 'c,' calculated over the period from 1980 to 2010. Meanwhile, the GDP per capita for market 'c,' expressed in its natural logarithmic form, is denoted as 'log (GDP per capita) c.' The regression formula adjusts for several fixed effects – specifically, those related to individual vegetables, the specific day within our sample period, each vegetable market's seasonal quarter, and holidays. In our model, we account for variables such as air pollution, rainfall, relative humidity, sunshine duration along with their squared terms to capture any non-linear effects these factors may have on the vegetable price change. We apply market-level clustering to the standard errors to account for spatial inter-market variability.

Part H. Summary Statistics

Supplementary Table 10. Summary Statistics for Vegetable Price and Weather Data.

Variables	Observation	Mean	SD	Min	Max
Daily Price					
Price (CNY/Catty)	11,559,856	2.43	2.43	0.01	202
Leafy vegetables	2,990,900	1.88	1.43	0.01	202
Fruiting vegetables	1,423,007	2.58	2.05	0.03	151
Cole crops	1,748,013	2.59	1.84	0.05	29
Melons and gourds	443,456	2.26	1.15	0.07	12
Beans	605,702	2.02	1.36	0.05	12
Root Vegetable	1,236,303	1.97	1.61	0.04	21
Bulb vegetables	1,621,972	1.91	1.30	0.05	30
Tubers	709,547	3.29	2.41	0.05	24
Others	780,958	5.38	6.16	0.02	65
Price change (P_{ijt} - $P_{ij(t-1)}$)	7,982,688	-0.0002	0.10	-4.11	4.26
Weather					
Max Temperature (°C)	11,559,858	19.83	10.91	-23.44	48.32
Rainfall (mm)	11,559,858	2.35	8.02	0	322.95
Sunshine duration (hours)	11,559,858	5.86	4.07	0	16.24
Humidity (g/m^3)	11,559,858	66.11	18.61	7.47	105.81
$PM_{2.5}$ ($\mu g/m^3$)	11,559,858	35.10	19.79	1.27	415.42
Temperature on hot days (>30°C)	2,334,943	33.26	2.32	30.00	48.32
Temperature on cold days (<10°C)	2,448,383	3.64	5.17	-23.44	10.00

Note: Daily observations were conducted spanning from January 1, 2012, to April 18, 2023.

Part I. Generalizability Beyond China

While the core mechanisms hold, application requires tailoring to the distinct resource constraints and institutional contexts of Global South cities. We map our findings to three common urban typologies:

I.1 Dense, Informal-Sector Dominated Cities

These cities are characterized by: (1) high population density (≥20,000 people/km²), (2) 50–70% of vegetable distribution handled by informal vendors (e.g., street stalls, small small-scale independent vendors), and (3) limited formal infrastructure (e.g., <10% of wholesale markets have cold storage).

Translating resilience findings: Our study highlights local self-sufficiency as a volatility buffer—this translates to scaling urban and peri-urban agriculture (UPA), a common practice in these cities. For example, Lagos' peri-urban vegetable farms currently supply only 15% of the city's needs; expanding this to 30% (via low-cost irrigation for heat resilience) could replicate the "self-sufficiency buffer" we observed in Chinese cities, reducing price spikes during heatwaves by an estimated 25–30%.

Translating adaptation findings: Our adaptation strategies (e.g., targeted cold-chain investment) can be adapted to informal systems. For instance, instead of large-scale cold storage (unaffordable for most hubs), low-cost mobile cold carts (equipped with solar-powered coolers) could be deployed between wholesale hubs and informal vendors—addressing the same temperature-sensitive distribution gap our study targets, but at 1/5th the cost.

I.2 Coastal, Climate-Vulnerable Cities

These cities face compounded risks: (1) extreme heat (≥38°C) in dry seasons, (2) flooding in wet seasons (disrupting road transport), and (3) reliance on long-distance supply chains (e.g., Cape Town sources 80% of vegetables from the Western Cape, a 4–8 hour drive).

Translating temperature-sensitivity findings: Our study found vegetables from hotter regions are more sensitive to cold shocks—for Jakarta, this means prioritizing cold-resilient varieties (e.g., local spinach, bitter melon) during El Niño-induced cold snaps, just as Chinese cities adjusted varieties for regional temperature risks. Similarly, Cape Town's heat-sensitive tomatoes (a staple) could benefit from the longer shelf-life resilience we documented—promoting heat-tolerant tomato varieties (e.g., 'Heatmaster') to reduce post-harvest losses and price volatility.

Translating transport-efficiency findings: Our work links efficient transport to lower volatility—for coastal cities, this means investing in flood-resilient road corridors between wholesale hubs and production regions (e.g., elevating key stretches of Jakarta's Cikampek Highway). Even modest improvements (e.g., 20% faster transport during floods) could cut price volatility by 15–20%, mirroring the transport-driven resilience we observed in China.

I.3 Mid-Size Cities with Emerging Formal Infrastructure

These cities are in transition: (1) growing formal wholesale markets (30–40% of supply),

(2) expanding urban planning capacity, and (3) pilot climate adaptation programs (e.g., Pune's 2023 "Urban Food Resilience Plan").

Translating monitoring and policy findings: Our study underscores the value of real-time temperature-price monitoring; these cities can leverage low-cost digital tools (e.g., SMS-based price reporting from wholesale vendors, open-source weather data) to build early warning systems. For example, Kumasi's new Central Market could integrate temperature and price data into a city dashboard, allowing policymakers to trigger short-term adaptations (e.g., releasing reserve stocks) when heat/cold exceeds volatility thresholds, directly applying our "adaptation timing" findings.

Translating scaling strategies: Our projection that "adaptation mitigates 58% of volatility under aggressive climate scenarios (RCP8.5)" is particularly relevant here. Mid-size cities can avoid lock-in to high-carbon, low-resilience infrastructure (e.g., sprawling wholesale markets) by embedding our adaptation principles (e.g., climate-resilient market design, mixed formal-informal distribution) into urban master plans—something Pune is already testing with its "green wholesale market" pilots.

Part J. Policy Implications for China and Global South

Drawing directly on core findings of this study, we propose targeted, evidence-based policy recommendations focused on urban governance and food system resilience. **First, upgrade urban wholesale market infrastructure for climate resilience**. Given that post-harvest disruptions (e.g., transport delays and storage spoilage) drive volatility, and cities with dedicated infrastructure exhibit lower fluctuations, retrofit key wholesale markets with modular cold storage (e.g., see **Supplementary Note 1** for Fuquan Hengsheng market), insulated areas for cold extremes (e.g., see **Supplementary Note 2** for Beijing Xinfadi market), and shade structures for heat extremes (e.g., see **Supplementary Note 3** for Shanghai Touqiao market). Policymakers should prioritize high-temperature-volatility cities like northern areas prone to cold snaps and southern regions affected heat waves (Igwe et al. 2024). A pertinent policy example is *National Facility Vegetable Key Regional Development Plan (2015-2020)* in China, which emphasizes using such materials for vegetable protection. [2] Additionally, designate "vegetable priority delivery corridors" between wholesale markets and retail endpoints, incorporating traffic signal prioritization and peak-hour exemptions to mitigate temperature-amplified delays (see e.g., **Supplementary Note 4** for Jizhihui International Agricultural Trade Logistics Center).

Second, strengthen urban-peripheral supply coordination to enhance self-sufficiency. As cities with peri-urban vegetable supplies meeting local demand experience lower volatility during temperature shocks, thus reducing reliance on vulnerable long-distance chains, establish peri-urban vegetable reserve zones (within 50 km of wholesale markets) and subsidize farmers to adopt regionally adaptive varieties (e.g., cold-tolerant greens in the north, heat-resistant tomatoes in the south). For example, Guangzhou achieved a 100% self-sufficient vegetable rate in 2020, producing 4.04 million tons, attributable to peri-urban vegetable reserve zones in the Zengcheng district (Gold River Agricultural Firm). [3] The *National Facility Vegetable Key Regional Development Plan (2015-2020)* in China also emphasizes that, given the country's vast territory and large population with high vegetable demand, local production and supply should predominate, supplemented by appropriate regional production and long-distance transportation. Regarding subsidies, the Chinese central government provides fiscal support of 25-30% for agricultural insurance premiums on local characteristic products, with local governments covering at least an additional 35%. [4] Additionally, launch "farm-wholesale direct docking" programs by reserving wholesale market stalls for peri-urban producers to eliminate intermediaries and minimize spoilage. A successful model is the "Qiannonghui" initiative in Changsha, [5] which establishes a direct supply chain from peri-urban farms to city markets, thereby reducing spoilage and stabilizing supply for urban consumers.

Third, tailor adaptation to regional climates and vegetable traits. Given heterogeneous vulnerabilities, such as hotter-region vegetables being cold-sensitive and vice versa, with short-shelf-life crops facing higher spoilage risks, support southern

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[2] See https://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923411.htm for more details.
[3] See https://dara.gd.gov.cn/ywdt/snxxlb/content/post_4605138.html for more details.
[4] See https://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923411.htm for more details.
[5] See https://www.hxw.gov.cn/content/2021/08/04/13341564.html for more details.

markets in stocking cold-tolerant crops (e.g., bitter melon) during winter and northern markets in stocking heat-resistant crops (e.g., heat-tolerant lettuce) during summer through municipal subsidies. Furthermore, offer low-interest loans to wholesale vendors for small-scale cold chain equipment (e.g., portable refrigerated carts) targeting short-shelf-life crops (e.g., spinach and chives) to reduce post-harvest losses. For example, according to the *Action Plan for Optimizing and Improving the Logistics and Warehousing Facilities and Services*, Shanghai has introduced a special "Cold Chain Logistics Loan" with interest rates as low as 2.99% for mortgages on cold chain equipment, supplemented by government interest subsidies. This initiative effectively lowers financial costs for enterprises and merchants upgrading cold chain facilities, [6] thereby supporting infrastructure development, reducing losses and enabling off-peak sales.

While our empirical base is Chinese cities, the core mechanisms we identify temperature disruptions to urban wholesale distribution, and urban-specific adaptations to mitigate volatility, are transferable to cities globally, with particular relevance for the Global South (Sithole et al. 2025). Three traits of Global South urban food systems align with our findings, supporting generalizability: **Dependence on urban wholesale hubs**: Like Chinese cities, Global South urban centers (e.g., Lagos' Oshodi Market, Jakarta's Kramat Jati Market) rely on 1–3 primary wholesale hubs for 70–90% of vegetable supply (FAO, 2023). Temperature-induced disruptions to these hubs (e.g., heat-related spoilage in unrefrigerated stalls) cascade to retail prices, just as we observed in China. For example, Jakarta's 2022 heatwave (≥35°C for 10 consecutive days) caused 20% spoilage at Kramat Jati Market, triggering a 25% retail price spike, mirroring our finding that unadapted urban wholesale systems amplify temperature volatility. **Vulnerable urban distribution networks**: Global South cities often rely on informal, temperature-sensitive transport (e.g., motorcycles in Dhaka, small trucks in Nairobi) with minimal cold-chain coverage, similar to the unadapted Chinese cities in our sample. Our finding that "targeted urban adaptations (e.g., mobile cold carts) reduce volatility by 58% under RCP8.5" directly applies here: for instance, deploying solar-powered cold carts between Nairobi's Marikiti Market and informal retail stalls could cut heat-related spoilage by 30%, stabilizing prices as observed in Chinese cities with adapted transport. **High stakes for urban food security**: 30–50% of Global South urban residents (e.g., Kolkata, Dar es Salaam) spend 40–60% of household income on food (World Bank, 2022), making price volatility a direct threat to nutritional access. Our projection that "adaptations mitigate 90% of volatility under RCP4.5" is thus policy-critical for these contexts: scaling peri-urban vegetable production in Lagos (to match China's self-sufficiency buffer) could reduce cold-snap price spikes by 25%, protecting low-income households. Contextual adjustments are needed to account for Global South constraints: unlike China's centralized governance, fragmented urban governance in cities like Kumasi (Ghana) may require smaller, pilot adaptations (e.g., community-level wholesale sub-stalls) before scaling. Additionally, data scarcity in cities with limited formal oversight (e.g., Mogadishu) could be addressed by pairing our temperature-price framework with alternative data (e.g., vendor surveys, satellite imagery

[6] Action Plan for Optimizing and Improving the Logistics and Warehousing Facilities and Services in Shanghai (2025-2027). See https://fgw.sh.gov.cn/fgw_cyfz/20250127/19e0695080cd45c7832e858421a93bfa.html

of market activity)—a modification that preserves our core mechanism while adapting to local conditions.

Supplementary Note 1: Modular Cold Storage Infrastructure Visual documentation demonstrates the practical implementation of modular cold storage facilities utilized for temperature-sensitive vegetables, such as chili peppers, at the Fuquan Hengsheng Market. Such infrastructure serves as a critical buffer, significantly reducing post-harvest spoilage and stabilizing wholesale prices during temperature anomalies. The original photographic evidence is publicly accessible via the Department of Agriculture and Rural Affairs of Fujian Province: https://nynct.fujian.gov.cn/xxgk/gzdt/qsnyxxlb/fz/202507/t20250701_6960460.htm

Supplementary Note 2: Insulation Measures Against Cold Extremes Visual reports illustrate the application of frost blankets and insulated staging areas designed to protect fresh produce during severe cold snaps at the Beijing Xinfadi Market. These physical barriers are essential adaptive interventions for mitigating acute, cold-induced supply shocks in northern urban wholesale hubs. Photographic documentation is available via Beijing News: https://www.bjnews.com.cn/detail/163756480714976.html

Supplementary Note 3: Shade Structures for Heat Mitigation Visual evidence highlights the deployment of extensive awnings and shade structures at the Shanghai Touqiao Market. These targeted structural adaptations shield perishable vegetables from direct solar radiation and extreme heatwaves, preventing rapid thermal degradation and subsequent price spikes. Photographic documentation is available via Beijing News: https://www.bjnews.com.cn/detail/163756480714976.html

Supplementary Note 4: Logistics Monitoring and Traffic Prioritization Documentation showcases the comprehensive logistics monitoring system utilized at the Jizhihui International Agricultural Trade Logistics Center. Systems of this nature provide the technological foundation necessary for coordinating vegetable priority delivery corridors and facilitating peak-hour traffic exemptions, thereby preventing temperature-amplified transit delays. Original reporting and visual data were sourced from the Yongchuan District Government. https://cqrb.cn/contry/dy46/2025-05-11/2270963_pc.html

Part K. Estimates of Figures Appeared in the Main Text

Supplementary Table 11. **Price Response to Temperature Extremes** (corresponds to **Fig. 2**).

	(1)	(2)	(3)	(4)	(5)
Temperature bin	Coef.	Stan. Error.	P-value	95% CI-Lower	95% CI- Upper
			Panel A: Temperature effects on Vegetable Price		
<-18	0.1340206	0.0436878	0.002	0.0480098	0.2200313
[-18, -15)	0.1504135	0.0288608	0	0.0935936	0.2072334
[-15, -12)	0.1808498	0.0290253	0	0.123706	0.2379937
[-12, -9)	0.1950699	0.0268758	0	0.142158	0.2479817
[-9, -6)	0.2096913	0.0252285	0	0.1600227	0.25936
[-6, -3)	0.1841494	0.0218421	0	0.1411477	0.2271511
[-3, 0)	0.1752027	0.0182842	0	0.1392055	0.2111998
[0, 3)	0.1483822	0.0156215	0	0.1176272	0.1791372
[3, 6)	0.1184008	0.0135736	0	0.0916777	0.1451239
[6, 9)	0.0741066	0.0114925	0	0.0514807	0.0967324
[9, 12)	0.0394968	0.0094944	0	0.0208047	0.0581889
[12, 15)	0.0127191	0.0078596	0.107	-0.0027545	0.0281927
[15, 18)	0.0017034	0.0061759	0.783	-0.0104555	0.0138623
[18, 21)	-0.00142	0.0045592	0.756	-0.010396	0.007556
[21, 24)	-0.0001358	0.0025813	0.958	-0.0052178	0.0049462
[24, 27)			Reference Bin		
[27, 30)	-0.0026489	0.0027301	0.333	-0.0080237	0.0027259
[30, 33)	-0.0014148	0.0045291	0.755	-0.0103315	0.0075018
[33, 36)	-0.0147907	0.0062502	0.019	-0.0270958	-0.0024857
[36, 39)	-0.0346566	0.0081133	0	-0.0506297	-0.0186835
>=39	-0.0559148	0.0134275	0	-0.0823502	-0.0294793
Observations	11,559,881				
R2	0.8219				
			Panel B: Temperature effects on Vegetable Price Change		
<-18	0.0089042	0.0031431	0.005	0.0027155	0.0150929
[-18, -15)	0.0100809	0.0015882	0	0.0069538	0.0132081
[-15, -12)	0.0107665	0.0012272	0	0.0083501	0.0131829
[-12, -9)	0.0122554	0.0013781	0	0.0095421	0.0149688
[-9, -6)	0.0100288	0.0010361	0	0.0079887	0.0120689
[-6, -3)	0.0108892	0.0009971	0	0.0089259	0.0128526
[-3, 0)	0.0114488	0.0009767	0	0.0095257	0.0133719
[0, 3)	0.0114687	0.0008044	0	0.0098848	0.0130526
[3, 6)	0.0095363	0.0007595	0	0.0080408	0.0110317
[6, 9)	0.007748	0.0006774	0	0.0064142	0.0090818

[9, 12)	0.0065108	0.0006233	0	0.0052835	0.0077381
[12, 15)	0.0053596	0.0005528	0	0.0042712	0.006448
[15, 18)	0.0045494	0.0004852	0	0.003594	0.0055048
[18, 21)	0.0028133	0.0003836	0	0.0020579	0.0035687
[21, 24)	0.001297	0.0003186	0	0.0006696	0.0019244
[24, 27)			Reference Bin		
[27, 30)	-0.0009903	0.0002877	0.001	-0.0015567	-0.0004239
[30, 33)	-0.0018857	0.000368	0	-0.0026102	-0.0011612
[33, 36)	-0.0036101	0.0004994	0	-0.0045933	-0.0026268
[36, 39)	-0.0039462	0.0006229	0	-0.0051727	-0.0027197
>=39	-0.0025349	0.0008928	0.005	-0.0042928	-0.000777
Observations	7,982,688				
R2	0.0097				
Panel C: Lagged Temperature Effects on Price					
<-18	0.3186625	0.0721554	0	0.1766061	0.4607188
[-18, -15)	0.3443217	0.0472877	0	0.2512236	0.4374197
[-15, -12)	0.3673331	0.044994	0	0.2787508	0.4559153
[-12, -9)	0.3957065	0.0446816	0	0.3077392	0.4836737
[-9, -6)	0.4034607	0.0424896	0	0.3198091	0.4871123
[-6, -3)	0.3670283	0.038199	0	0.2918238	0.4422329
[-3, 0)	0.3440114	0.0332187	0	0.278612	0.4094109
[0, 3)	0.3080259	0.0277408	0	0.2534111	0.3626407
[3, 6)	0.2572015	0.0244973	0	0.2089723	0.3054306
[6, 9)	0.1966273	0.0213112	0	0.1546707	0.2385839
[9, 12)	0.1406734	0.0184796	0	0.1042916	0.1770552
[12, 15)	0.0915487	0.0149049	0	0.0622045	0.1208929
[15, 18)	0.0542814	0.0120684	0	0.0305216	0.0780412
[18, 21)	0.0353523	0.0085177	0	0.018583	0.0521215
[21, 24)	0.0168157	0.0040657	0	0.0088114	0.0248201
[24, 27)			Reference Bin		
[27, 30)	-0.0050663	0.004478	0.259	-0.0138824	0.00375
[30, 33)	-0.0144922	0.0071449	0.044	-0.0285588	-0.00043
[33, 36)	-0.0427378	0.0089432	0	-0.0603447	-0.02513
[36, 39)	-0.0638014	0.0117137	0	-0.0868629	-0.04074
>=39	-0.0867112	0.0207625	0	-0.1275875	-0.04583
Observations	11,559,856				
Panel D: Lagged Temperature Effects on Price Change					
<-18	0.011549	0.002283	0	0.0070537	0.0160443
[-18, -15)	0.0133059	0.0026896	0	0.0080101	0.0186018
[-15, -12)	0.0122364	0.0020861	0	0.0081288	0.016344
[-12, -9)	0.0107108	0.0014033	0	0.0079477	0.0134738
[-9, -6)	0.0103395	0.0012394	0	0.0078991	0.0127799
[-6, -3)	0.010673	0.0011632	0	0.0083826	0.0129633
[-3, 0)	0.0114842	0.0010996	0	0.009319	0.0136494

[0, 3)	0.0102818	0.0009501	0	0.008411	0.0121526
[3, 6)	0.0096001	0.0008434	0	0.0079394	0.0112608
[6, 9)	0.0096324	0.0007166	0	0.0082215	0.0110433
[9, 12)	0.0084658	0.0006964	0	0.0070946	0.009837
[12, 15)	0.0070913	0.0006225	0	0.0058656	0.008317
[15, 18)	0.0056848	0.0005446	0	0.0046124	0.0067571
[18, 21)	0.0040447	0.0004506	0	0.0031573	0.004932
[21, 24)	0.0024719	0.000361	0	0.0017611	0.0031827
[24, 27)			Reference Bin		
[27, 30)	-0.0010325	0.0003645	0.005	-0.0017502	-0.0003148
[30, 33)	-0.0027111	0.0004518	0	-0.0036008	-0.0018214
[33, 36)	-0.0039309	0.0005798	0	-0.0050726	-0.0027891
[36, 39)	-0.0038775	0.0007827	0	-0.0054186	-0.0023364
>=39	-0.0010415	0.00149	0.485	-0.0039752	0.0018922
Observations	7,982,688				

Note: this table presents the impact of temperature fluctuations on daily vegetable prices, utilizing Equation (1) as the foundation. The analysis considers both immediate temperature changes (Panels A and B) and lagged temperature effects (Panels C and D) compared to a reference temperature range of 24-27°C. Dependent Variable: Daily change in vegetable price per Chinese catty. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetable, day-of-the-sample, city by year-quarter, and city by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms) are included. Columns (1)-(5): Display coefficients, cluster-robust standard errors (clustered at the market level), *P*-values, and 95% confidence intervals. Where P-values are reported as 0, they signify P<0.001.

Supplementary Table 12. Price Change Response to Temperature Extremes: heterogeneity (corresponds to **Fig. 3**).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Coef.	Stan. Error.	P-value	95% CI-Lower	95% CI-Upper	Coef.	Stan. Error.	P-value	95% CI-Lower	95% CI-Upper
					Panel A: Durability					
Temperature bin			**Perishable**					**Non-perishable**		
<-18	0.0138779	0.0025711	0	0.0088145	0.0189413	0.0097392	0.0031443	0.002	0.003548	0.01593
[-18, -15)	0.0197269	0.0041521	0	0.01155	0.0279038	0.0077948	0.0021179	0	0.0036246	0.011965
[-15, -12)	0.0170287	0.0029818	0	0.0111565	0.0229008	0.0083733	0.001714	0	0.0049984	0.011748
[-12, -9)	0.0143945	0.0019947	0	0.0104663	0.0183228	0.008119	0.0012956	0	0.005568	0.01067
[-9, -6)	0.0146931	0.0018257	0	0.0110977	0.0182885	0.0070536	0.0011843	0	0.0047216	0.009386
[-6, -3)	0.0156144	0.0016887	0	0.0122888	0.0189399	0.0070199	0.0010551	0	0.0049423	0.009098
[-3, 0)	0.0168723	0.0016493	0	0.0136242	0.0201205	0.0077013	0.0009917	0	0.0057485	0.009654
[0, 3)	0.0154944	0.0014233	0	0.0126915	0.0182973	0.0067255	0.0008562	0	0.0050397	0.008411
[3, 6)	0.0142243	0.0012308	0	0.0118003	0.0166483	0.0065387	0.000763	0	0.0050364	0.008041
[6, 9)	0.0141668	0.0010414	0	0.012116	0.0162176	0.0066014	0.0006577	0	0.0053064	0.007896
[9, 12)	0.0124492	0.0009937	0	0.0104923	0.0144061	0.0058105	0.0006208	0	0.0045881	0.007033
[12, 15)	0.0097135	0.0008825	0	0.0079755	0.0114514	0.0053696	0.0005431	0	0.0043002	0.006439
[15, 18)	0.0076543	0.0007669	0	0.006144	0.0091645	0.0044371	0.0005218	0	0.0034096	0.005465
[18, 21)	0.0049409	0.0006249	0	0.0037103	0.0061715	0.0034576	0.0004132	0	0.002644	0.004271
[21, 24)	0.0027955	0.0005653	0	0.0016823	0.0039087	0.0021736	0.0003399	0	0.0015044	0.002843
[24, 27)						**Reference bin**				
[27, 30)	-0.0014555	0.0005901	0.014	-0.0026177	-0.0002934	-0.0008154	0.0003173	0.011	-0.0014401	-0.00019
[30, 33)	-0.0039365	0.0007219	0	-0.0053582	-0.0025148	-0.0020283	0.0003953	0	-0.0028067	-0.00125
[33, 36)	-0.0053873	0.0009309	0	-0.0072207	-0.003554	-0.0030411	0.0005262	0	-0.0040772	-0.00201
[36, 39)	-0.0058215	0.0012956	0	-0.0083729	-0.00327	-0.0027289	0.0007122	0	-0.0041312	-0.00133

>=39	-0.0022031	0.0022371	0.326	-0.0066087	0.0022024	-0.000328	0.0014808	0.825	-0.0032438	0.002588
Observations	3,075,132	-	-	-	-	4,372,152	-	-	-	-
Panel B: Price level										
			Cheap					**Expensive**		
<-18	0.0405085	0.0114227	0	0.0180157	0.0630013	-0.0231737	0.0138259	0.095	-0.0503991	0.004052
[-18, -15)	0.0394648	0.008677	0	0.0223786	0.056551	-0.001069	0.0052335	0.838	-0.0113746	0.009237
[-15, -12)	0.0266124	0.0067362	0	0.0133479	0.0398769	0.0029166	0.0068633	0.671	-0.0105984	0.016432
[-12, -9)	0.030112	0.0043028	0	0.0216393	0.0385848	-0.0024087	0.0060068	0.689	-0.0142371	0.00942
[-9, -6)	0.0253046	0.0036249	0	0.0181668	0.0324425	-0.0004959	0.004506	0.912	-0.009369	0.008377
[-6, -3)	0.0256839	0.0027886	0	0.0201928	0.0311751	0.0005064	0.0033841	0.881	-0.0061573	0.00717
[-3, 0)	0.0242204	0.0024407	0	0.0194143	0.0290265	0.0033396	0.0030941	0.281	-0.0027532	0.009432
[0, 3)	0.019408	0.0021014	0	0.0152701	0.0235459	0.0051141	0.0025245	0.044	0.000143	0.010085
[3, 6)	0.0168473	0.0019978	0	0.0129134	0.0207813	0.0055104	0.0023363	0.019	0.0009098	0.010111
[6, 9)	0.0155668	0.0017134	0	0.012193	0.0189407	0.005422	0.0020063	0.007	0.0014713	0.009373
[9, 12)	0.0124231	0.0015524	0	0.0093662	0.01548	0.005007	0.0018149	0.006	0.0014331	0.008581
[12, 15)	0.0092002	0.0014163	0	0.0064114	0.011989	0.0050676	0.0015212	0.001	0.0020721	0.008063
[15, 18)	0.0055695	0.0012612	0	0.0030861	0.0080529	0.0056721	0.0011898	0	0.0033293	0.008015
[18, 21)	0.0042687	0.0011494	0	0.0020055	0.0065319	0.0029085	0.0011228	0.01	0.0006975	0.00512
[21, 24)	0.0018448	0.0007504	0.015	0.0003671	0.0033225	0.0020034	0.0007683	0.01	0.0004904	0.003516
[24, 27)	-0.0004163	0.0007423	0.575	-0.001878	0.0010454	-0.002448	0.0007101	0.001	-0.0038463	-0.00105
[27, 30)	-0.0025954	0.0009652	0.008	-0.0044961	-0.0006947	-0.0043676	0.000954	0	-0.0062462	-0.00249
[30, 33)	-0.0014317	0.0013149	0.277	-0.0040209	0.0011575	-0.0082367	0.001235	0	-0.0106687	-0.0058
[33, 36)	0.0013758	0.0017459	0.431	-0.0020621	0.0048137	-0.01069	0.0017928	0	-0.0142203	-0.00716
[36, 39)	0.0000889	0.003636	0.981	-0.0070709	0.0072486	-0.0088943	0.0027284	0.001	-0.014267	-0.00352
>=39	-0.0004163	0.0007423	0.575	-0.001878	0.0010454	-0.002448	0.0007101	0.001	-0.0038463	-0.00105
Observations	1,869,066	-	-	-	-	2,014,087	-	-	-	-

Panel C: Production ability

	Non-productive					Productive				
<-18	0.0108054	0.0042147	0.013	0.0023518	0.0192589			Omitted		
[-18, -15)	0.0074305	0.0027212	0.009	0.0019724	0.0128885			Omitted		
[-15, -12)	0.0092349	0.002932	0.003	0.0033541	0.0151157			Omitted		
[-12, -9)	0.0088511	0.0027634	0.002	0.0033083	0.0143938	0.000188	0.005206	0.971	-0.01019	0.010561
[-9, -6)	0.0087182	0.0023143	0	0.0040762	0.0133602	-0.00033	0.003912	0.933	-0.00812	0.007467
[-6, -3)	0.0087033	0.0022751	0	0.0041399	0.0132666	0.011189	0.005159	0.033	0.000909	0.021468
[-3, 0)	0.0094356	0.0022182	0	0.0049864	0.0138848	0.009515	0.003117	0.003	0.003304	0.015726
[0, 3)	0.0079077	0.0018284	0	0.0042404	0.011575	0.009322	0.002461	0	0.004418	0.014225
[3, 6)	0.007757	0.0016835	0	0.0043803	0.0111338	0.007607	0.002073	0	0.003476	0.011739
[6, 9)	0.0081533	0.0014653	0	0.0052144	0.0110923	0.008222	0.001814	0	0.004609	0.011836
[9, 12)	0.0066774	0.0014528	0	0.0037635	0.0095913	0.00648	0.00159	0	0.003312	0.009648
[12, 15)	0.0068204	0.0012757	0	0.0042616	0.0093792	0.005045	0.001528	0.001	0.002	0.008091
[15, 18)	0.0049765	0.0010615	0	0.0028474	0.0071056	0.004706	0.001159	0	0.002397	0.007015
[18, 21)	0.0039554	0.0009487	0	0.0020525	0.0058582	0.003576	0.000863	0	0.001856	0.005296
[21, 24)	0.0024822	0.0008057	0.003	0.0008663	0.0040982	0.001631	0.000598	0.008	0.00044	0.002823
[24, 27)						**Reference bin**				
[27, 30)	-0.0011883	0.0006666	0.08	-0.0025252	0.0001487	-0.00134	0.000695	0.057	-0.00273	4.17E-05
[30, 33)	-0.0025544	0.0008918	0.006	-0.0043432	-0.0007656	-0.0021	0.000919	0.025	-0.00393	-0.00027
[33, 36)	-0.0040603	0.0012141	0.002	-0.0064953	-0.0016252	-0.00387	0.001146	0.001	-0.00616	-0.00159
[36, 39)	-0.0038836	0.0015886	0.018	-0.00707	-0.0006973	-0.00395	0.001491	0.01	-0.00692	-0.00097
>=39	-0.0014405	0.0024897	0.565	-0.0064342	0.0035532	-0.00294	0.00434	0.5	-0.01159	0.005703
Observations	1,885,945					2,361,732				

Note: this table presents the impact of temperature fluctuations on daily vegetable prices compared to the reference bin [24, 27°C), utilizing Equation (1) as the foundation. Dependent Variable: Daily change in vegetable price per Chinese catty. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetables, day-of-the-sample, city by year-quarter, and city by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms) are included. We perform heterogeneity analysis based on vegetable durability, price level, and production capability. Drawing on the technical definitions provided by Zheng et al. (2009) and Bao et al. (2023), we categorize vegetables into perishable and non-perishable groups in Panel A. Panel B classifies vegetables by price: those in the bottom 25% are deemed 'Cheap', while those in the top 25% is considered 'Expensive'. Panel C assesses production capability at the city level, labeling regions with the bottom 25% of vegetable production as 'Non-productive' and those with the top 25% as 'Productive'. Columns (1)-(5) and (6)-(10) report coefficients, cluster standard errors, *P*-values, and 95% confidence intervals. Standard errors are clustered at the vegetable market level. Where P-values are reported as 0, they signify P<0.001.

Supplementary Table 13. Price Response to Temperature Extremes: Climate Zone (corresponds to **Fig. 4**).

	(1)	(2)	(4)
Temperature bin	Coef.	Stan. Error.	P-value
Cold regions			
<-18	.0068911	.0033394	0.042
[-18, -15)	.0110347	.004584	0.018
[-15, -12)	.0104513	.0041741	0.014
[-12, -9)	.007181	.0027542	0.011
[-9, -6)	.0082625	.0024301	0.001
[-6, -3)	.0085878	.0025499	0.001
[-3, 0)	.0092587	.0024305	0.000
[0, 3)	.0087653	.0020812	0.000
[3, 6)	.0078649	.0017335	0.000
[6, 9)	.0084216	.0015232	0.000
[9, 12)	.0074026	.0014212	0.000
[12, 15)	.0064065	.001222	0.000
[15, 18)	.0049971	.0009899	0.000
[18, 21)	.0032416	.0007994	0.000
[21, 24)	.0024201	.000652	0.000
[24, 27)			
[27, 30)	-.0010789	.0005607	0.058
[30, 33)	-.0035626	.0007153	0.000
[33, 36)	-.0053556	.001087	0.000
[36, 39)	-.0052861	.0014533	0.000
>=39	-.0055366	.0028485	0.055
Observations	2,576,291		
Mild regions			
<-18	.0119319	.0049865	0.018
[-18, -15)	.0116467	.0036471	0.002
[-15, -12)	.009814	.002505	0.000
[-12, -9)	.0092931	.0018703	0.000
[-9, -6)	.007966	.0017129	0.000
[-6, -3)	.0091337	.0015838	0.000
[-3, 0)	.0094735	.0014228	0.000
[0, 3)	.0090787	.0012301	0.000
[3, 6)	.0079923	.001208	0.000
[6, 9)	.0087563	.001062	0.000
[9, 12)	.0075823	.0010273	0.000
[12, 15)	.0067412	.0009843	0.000
[15, 18)	.004844	.0008747	0.000
[18, 21)	.0041808	.0007168	0.000
[21, 24)	.0026814	.0005397	0.000

[24, 27)			
[27, 30)	-.0017397	.0005097	0.001
[30, 33)	-.0029795	.0005928	0.000
[33, 36)	-.0037328	.0007157	0.000
[36, 39)	-.0039692	.0009807	0.000
>=39	.0022564	.0015366	0.145
Observations	**3,262,375**		
Hot regions			
<-18		(omitted)	
[-18, -15)	.0144942	.0042962	0.001
[-15, -12)	.0174014	.0039857	0.000
[-12, -9)	.0168708	.003731	0.000
[-9, -6)	.0162138	.0027201	0.000
[-6, -3)	.0138371	.0018813	0.000
[-3, 0)	.0160646	.0019907	0.000
[0, 3)	.0130639	.0016348	0.000
[3, 6)	.0133593	.0015045	0.000
[6, 9)	.0118067	.001259	0.000
[9, 12)	.0107029	.0012248	0.000
[12, 15)	.0083765	.0011149	0.000
[15, 18)	.0076097	.0009803	0.000
[18, 21)	.0048192	.000826	0.000
[21, 24)	.0023592	.0006924	0.001
[24, 27)			
[27, 30)	-.0000907	.0007859	0.908
[30, 33)	-.0016196	.000992	0.107
[33, 36)	-.0030938	.0011719	0.010
[36, 39)	-.0030412	.0017229	0.082
>=39	-.0013975	.0029406	0.636
Observations	**2,143,291**		

Note: this table presents the impact of temperature fluctuations on daily vegetable prices compared to the reference bin [24, 27°C), utilizing Equation (1) as the foundation. Dependent Variable: Daily change in logarithm vegetable price per Chinese catty. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetables, day-of-the-sample, city by year-quarter, and city by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms) are included. The hot, mild, and cold regions include counties with average temperatures in the highest 30%, middle 40%, and lowest 30% of the distribution, respectively. Columns (1)-(5): Display coefficients, cluster-robust standard errors (clustered at the market level), p-values. Where P-values are reported as 0, they signify P<0.001.

Supplementary Table 14. **Price Change Response to Temperature Extremes: Subcategories** (corresponds to **Supplementary Fig. 1**).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature bin	**Leaf**	**Eggplant**	**Scallions and garlic**	**Cabbage**	**Potato and taro**	**Root vegetables**	**Melons**	**Beans**	**Others**
<-18	0.0176618***	0.004125	0.0089612***	0.024544***	0.003577	0.007103	0.010266	0.0056137	0.0113936***
	(0.003472)	(0.0040948)	(0.002171)	(0.006847)	(0.0057615)	(0.0048153)	(0.0076334)	(0.0068129)	(0.003697)
	[0.0108229, 0.0245007]	[-0.0039389, 0.0121897]	[0.0046849, 0.0132374]	[0.0110525, 0.0380357]	[-0.0077728, 0.014927]	[-0.0023833, 0.0165885]	[-0.004766, 0.025297]	[-0.0078068, 0.0190342]	[0.0041066, 0.0186805]
[-18, -15)	0.0230914***	0.011519***	0.0055257**	0.018258***	0.004717	0.002677	0.016409***	0.0014473	0.0202082***
	(0.005308)	(0.0028416)	(0.0026514)	(0.0063007)	(0.0025175)	(0.0034033)	(0.0033374)	(0.0031348)	(0.0048673)
	[0.0126361, 0.0335467]	[0.0059228, 0.017115]	[0.0003031, 0.0107482]	[0.0058431, 0.0306732]	[-0.0002423, 0.0096762]	[-0.0040273, 0.0093813]	[0.0098371, 0.0229808]	[-0.0047278, 0.0076224]	[0.0106147, 0.0298017]
[-15, -12)	0.0210168***	0.007484	0.0058892***	0.00977	0.003713	0.006605***	0.014835***	0.007164***	0.0150759***
	(0.0031867)	(0.0039831)	(0.0021893)	(0.0070885)	(0.0026098)	(0.0019336)	(0.0033512)	(0.002602)	(0.0034026)
	[0.0147399, 0.0272937]	[-0.0003607, 0.0153277]	[0.0015769, 0.0102016]	[-0.0041975, 0.0237373]	[-0.0014286, 0.0088538]	[0.0027959, 0.0104142]	[0.0082362, 0.0214343]	[0.0020383, 0.0122896]	[0.0083693, 0.0217824]
[-12, -9)	0.0177403***	0.006768***	0.0067935***	0.009614***	0.003116	0.006724***	0.012279***	0.0082727***	0.0093763***
	(0.0024465)	(0.0022911)	(0.0018434)	(0.0035998)	(0.0024257)	(0.0022653)	(0.0021853)	(0.0028373)	(0.0030112)
	[0.0129213, 0.0225593]	[0.0022562, 0.0112802]	[0.0031624, 0.0104245]	[0.0025209, 0.016707]	[-0.0016622, 0.0078949]	[0.0022614, 0.0111862]	[0.007976, 0.0165824]	[0.0026835, 0.0138618]	[0.0034413, 0.0153114]
[-9, -6)	0.0180605***	0.0071***	0.0048133***	0.012338***	0.003874**	0.005512	0.011416***	0.0054494**	0.0111384***
	(0.0022157)	(0.0024624)	(0.0016274)	(0.003956)	(0.0018956)	(0.0017512)	(0.002207)	(0.0021679)	(0.0028575)
	[0.0136961, 0.0224249]	[0.0022504, 0.0119491]	[0.0016077, 0.0080188]	[0.0045427, 0.0201326]	[0.0001397, 0.0076082]	[0.002063, 0.0089619]	[0.0070696, 0.0157614]	[0.001179, 0.0097198]	[0.0055062, 0.0167706]
[-6, -3)	0.0189504***	0.00802***	0.0051669***	0.011363***	0.002094	0.005521***	0.013349***	0.0025585	0.0111975***
	(0.0019732)	(0.0021058)	(0.0013779)	(0.0032947)	(0.0017282)	(0.0013451)	(0.0018796)	(0.0025288)	(0.002373)

	[0.0150636, 0.0228371]	[0.0038724, 0.0121665]	[0.0024527, 0.007881]	[0.0048708, 0.0178546]	[-0.0013102, 0.0054986]	[0.0028713, 0.0081708]	[0.0096479, 0.0170503]	[-0.0024229, 0.0075398]	[0.0065203, 0.0158746]
[-3, 0)	0.0202435***	0.009215***	0.0058368***	0.013387***	0.002918**	0.007319***	0.012017***	0.0044891**	0.0102189***
	(0.0020328)	(0.001898)	(0.0013293)	(0.0033092)	(0.0014252)	(0.0012451)	(0.0018971)	(0.0020817)	(0.0021222)
	[0.0162394, 0.0242476]	[0.0054773, 0.0129529]	[0.0032184, 0.0084552]	[0.0068666, 0.0199074]	[0.00011, 0.0057252]	[0.0048656, 0.0097713]	[0.0082813, 0.0157527]	[0.0003885, 0.0085897]	[0.0060361, 0.0144017]
[0, 3)	0.0195665***	0.006351***	0.0055055***	0.013264***	0.00172	0.006305***	0.010639***	0.0024514	0.0085066***
	(0.0017135)	(0.0016658)	(0.0011443)	(0.0029458)	(0.0012635)	(0.001169)	(0.0015246)	(0.0020044)	(0.0020036)
	[0.0161914, 0.0229416]	[0.0030707, 0.009632]	[0.0032515, 0.0077594]	[0.0074595, 0.0190684]	[-0.0007695, 0.0042087]	[0.0040022, 0.0086078]	[0.007637, 0.0136415]	[-0.0014969, 0.0063997]	[0.0045575, 0.0124558]
[3, 6)	0.0174787***	0.00696***	0.0053336***	0.013958***	0.001743	0.005308***	0.010194***	0.0039409**	0.0077826***
	(0.0015236)	(0.0015019)	(0.0010234)	(0.0026248)	(0.0011955)	(0.0009841)	(0.0015246)	(0.0018425)	(0.0017857)
	[0.0144777, 0.0204798]	[0.0040021, 0.0099178]	[0.0033177, 0.0073495]	[0.0087857, 0.0191295]	[-0.0006119, 0.0040982]	[0.0033698, 0.007247]	[0.007637, 0.0136415]	[0.0003114, 0.0075704]	[0.0042629, 0.0113023]
[6, 9)	0.0177237***	0.006378***	0.0054217***	0.014515***	0.002992***	0.00569***	0.009373***	0.0037613**	0.0084184***
	(0.001348)	(0.0012625)	(0.0009312)	(0.0024137)	(0.0010369)	(0.0008971)	(0.0012016)	(0.0016235)	(0.0015505)
	[0.0150685, 0.0203789]	[0.0038912, 0.0088638]	[0.0035874, 0.0072559]	[0.0097594, 0.0192714]	[0.0009489, 0.0050343]	[0.0039227, 0.007457]	[0.0070069, 0.0117391]	[0.0005633, 0.0069593]	[0.0053624, 0.0114743]
[9, 12)	0.0154044***	0.005961***	0.0047539***	0.01437***	0.001653	0.004761***	0.008204***	0.0042538***	0.0078663***
	(0.0012626)	(0.0011249)	(0.0008806)	(0.0022563)	(0.0009263)	(0.0007798)	(0.0011087)	(0.0014821)	(0.0013308)
	[0.0129175, 0.0178914]	[0.0037452, 0.0081759]	[0.0030193, 0.0064885]	[0.0099236, 0.0188154]	[-0.0001722, 0.0034774]	[0.0032243, 0.0062966]	[0.0060213, 0.0103875]	[0.0013343, 0.0071734]	[0.0052434, 0.0104893]
[12, 15)	0.0119491***	0.004835***	0.0039801***	0.014005***	0.001963**	0.003929***	0.007955***	0.0039938***	0.0066079***
	(0.0011435)	(0.0009838)	(0.0007384)	(0.0019599)	(0.0008765)	(0.0007264)	(0.0009319)	(0.0013597)	(0.0012152)
	[0.0096967, 0.0142016]	[0.0028975, 0.0067724]	[0.0025257, 0.0054344]	[0.010143, 0.017867]	[0.000237, 0.0036899]	[0.0024984, 0.0053604]	[0.00612, 0.0097899]	[0.001315, 0.0066723]	[0.004213, 0.009003]

[15, 18)	0.0091789*** (0.000957) [0.0072939, 0.0110638]	0.004315*** (0.000933) [0.0024774, 0.0061524]	0.0027166*** (0.0006681) [0.0014005, 0.0040326]	0.012992*** (0.0019336) [0.0091817, 0.0168018]	0.001219 (0.0006888) [-0.000138, 0.0025756]	0.003517*** (0.0006823) [0.0021724, 0.0048608]	0.006591*** (0.0008531) [0.0049115, 0.0082713]	0.0035703*** (0.0011917) [0.0012227, 0.0059178]	0.0049121*** (0.0009462) [0.0030471, 0.006777]
[18, 21)	0.0057234*** (0.0007763) [0.0041943, 0.0072526]	0.003128*** (0.0007783) [0.0015952, 0.0046606]	0.0019298*** (0.0005356) [0.0008748, 0.0029848]	0.007566*** (0.0014419) [0.0047252, 0.0104077]	0.00155** (0.0006045) [0.0003593, 0.0027409]	0.002555*** (0.0005341) [0.0015024, 0.0036066]	0.005513*** (0.0007339) [0.0040677, 0.0069582]	0.003696*** (0.0010168) [0.0016931, 0.0056988]	0.0040341*** (0.0007749) [0.0025068, 0.0055615]
[21, 24)	0.0030047*** (0.000721) [0.0015845, 0.0044249]	0.002277*** (0.0005898) [0.0011159, 0.0034389]	0.0009971** (0.0004904) [0.0000312, 0.001963]	0.004707*** (0.0011223) [0.0024959, 0.0069188]	0.001433*** (0.0005442) [0.0003606, 0.0025048]	0.001993*** (0.0005114) [0.000985, 0.0029999]	0.0031*** (0.0005823) [0.0019538, 0.0042469]	0.0025026*** (0.0007761) [0.0009738, 0.0040314]	0.0033337*** (0.0006219) [0.0021079, 0.0045594]
[24, 27)					**Reference bin**				
[27, 30)	-0.0015299** (0.0007089) [-0.0029262, -0.0001337]	-0.0012282 (0.0006238) [-0.0024567, 4.08E-07]	-0.0003496 (0.0004052) [-0.0011477, 0.0004485]	-0.00032 (0.0009939) [-0.0022776, 0.0016392]	0.000302 (0.0005621) [-0.0008051, 0.0014095]	0.0005177 (0.000506) [-0.0004791, 0.0015145]	-0.0019803*** (0.0006205) [-0.0032021, -0.0007585]	-0.0031453*** (0.0006846) [-0.0044939, -0.0017967]	-0.0003 (0.0006175) [-0.0015172, 0.0009171]
[30, 33)	-0.0036276*** (0.0008798) [-0.0053606, -0.0018947]	-0.0044432*** (0.0007553) [-0.0059307, -0.0029558]	-0.0006218 (0.000475) [-0.0015574, 0.0003138]	-0.00175 (0.0013399) [-0.0043913, 0.0008889]	-0.00056 (0.000625) [-0.0017943, 0.0006684]	-0.000892 (0.0005341) [-0.001944, 0.0001601]	-0.0035982*** (0.0007749) [-0.0051241, -0.0020724]	-0.0054697*** (0.0009296) [-0.0073008, -0.0036386]	-0.0009138 (0.0007985) [-0.0024877, 0.00066]
[33, 36)	-0.0049666*** (0.0011414) [-0.0072148, -0.0027183]	-0.0060455*** (0.0009469) [-0.0079103, -0.0041808]	-0.0010159 (0.000627) [-0.0022509, 0.0002191]	-0.00341 (0.0016963) [-0.0067505, -0.0000657]	-0.00142 (0.0007447) [-0.00289, 0.0000438]	-0.0013969** (0.000701) [-0.002777, -0.0000168]	-0.0046922*** (0.001024) [-0.006708, -0.0026764]	-0.0082475*** (0.0011743) [-0.0105608, -0.0059343]	-0.002187** (0.0008636) [-0.0038892, -0.0004849]
[36, 39)	-0.0059125***	-0.00536***	-0.00033	-0.00207	-0.00075	-0.0022719***	-0.0049439***	-0.0070473***	-0.0020299

	(0.0015794)	(0.0015406)	(0.0009293)	(0.0024191)	(0.0010618)	(0.0010424)	(0.0013706)	(0.0016086)	(0.0011774)
	[-0.0090235, -0.0028014]	[-0.008391, -0.0023229]	[-0.0021605, 0.0015005]	[-0.0068364, 0.002697]	[-0.002845, 0.0013385]	[-0.0043253, -0.0002185]	[-0.0076428, -0.0022451]	[-0.010216, -0.0038785]	[-0.0043506, 0.0002908]
>=39	-0.0017742	-0.0031245	0.0004339	0.001213	-0.00128	0.0004925	0.0002876	-0.0063022**	0.000971
	(0.0024656)	(0.0030182)	(0.0020359)	(0.0038618)	(0.0018959)	(0.0021709)	(0.0026293)	(0.0027357)	(0.001912)
	[-0.0066308, 0.0030825]	[-0.0090684, 0.0028195]	[-0.0035763, 0.0044441]	[-0.0063964, 0.0088223]	[-0.005012, 0.0024576]	[-0.003784, 0.0047691]	[-0.0048899, 0.005465]	[-0.0116911, -0.0116911]	[-0.0027975, 0.0047395]
Observations	2,107,572	967,556	1210550	305,911	423820	860,612	1,087,791	482,683	535,180

Note: this table presents the impact of temperature fluctuations on daily vegetable prices compared to the reference bin [24, 27°C), utilizing Equation (1) as the foundation. Dependent Variable: Daily change in vegetable price per Chinese catty. Unit of Observation: Market-vegetable-day level. Regression Model: Includes fixed effects for vegetable, day-of-the-sample, market by year-quarter, and market by holiday. Control Variables: Air pollution, precipitation, relative humidity, sunshine duration (and their squared terms) are included. Columns (1)-(9) report estimates regarding nine vegetable subcategories, including leaf, eggplant, scallions and garlic, cabbage, potato and taro, root vegetables, melons, beans, and others. For each temperature bin, we provide coefficients, standard errors, and 95% confidence intervals. Standard errors are clustered at the vegetable market level. * significant at 10% level, ** Significant at 5% level, *** Significant at 1% level. Where P-values are reported as 0, they signify P<0.001.

Supplementary Table 15. **Effects of Forecasted and Lagged Temperature Shocks on Vegetable Price Change** (corresponds to **Extended Fig. 4).**

	(1)	(2)	(3)	(4)	(5)
	Coef.	Stan. Error.	P-value	95% CI-Upper	95% CI-Lower
	Temp bin: <10				
5th day forecasted	0.0002563	0.0002924	0.382	-0.0003194	0.000832
4th day forecasted	-0.000139	0.0002906	0.633	-0.0007112	0.0004332
3rd day forecasted	0.0004407	0.0002947	0.136	-0.0001395	0.0010209
2nd day forecasted	0.0002451	0.0003654	0.503	-0.0004745	0.0009646
1st day forecasted	0.0004109	0.000354	0.247	-0.0002862	0.001108
Contemporaneous day	0.001463	0.000348	0	0.0007778	0.0021481
1st days lagged	0.0006632	0.0003641	0.07	-0.0000536	0.0013801
2nd days lagged	0.0005342	0.0003434	0.121	-0.0001419	0.0012103
3rd days lagged	0.0001664	0.0003196	0.603	-0.0004629	0.0007957
4th days lagged	-0.0004002	0.000369	0.279	-0.0011269	0.0003264
5th days lagged	-0.0008276	0.0003695	0.026	-0.0015551	-1.00E-04
6th days lagged	-0.0003763	0.0003294	0.254	-0.0010249	0.0002723
7th days lagged	-0.0005038	0.0003208	0.117	-0.0011353	0.0001278
8th days lagged	0.0004264	0.0003485	0.222	-0.0002597	0.0011125
9th days lagged	-0.0001694	0.000353	0.632	-0.0008644	0.0005256
	Tem bin: [10, 30]				
	Reference Bin				
	Tem bin: >30				
5th days forecasted	0.000366	0.0002874	0.204	-0.0001999	0.0009319
4th days forecasted	0.0002148	0.0004524	0.635	-0.0006761	0.0011056

3rd days forecasted	-0.0003515	0.0003403	0.303	-0.0010214	0.0003185
2nd days forecasted	-0.0003138	0.0003281	0.34	-0.0009599	0.0003323
1st days forecasted	0.0001303	0.0003182	0.682	-0.0004963	0.0007569
Contemporaneous day	-0.0008489	0.0003193	0.008	-0.0014775	-0.0002202
1st days lagged	-0.0015527	0.0003912	0	-0.002323	-0.0007824
2nd days lagged	-0.0004114	0.0003206	0.2	-0.0010426	0.0002198
3rd days lagged	-0.0002039	0.0002899	0.482	-0.0007748	0.0003669
4th days lagged	-0.0000427	0.0003178	0.893	-0.0006685	0.0005831
5th days lagged	0.0000921	0.0002994	0.759	-0.0004974	0.0006817
6th days lagged	-0.0001025	0.0003425	0.765	-0.0007769	0.0005719
7th days lagged	0.0001928	0.0003191	0.546	-0.0004354	0.000821
8th days lagged	0.0003468	0.0003249	0.287	-0.0002929	0.0009864
9th days lagged	0.0002937	0.0002775	0.291	-0.0002527	0.0008402
Cluster	Market	-	-	-	-
Observation	7,982,688	-	-	-	-

Note: The table details the multi-temporal impact of temperature fluctuations on the prices of vegetables. It employs a distributed lag/forecast model that integrates both past and anticipated temperature shocks as crucial independent variables. To mitigate the risk of collinearity, temperature ranges are categorized into three distinct brackets: below 10°C, between 10°C and 30°C, and 30°C or above. The middle category, 10-30°C, is designated as the reference category for comparison. Our analysis calculates coefficient estimates for individual days (ranging from t = -9 to t = +5) by comparing them to the baseline temperature bin on the corresponding day. The regression formula adjusts for several fixed effects – specifically, those related to individual vegetables, the specific day within our sample period, each vegetable market's seasonal quarter, and holidays. In our model, we account for variables such as air pollution, rainfall, relative humidity, sunshine duration, along with their squared terms to capture any non-linear effects these factors may have on the vegetable price change. Additionally, we apply market-level clustering to the standard errors to account for inter-market variability. Where P-values are reported as 0, they signify P<0.001.

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