Mitigation of Temperature-Induced Vegetable Price Volatility in Urban Wholesale Markets

Xiaodong Chen[1], Anda Guo[2], and Pengyu Zhu[1]*

[1] Division of Public Policy, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong.

[2] School of Economics, Southwestern University of Finance and Economics, Chengdu, China.

E-mail: pengyuzhu@ust.hk

Abstract

Vegetables are vital for urban nutrition security, yet their wholesale price stability in response to temperature extremes is poorly understood. Analyzing a decade of daily data from 265 Chinese wholesale markets, we find that extreme heat and cold significantly disrupt urban vegetable distribution, raising price volatility. We project that without adaptive interventions, future climate scenarios could translate changes in average wholesale prices into annual national-scale monetary impacts of 57 to 188 billion CNY by the end of the century. However, our analysis identifies powerful buffers: cities with robust self-sufficiency and efficient transport, alongside vegetables with longer shelf lives and higher market values, exhibit markedly stronger resilience. Most importantly, we show that strategic urban adaptations, such as investing in cold chains and shortening supply chains, could mitigate 56% to 89% of these projected monetary impacts. These findings highlight that targeted investments in urban supply chains are a critical strategy for safeguarding food security in a warming world.

Main

Global climate change threatens agricultural productivity and urban food systems[1,2]. Building climate-resilient urban food systems is therefore essential for ensuring food security and equitable nutrition access in rapidly urbanizing regions[3,4]. While extensive research has examined the impact of extreme temperatures on crop yields[5], a critical gap remains in understanding how these extremes affect the distribution of food within cities. Specifically, the vulnerability of urban vegetable supply chains to climate shocks, particularly as revealed through price mechanisms, is underexplored. Vegetable wholesale prices in urban markets serve as a powerful lens into this hidden vulnerability. They are a critical indicator of supply chain efficiency, bridging the producer-consumer continuum and reflecting downstream transportation, storage, and market dynamics[6]. While retail prices are vital for assessing household food security and have been widely investigated regarding urban residents' access to affordable produce[7], our focus on wholesale prices aims to fill a complementary gap. Specifically, it unpacks supply chain vulnerabilities, a dimension less explored in the literature, where most studies have centered on retail price dynamics. Assessing the net socioeconomic impacts of extreme weather disruptions on high-volume, perishable vegetable crops in urban wholesale hubs can inform nutrition-focused urban policy measures, such as investments in resilient infrastructure, and advance climate adaptation frameworks tailored to city environments.

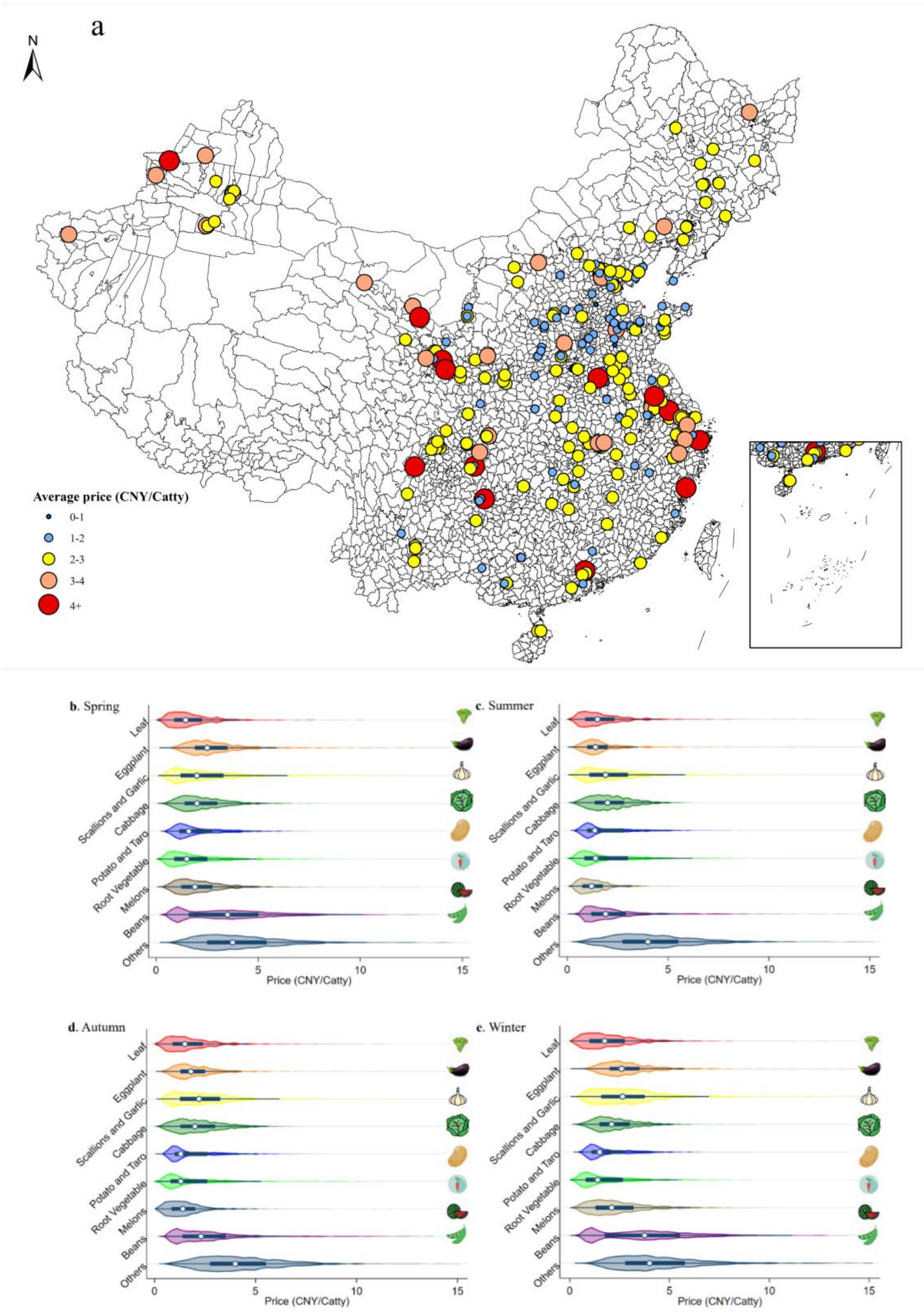
This study addresses this gap by analyzing vegetable wholesale price dynamics to pinpoint climate vulnerabilities in post-harvest logistics and distribution, thereby positioning cities as critical nodes in the food system. Based on a spatial Market Equilibrium Framework (see Supplementary Part A), we theoretically deduce that while production costs and consumer preferences determine long-term price levels, they remain rigid within a daily window. Consequently, distribution frictions (transportation costs and spoilage rates) are the primary drivers of short-term volatility. By focusing on the wholesale stage, we isolate this climate-driven volatility, capturing how thermal shocks affect perishable goods under urban constraints like limited storage and transportation disruptions. Specifically, our model—anchored by a Constant Elasticity of Substitution (CES) utility function—identifies two key channels of climate impact: (1) post-harvest storage vulnerability, where regions lacking robust infrastructure (e.g., refrigerated systems) face greater price volatility during extreme events; (2) logistics-stage vulnerability, where heat or cold waves induce transport delays, disproportionately escalating prices for time-sensitive vegetables like leafy greens.[8] These insights directly inform targeted urban adaptation. Our analysis demonstrates how investments in climate-resilient infrastructure, such as cold chains to mitigate heat impacts or improved road networks to alleviate cold-wave disruptions, can effectively buffer these shocks. By quantifying these effects, this study provides actionable insights for policymakers to prioritize investments in peri-urban agriculture and integrated planning, ultimately strengthening urban nutritional and economic stability. Supplementary Part B provides background information, including vegetable supply chain and wholesale prices in an urban context and China's vegetable production, with an extension to the Global South.

Fig. 1a presents the spatial distribution of China's 265 vegetable wholesale markets in major urban centers, alongside seasonal price distributions for nine subcategories (Leafy vegetables, Eggplant, Scallions and Garlic, Cabbage, Potato and Taro, Root Vegetables, Melons, Beans, and Others) across the four seasons (Fig. 1b-1e). Price trends for the nine vegetable categories are reported in Extended Fig. 1. Extended Fig. 2 illustrates the correlation between changes in vegetable wholesale prices and market-level local temperatures in these urban settings, with an inverse relationship observed. However, this observed correlation may not be causal and could be influenced by other urban economic or environmental conditions. This paper aims to fill a critical gap by quantifying the immediate temperature effects on urban vegetable wholesale price changes and mapping sustained adaptive trends via extrapolation[9]. We utilize daily data for vegetable wholesale prices and daily maximum temperatures, paired with climate scenarios for projections. Covering January 1, 2012, to April 18, 2023, the dataset includes 386 vegetable types across nine categories from 265 major urban wholesale markets in 30 provinces, representing over 70% of China's vegetable consumption[10], and one of the world's largest urban vegetable supply chain networks. Extended Fig. 3 illustrates the role of wholesale markets in the vegetable supply chain in China.

We use fixed-effects panel regressions with temperatures categorized into 3°C bins over a six-day average, aligned with our lag analysis (Extended Fig. 4), to capture short-term supply chain impacts. Controls include weather variables (e.g., humidity, precipitation, and sunshine duration), air pollution, and fixed effects for regions, vegetable types, concurrent exogenous shocks in China, and regional temporal trends (see Methods). This methodology infers causal relationships between temperature and price dynamics in an urban context. This approach ensures that the remaining variations in extreme temperatures are unlikely to correlate with unobserved economic or environmental factors affecting urban consumption. As a falsification test, we estimate the impact of future temperatures on current wholesale vegetable prices to further support causality. Additionally, we analyze temperature effects across vegetable subcategories, investigate nonlinear impacts over multiple days, and assess heterogeneous effects across different urban climate regions.

Our analysis provides five insights with urban policy relevance. First, extreme heat and cold directly drive wholesale price volatility in urban markets, robust across models. Second, per the CES model, storable, high-priced vegetables and cities with strong transport and self-sufficiency show resilience, guiding food hub planning. Third, without adaptation, climate change amplifies fluctuations under RCP4.5 and RCP8.5 by century's end, but adaptation mitigates these substantially. Fourth, adaptations like cold chain logistics, peri-urban incentives, and smart infrastructure render RCP4.5 effects negligible and cut RCP8.5 impacts by 58%, underscoring adaptability's role in price stability. Lastly, all regions—hot, temperate, or cold (defined in Fig. 5)—benefit from extreme-temperature adaptations, often fully offsetting volatility under moderate warming in milder areas.

Fig. 1 | Spatial distribution of wholesale markets and seasonal price variations across vegetable categories.



a, Spatial distribution of the 265 monitored wholesale vegetable markets across China. Markets are represented by distinctive colors and marker sizes corresponding to their overall vegetable price levels. **b-e**, Price distributions for nine vegetable categories across the four seasons: Spring (March 1 to May 31) (**b**), Summer (June 1 to August 31) (**c**), Autumn (September 1 to November 30) (**d**), and Winter, from December 1 (previous year) to February 28/29 (current year) (**e**). In panels **b–e**, For each box plot, the centre marker indicates the median (50th percentile), the bounds of the box represent the interquartile range (25th and 75th percentiles), and the whiskers extend to the upper and lower adjacent values. Overlaid with this box plot is a data distribution estimated via kernel density. For visualization purposes, we exclude observations with prices exceeding 15 CNY, which account for less than 0.25% of our sample. The nine categories of vegetables 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). Maps and plots were generated using ArcGIS and Stata.

Results

Estimation Results

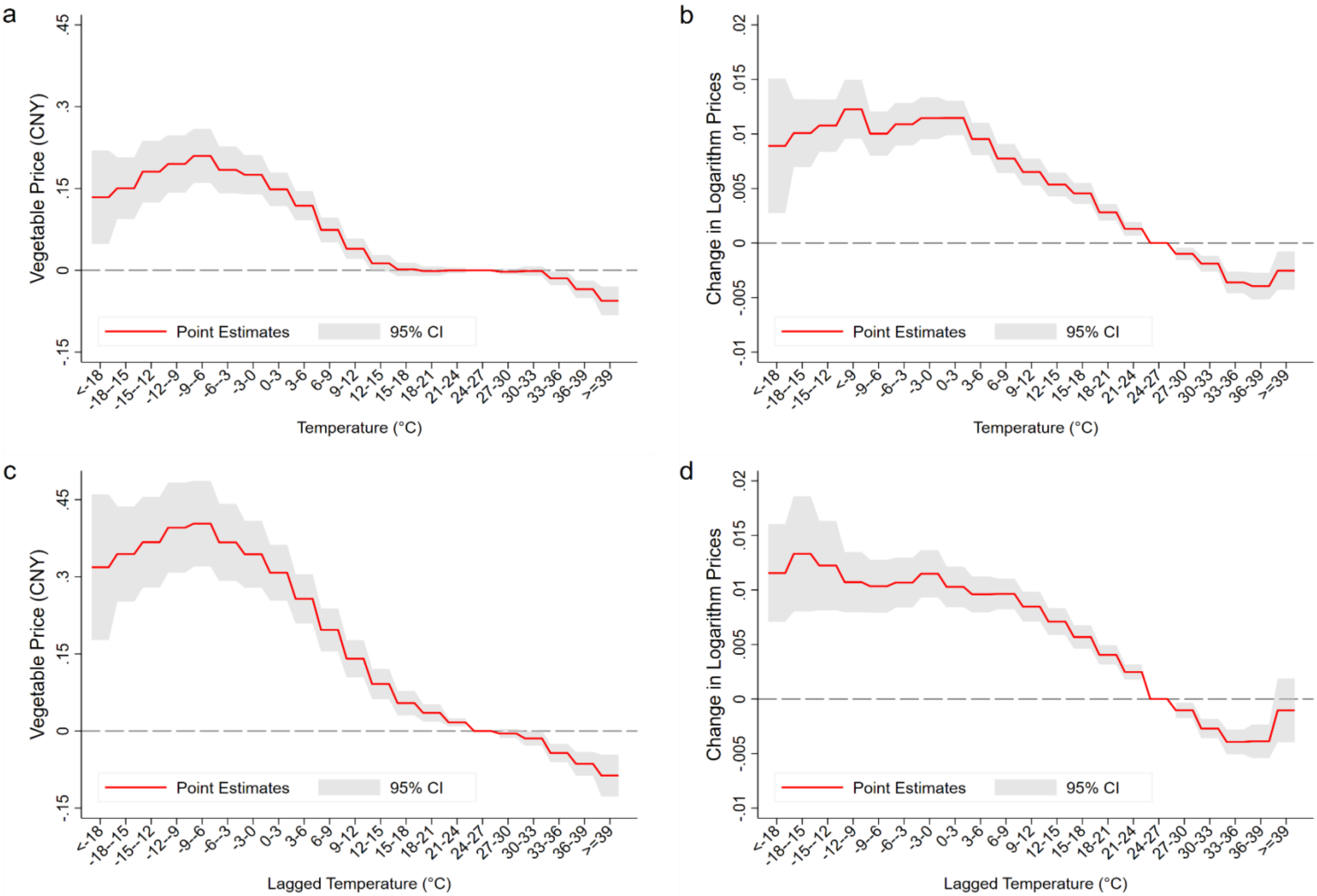
To fully capture the direct effects of daily maximum temperature on vegetable wholesale prices and volatility, and to identify adaptation patterns and long-term impacts under climate scenarios, we employ daily estimates[11] and lag-based approaches[1]. This robustly identifies the weather-price relationship. We use four specifications: (1) temperature effects on price, (2) temperature effects on log-price changes $\log(P_{i,t}) - \log(P_{i,t-1})$, (3) lagged temperature effects on price, and (4) lagged temperature effects on log-price changes. Employing Equation (1), Fig. 2a illustrates daily temperature effects on prices, with the 24-27°C bin as reference. At 39°C, prices decrease by 0.06 CNY/Catty (P<0.001, 95% CI: -0.08 to -0.04), representing a 2.5% reduction from the average 2.43 CNY/Catty. This persists, though diminishing, for 36-39°C and 33-36°C, becoming negligible at 12-33°C. Based on China's Dietary Guidelines[12] (2022), recommending 300g daily vegetable intake for adults and a 1.41 billion population in 2020, the annual economic loss for producers from 39°C price reduction is 18.53 billion CNY (P<0.001, 95% CI: 12.36 to 24.72). However, due to inelastic demand, this benefits consumers at producers' expense[13,14].

Conversely, low temperatures raise prices: the -9 to -6°C range increases prices by 0.21 CNY/Catty (P<0.001, 95% CI: 0.16 to 0.26), an 8.6% rise, yielding an annual consumer loss of 64.86 billion CNY. This effect holds below 12°C, from <-18°C to 12°C. Fig. 2b, on log-price changes (aligning with Heinen et al., 2019; Bao et al., 2023)[7,15], reinforces these findings.

Temperature extremes often have lagged effects on human cognition[16], mortality[9], yields[17], and economic activity[1,18]. For vegetables, immediate disruptions affect harvest, sorting, and transport[19], while lags impact growth via frost, waterlogging, or damage[7]. We use lag-based estimates to assess price substitution and optimal lags. To avoid autocorrelation from 21 daily variables, we bin temperatures into <10°C, 10-30°C (reference), and >30°C[20,21]. The 10–30°C bin is the comfort zone for most vegetables, minimizing volatility (Fig. 3a), validating it as baseline. Results show significant effects only from the current day and prior 5 days (Extended Fig. 4).

Fig. 2c presents 6-day average temperature effects (current and 5 lags), consistent with prior patterns: low ranges increase prices and high ranges decrease them, with amplified magnitudes from multi-day measures. Fig. 2d shows lag-based effects on price changes, confirming validity. As lagged temperatures and log-price changes accurately isolate responses to extremes, we treat this as baseline. Below 24°C (vs. 24-27°C reference), price changes rise by 0.2%-1.3%; e.g., -18 to -15°C yields a 1.3% increase (P<0.001, 95% CI: 0.8%-1.9%). Above 27°C, changes fall by 0.1%-0.4%. Supplementary Part C (Supplementary Fig. 1) provides subcategory estimates (Leaf, Eggplant, Scallions and Garlic, Cabbage, Potato and Taro, Root Vegetables, Melons, Beans). Supplementary Part D reports robustness for alternative models and data specifications (Supplementary Figs. 2-8 and Supplementary Tables 1-5).

Fig. 2 | Temperature Effects on Vegetable Wholesale Price.



a, The marginal effects are defined as the temperature (independent variable) effects on vegetable wholesale price (dependent variable). **b**, the marginal effects are measured as the temperature effects on changes of logarithm vegetable wholesale price, defined as $lnp_{ict} - lnp_{ic(t-1)}$. **c**, the marginal effects are measured as the lagged temperature effects (defined as six-day averaged temperature, see the Section Methods for more details) on vegetable wholesale prices. **d**, the marginal effects are measured as the lagged temperature effects on changes of logarithm prices. Observations for **a** and **c** are 11,559,881, while observations for **b** and **d** 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), 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. Data are presented as point estimates (representing the mean marginal effects) with shaded regions indicating the 95% confidence intervals. We addressed potential within-market correlation by clustering standard errors at the market level.

Heterogeneity: Storability and Transportation, Price Tiers and Local Self-sufficiency

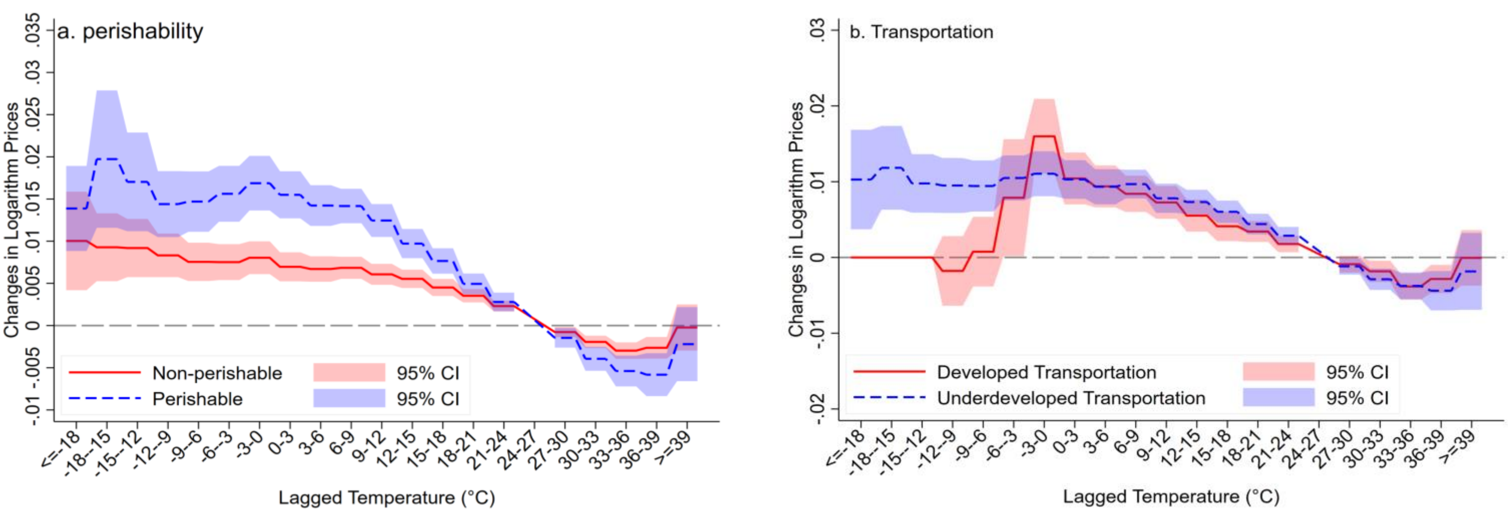
Vegetable storability, which measures the ease and cost of storage (e.g., perishability, space needs), significantly influences price responses to temperature shocks. Non-storable vegetables, per classifications by Zhang et al. (2009)[22] and Bao et al. (2023)[7], exhibit greater volatility under temperature extremes than storable ones. Fig. 3a demonstrates that in extreme cold ([-18°C, -15°C)), non-storable varieties face a 2.0% price premium, double that of storable counterparts. This aligns with theory, as perishable spoilage amplifies volatility during thermal events and cold snaps, underscoring the importance of storage capabilities in mitigating economic impacts.

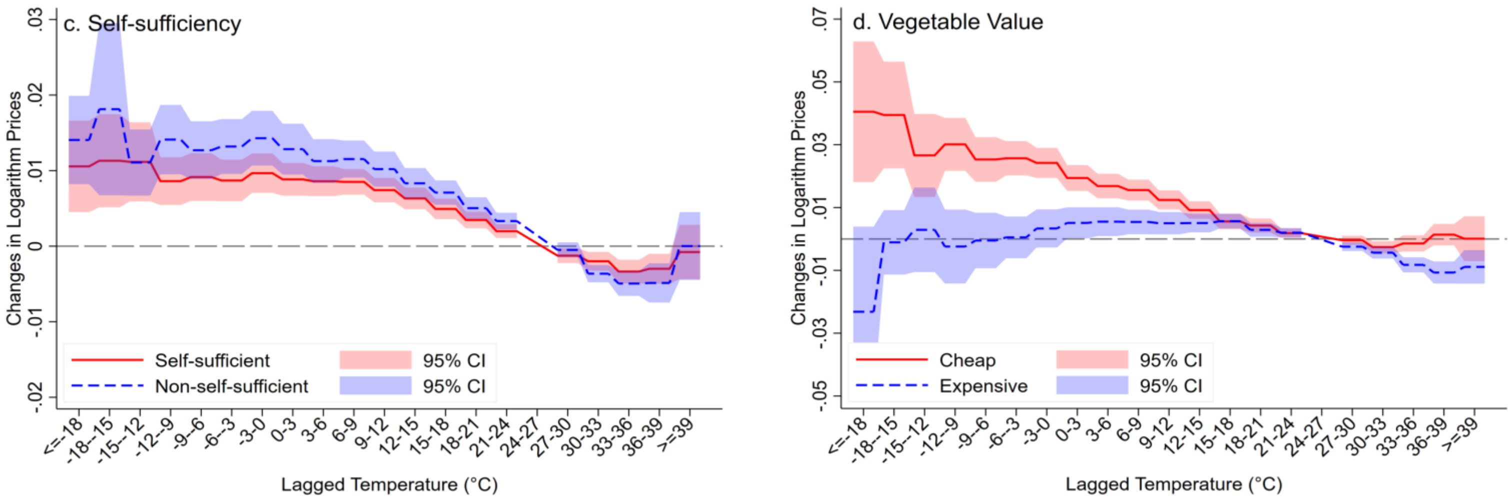
Legacy transportation networks are vulnerable to temperature extremes[23], specifically amid labor productivity declines despite intercity vegetable trade[24]. We hypothesize that robust transportation networks enhance resilience against disruptions[25]. To empirically validate this, we stratified cities by highway density (high vs. low, split by the sample median). Applying equation (1), Fig. 3b reveals low-density cities experience amplified volatility during cold days compared to high-density ones, while heatwave responses (above 27°C) are similar across groups. This suggests cold vulnerabilities arise from perishability-driven shortages and infrastructure limits in low-density areas. This asymmetry arises because cold weather induces acute supply-side shocks—such as direct crop damage from frost and transportation disruptions like icy roads—that are amplified in low-density highway networks due to limited alternative routes and longer hauling distances, leading to greater price volatility. In contrast, heatwave responses are similar across transport-network groups because the negative price effect of heat appears to operate less through intercity transport bottlenecks and more through common within-market mechanisms, including short-run demand softening and faster inventory clearance for highly perishable vegetables under thermal stress. These forces can compress wholesale clearing prices across cities regardless of highway density.

For verification, Supplementary Part E (Supplementary Table 6) uses prefecture-level highway density (km/km²) as a proxy for accessibility. Interacting with temperature in Column (1), a 10% increase in highway density reduces volatility by 0.18% (P=0.002, 95% CI: 0.05% to 0.23%). This highlights infrastructure's buffering effects on temperature shocks by efficient distribution. Additionally, vegetables are typically stored and traded through wholesale markets, where their durability influences price responses to temperature fluctuations. We hypothesize less fluctuation for non-perishable types due to lower spoilage. To test this, we construct a dummy variable classifying vegetables as non-perishable based on technical standards[722]. Using a dummy based on vegetable durability[722], interacting temperature bins with this durability in Column (2) shows non-perishables reduce price changes by 0.41% (P<0.001, 95% CI: 0.37% to 0.46%) below 10°C and 0.28% (P<0.001, 95% CI: 0.25% to 0.33%) above 30°C relative to perishables, reinforcing durability's moderating role.

We then integrate local self-sufficiency and price tier differentiation to examine perishability-transport-price dynamics. We define local self-sufficiency according to the National Vegetable Industry Development Plan (2011–2020), which requires 36 major cities to maintain minimum annual vegetable land reserves or establish dedicated production bases in adjacent areas. By shortening supply chains, this reliance on local production mitigates perishability risks and minimizes exposure to price fluctuations. Meanwhile, price tiers reflect logistics, as high-value items use specialized preservation (e.g., climate-controlled facilities) and prioritized transport (e.g., air freight) to offset perishability costs, while affordable ones lack it. Fig. 3c shows self-sufficient cities have resilient markets during cold weather, with higher volatility in non-self-sufficient ones due to supply shortages and external reliance. Self-sufficient cities, with production mandates, use local farms/greenhouses for steady supply, especially non-storable vegetables facing 2.0% price premiums in extreme cold. Price tier analysis (Fig. 3d) segments vegetables into the top and bottom 25% price tiers. Affordable vegetables show cold sensitivity, with 4.1% increases (*P*<0.001, 95% CI: 1.80% to 6.30%) per day below -18°C across sub-zero ranges, while high-value ones have minimal impact below -3°C. This reflects advanced preservation for premiums, unavailable for cheaper varieties, exacerbating cold vulnerability[26].

Fig. 3 | Temperature Effects on Price Change by Heterogeneous Perishability, Transportation, Self-sufficiency, and Price Level





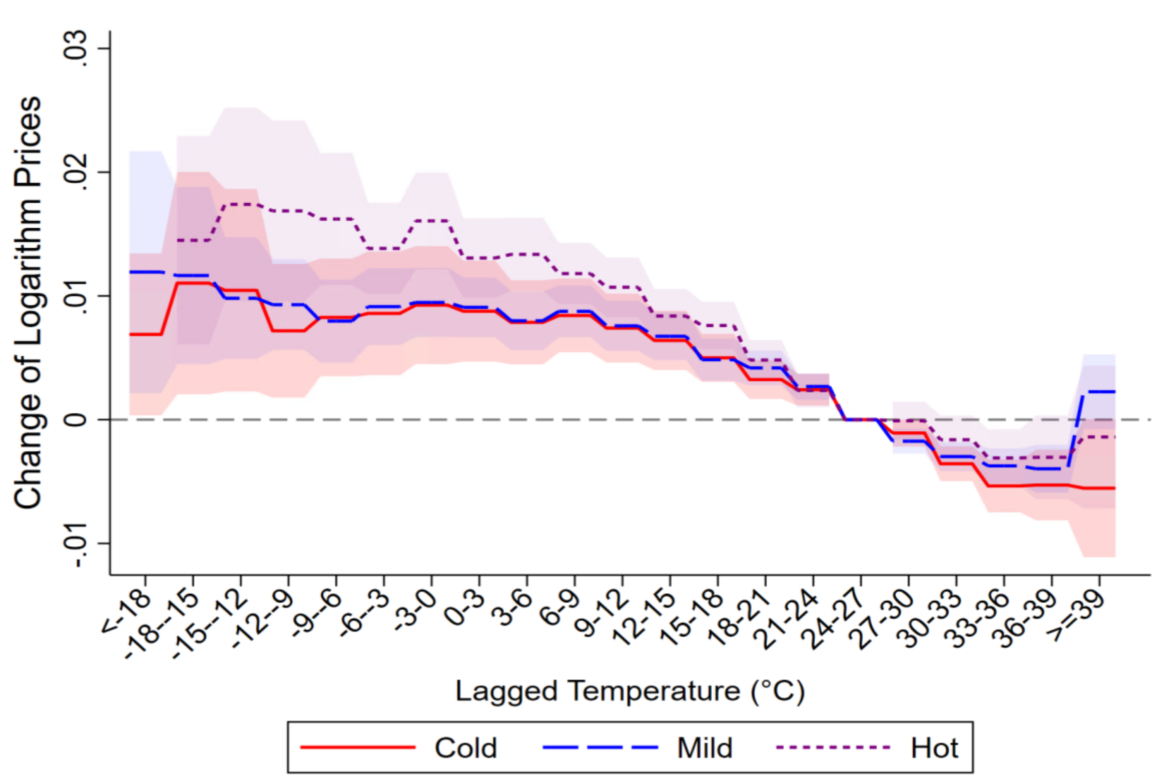
a–d, Marginal effects of temperature on changes in logarithmic vegetable wholesale prices, stratified by: (**a**) perishability (perishable *N*=3,075,132; non-perishable *N*=4,372,152); (**b**) regional transportation density, based on median highway length per square kilometre (developed *N*=3,193,283; underdeveloped *N* =3,199,323); (**c**) municipal self-sufficiency mandates (self-sufficient *N*=5,098,212; non-self-sufficient *N*=2,884,421); and (**d**) vegetable price tiers (cheap/bottom 25% *N*=1,869,066; expensive/top 25% *N* =2,014,087). Detailed classification criteria and policy backgrounds for each subgroup are described in the Main Text. Data are presented as point estimates (representing the mean marginal effects) with shaded regions indicating 95% confidence intervals derived from Equation (1). All regression models account for environmental controls (air pollution, precipitation, relative humidity, sunshine duration, and their squared terms) alongside fixed effects for vegetables, day-of-the-sample, market-by-year-quarter, and market-by-holiday. Standard errors are clustered at the market level.

Heterogeneous Climate Zones

To explore heterogeneity in vegetable wholesale price responses to temperature shocks across climate zones, we estimated Equation (1) separately for cold, mild, and hot markets. Classifications used historical average temperatures (1981–2010), with the top 30% as hot, the bottom 30% as cold, and the middle 40% as mild[21]. The findings, depicted in Fig. 4, indicate substantial disparities, as cold regions exhibit resilience to extreme cold, while hot regions adapt to high temperatures. Statistical tests confirm differences between hot and cold zones (Supplementary Table 7).

These findings underscore the critical importance of adaptation strategies in mitigating the adverse impacts of temperature shocks on vegetable distribution. Adaptation measures can encompass a range of human behavioral changes and infrastructural enhancements, such as purchasing fresh-keeping equipment in transportation and storage, installing indoor cooling or heating systems,[27] and enacting new landscape and urban planning policies[28]. A pertinent instance underpinning our conclusion is the heating policy implemented in northern China, which protects both residences and vegetable storage facilities from extreme subfreezing conditions[29].

Fig. 4 | Heterogeneous Temperature Effects Across Different Climate Zones.



The analysis examines how a temperature shift from the reference range of [24, 27°C) to a different temperature bin impacts the daily change in logarithm price over a six-day period in different climate zones. 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 at the highest 30%, middle 40%, and lowest 30% of the distribution, respectively. The sample sizes for the cold, mild, and hot regions are 2,576,291; 3,262,375; and 2,143,291, respectively. 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). The model also includes controls for air pollution, precipitation, relative humidity, sunshine duration, and their squared terms. Data are presented as point estimates (representing the mean marginal effects) with shaded regions indicating the 95% confidence intervals. We addressed potential within-market correlation by clustering standard errors at the market level.

Long-run Climate Risk Scenarios

We mainly focus on the long-term predictions of temperature under RCP4.5 and RCP8.5 scenarios to gauge vegetable wholesale prices variations between the historical period and century's end (2090–2099), following Heutel et al. (2021)[30], Lai et al. (2022)[21], and Carleton et al. (2022)[9]. To highlight regional disparities and adaptation, we base estimates on three assumptions, showing spatial and temporal variations in temperature impacts on price changes. Details are in Methods. We incorporate a flexible semi-parametric function for daily temperature variations and other climate aspects. Since income influences adaptation to extremes, we allow the temperature-price relationship to vary with GDP per capita[9,21]. Estimation coefficients for equation (2) in Supplementary Tables 8 and 9.

Simulation Results

We use two Representative Concentration Pathways (RCPs) from the IPCC Sixth Assessment Report (2023)[31] for climate scenarios. RCP4.5 assumes emissions peak mid-century via mitigation, and RCP8.5 represents 'business-as-usual' with rising emissions. In each RCP scenario, we generate our principal simulation outcomes by employing the median values of temperature and climate data derived from a suite of 21 General Circulation Models (GCMs). For a comprehensive understanding of data inputs and the methodological foundation of our simulations, the Methods section elucidates how the results account for three distinct types of uncertainty: those related to emissions, climate variability, and the regression model itself.

Fig. 5 projects average vegetable wholesale price change for the century's final decade (2090-2099) in comparison to the baseline period. The figure offers projections for both scenarios, with and without climate adaptation. To depict the scenario without adaptation, we retain a constant price-temperature relationship, implying that any changes in the average price of vegetables are attributed exclusively to temperature fluctuations. Conversely, the adaptation scenario modifies this price-temperature correlation to account for future climate conditions, thus integrating adaptation strategies into the projection. Fig. 5a is based on a moderate emission scenario (RCP4.5), while Fig. 5b contrasts this by assuming an extreme emission scenario (RCP8.5). Each figure not only shows the projected nationwide average impact but also details the impact across the three defined climate zones.

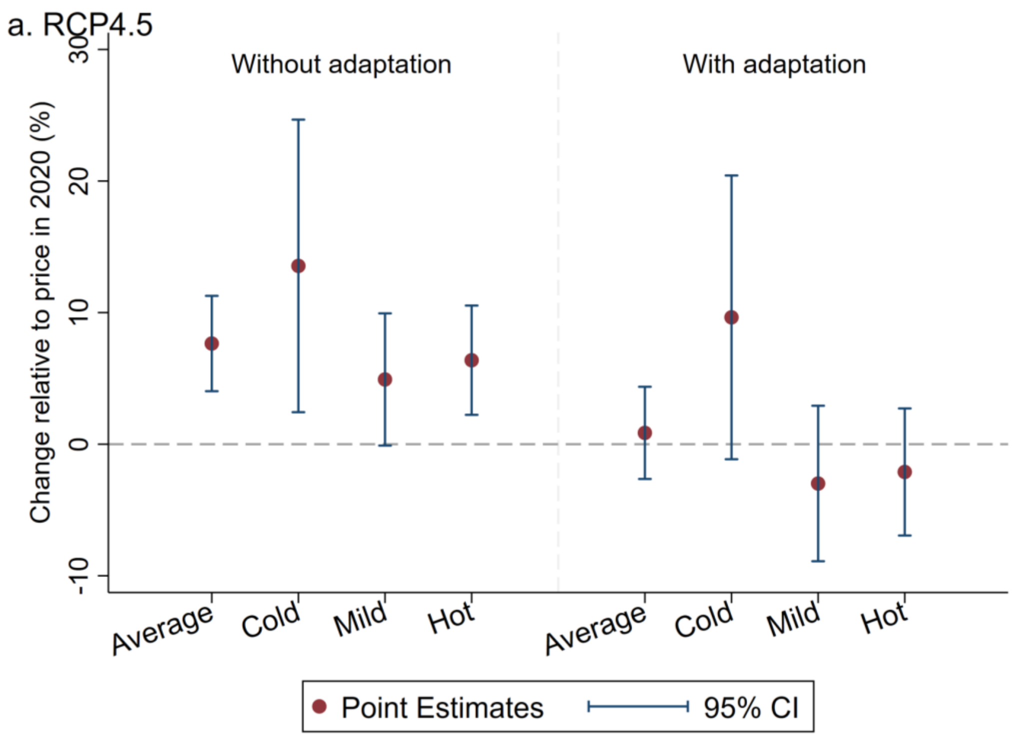
Our analysis identifies two prominent patterns. First, without adaptation under RCP4.5, temperature changes correlate with a 7.65% price increase (P<0.001, 95% CI: 4.03% to 11.27%). Hot and cold regions, which are particularly susceptible to future climatic alterations, could experience notable economic setbacks, with vegetable wholesale prices projected to increase by 6.38% (P=0.003, 95% CI: 2.23% to 10.54%) in hot regions and 13.55% (P=0.018, 95% CI: 2.43% to 24.67%) in cold regions, respectively. Per FAO and WHO dietary recommendations, a 7.65% price elevation could translate to an economic loss amounting to approximately 57 billion CNY for consumers on a national scale, based on a calculation involving 1.4 billion individuals, with the designated fruit and vegetable consumption rate and current prices (1.41 billion people*2.43 CNY/500g*300g*7.65%*365days=57 billion CNY).

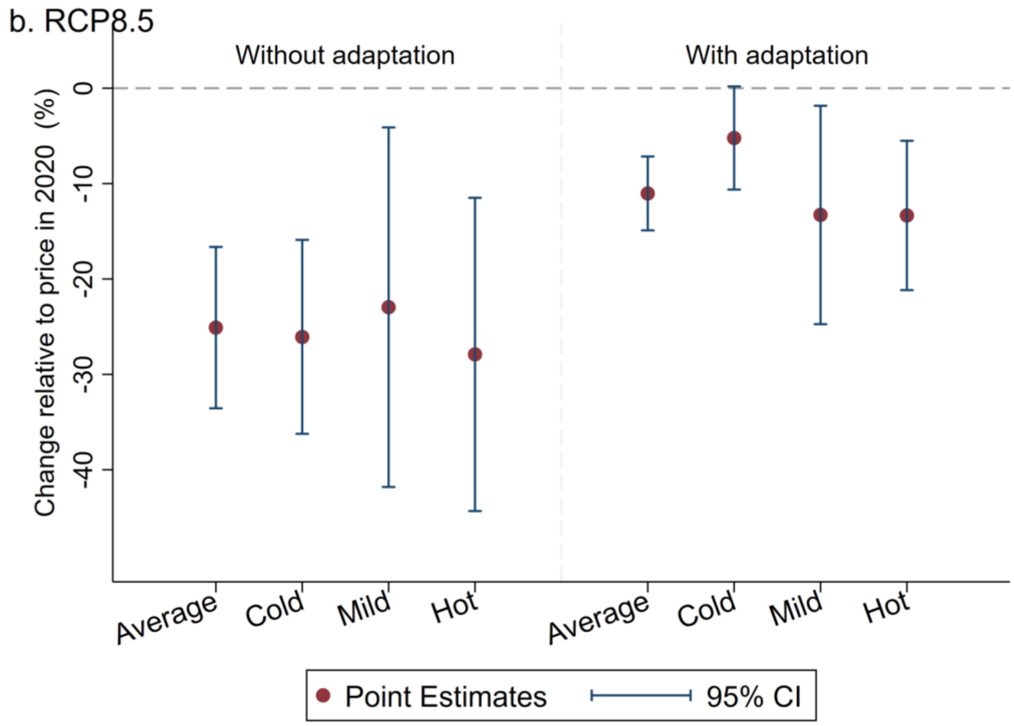
Under RCP8.5 without adaptation, prices decrease by 25.10% (P<0.001, 95% CI: -33.56% to -16.64%). While this reduction signifies a substantial financial benefit for consumers, reflected in an increase in consumer surplus quantified at 188.39 billion CNY, the converse effect is felt by vegetable farmers, who are projected to incur equivalent losses. Our estimates remain aligned with the baseline data established, especially considering the average temperature rise of 1.73°C under RCP8.5 as compared with RCP4.5. Regional variations in response to temperature change were also explored, revealing negligible disparities in impact amongst Hot and Mild regions. However, hot regions displayed a slightly higher vulnerability. For these regions, the forecasted price reduction is 27.90% (P<0.001, 95% CI: -44.33% to -11.49%).

Second, with adaptation under RCP4.5 scenario, temperature effects are negligible (coefficient 0.0086, P=0.629). Under RCP8.5, negative impacts drop from 25.10% (P<0.001, 95% CI: -33.56% to -16.64%) to 11.03% (P<0.001, 95% CI: -14.91% to -7.16%). Regionally under RCP4.5, hot and cold zones adapt strongly (coefficients=-0.021, P=0.388; -0.096, P=0.079), with insignificant effects; mild zones shift from 4.92% (P=0.055, 95% CI: -0.10% to 9.94%) to -2.99% (P=0.317, 95% CI: -8.90% to 2.92%). Under RCP8.5, hot zones adapt to -13.34% (P<0.001, 95% CI: -21.16% to -5.51%), a 52.2% reduction; cold zones to -5.22% (P=0.058, 95% CI: -10.62% to 0.18%); mild zones to -13.28% (P=0.024, 95% CI: -24.74% to -1.84%).

These results underscore the effectiveness of adaptation in mitigating temperature changes on wholesale vegetable pricing across various climatic conditions.

Fig. 5 | End-of-Century price projection by climate condition





a,b, our analysis quantifies the simulated shifts in vegetable wholesale prices by the close of the century (2090–2099) compared to the 2020 baseline. This assessment encompasses both the national level and three distinct geographical regions or climate zones, considering two divergent climate scenarios: RCP4.5 (a) and RCP8.5 (b). These estimates are derived from the regression models detailed in Equations (2) and (3) in the Methods. We classify markets as 'hot,' 'mild,' or 'cold' based on a temperature-based climate zoning system. Markets are classified as hot, mild, or cold based on the 1981–2010 average temperature (top 30%, middle 40%, bottom 30%), with whole-sample and subgroup sizes of 7,520,901, 2,576,291, 3,262,375, and 2,143,291, respectively; data are point estimates with 95% confidence intervals, and significance is derived from two-sided t-tests using cluster-robust standard errors. No adjustments were made for multiple comparisons. For the RCP4.5 scenario in panel **a**, the *P* values, reported without adaptation and within parentheses with adaptation, are <0.001 (0.629), 0.003 (0.388), 0.055 (0.317), and 0.018 (0.079) for the national average, cold, mild, and hot regions, respectively. In panel **b**, under the RCP8.5 scenario, these *P* values are <0.001 (<0.001), 0.001 (0.001), 0.018 (0.024), and <0.001 (0.058) correspondingly. The 'without adaptation' assumption in both panels implies that the vegetable wholesale price-temperature relationship remains constant, reflecting the current climate and excluding any adaptation to climate change. In contrast, the 'with adaptation' assumption allows this relationship to adjust based on simulated climate conditions, thereby incorporating potential adaptation strategies into the forecasts. Both panels account for the simulated end-of-century GDP per capita (2090–2099) when projecting vegetable wholesale price changes.

Discussion

This study reframes climate-food dynamics by introducing a CES theoretical framework, shifting analytical focus from agricultural production and retail prices to the urban food system's core: wholesale distribution networks. This approach yields novel, granular evidence on how temperature shocks disrupt post-harvest urban logistics and storage, inducing price volatility before food reaches consumers.

Stable food prices are vital for household welfare[32], as high prices erode consumer surplus and low prices threaten producers[33]. Existing studies have extensively investigated extreme weather effects on crop prices, identifying indirect pathways via yields, production, or consumption,[3435] and direct pathways through spatial transmission, market integration, trade, or arbitrage[3638]. Research also links weather to global commodity disruptions,[39] regional conflicts[40] and pre-harvest trader expectations [41]. However, two key gaps persist, distinguishing our urban-focused research. First, vegetable-specific studies (crucial for urban diets) are scarce, emphasizing tropical storms on Chinese retail prices[7], temperature shocks on Mexico's consumer prices[42], or global retail vulnerability[6], but none prioritize urban wholesale markets, the vital link between rural production and urban consumption. Second, prior research overemphasizes production-side effects (e.g., drought-induced yield losses) or macro-trade dynamics, neglecting urban distribution processes (e.g., intra-city transport and storage) that mediate temperature-price links. This oversight is notable, as urban wholesale markets handle 70–90% of vegetable supply to cities[43], serving as primary sites for translating temperature disruptions into price volatility.

This article fills these gaps by examining high-resolution daily wholesale price data, revealing an overlooked causal chain between extreme temperatures and vegetable pricing. Short-term cold correlates with price increases, while heat leads to decreases, driven by post-harvest vulnerabilities (Extended Fig. 4 rules out intertemporal substitution). While our findings are causal, they mainly highlight vulnerabilities in distribution systems, rather than on-farm yield changes. These vulnerabilities serve as the key mechanism connecting temperature shocks to volatility in urban wholesale prices. This temperature-price correlation varies by durability, value, local yields[546], cropping frequency/intensity, and transportation.[5] Furthermore, it is evident that this temperature-price dynamic differs across various climatic regions. In our simulations, we consider both the immediate impacts of temperature and the potential for adaptation to predict the long-run effects of temperature change on vegetable pricing. Existing literature suggests that human adaptations play an important role in mitigating mortality increases and consumption declines associated with temperature extremes[930]. Our findings suggest that adaptive measures may mitigate the adverse effects of temperature shocks, leading to more stable vegetable wholesale prices amidst climate change. Our findings indicate that examining only the impact of climate change on crop intensity, growing seasons, and yields paints an incomplete picture of its economic consequences[49]. The incidence of extreme temperatures, both cold and hot, can lead to fluctuations in vegetable wholesale prices, resulting in potential losses in economic surplus for both consumers and producers under different circumstances.

Our analysis reveals critical inter-regional and inter-city heterogeneities, underscoring the need for tailored adaptation strategies. Vegetable price vulnerability to temperature shocks varies across China's vast landscape, with a pronounced climatic divide: historically colder northern cities exhibit greater sensitivity to extreme heat due to less acclimatized infrastructure and supply chains, while southern cities, better adapted to heat, show heightened vulnerability to unseasonal cold spells. This pattern aligns with prior literature across contexts from human health to economic activity, positing that the greatest vulnerability arises from extremes deviating from a region's long-term climatic norm[2150]. Beyond climate, urban form and economic structure are key determinants. For example, megacities with dense transportation networks face different disruption patterns than smaller cities with less resilient supply chains[751]. Notably, robust transport mitigated cold-wave impacts more strongly in northern cities than in southern cities, suggesting high returns from investments in road density and anti-freezing logistics there (Panel C, Supplementary Table 6). These variations indicate that a one-size-fits-all approach to enhancing urban food system resilience is inadequate; policy interventions must be context-specific, prioritizing heat-resilient infrastructure in northern centers and cold-chain continuity in southern supply chains. Supplementary Parts I and J (Supplementary Figs. 9-11) provide detailed policy implications for China and the Global South.

These findings should be interpreted in light of several limitations. Our heterogeneity and adaptation estimates are inferred from observed responses under current climate conditions and extrapolated to future scenarios using climate-model projections; future risks may nonetheless involve non-linear responses and adaptive behaviours beyond those observed historically. In addition, wholesale price volatility reflects the joint influence of multiple factors—including trade disruptions, global conflicts and exogenous shocks such as pandemics and natural disasters—that cannot be fully isolated in a reduced-form framework. Data constraints also limit mechanism identification: the absence of daily farm-gate prices prevents direct estimation of the origin-to-wholesale price wedge, and the lack of household-level consumption data constrains our ability to assess downstream dietary responses. Our economic estimates should therefore be interpreted as conservative lower bounds of the broader social cost, as a full accounting of health impacts would require additional evidence on dietary substitution, willingness to pay and disease incidence. Finally, although our long-run projections incorporate climate-related adaptation, they do not capture all dynamic feedbacks, such as endogenous policy responses or long-term shifts in agricultural production. Future research could build on this work by embedding these mechanisms in a structural framework and by extending the analysis to discrete extreme-weather events, such as typhoons and hurricanes, to test whether robust logistics and storage infrastructure can mitigate supply disruptions and price spikes during major disasters.

Methods

Data

Temperature, Other Weather, and Pollution Controls

The weather data utilized in this study, which include temperature, rainfall, relative humidity and sunshine duration, were sourced from China's National Meteorological Information Center. As the premier institution tasked with the collection and dissemination of national weather statistics, it offered a comprehensive dataset for our analysis. We compiled station-day records that spanned from 2012 to 2023, incorporating data from a total of 824 stations strategically spread across China. To translate the weather statistics from the station level to the market level, we employed the inverse distance weighting (IDW) method, a method well-established within economic research[1754]. Initially, we designated a circular perimeter, centered on the centroid of each market, with a 200-kilometer radius. In this designated perimeter, we computed the weighted mean of the weather data, factoring in the proximity of the stations to the market's centroid, where the weights were inversely proportional to each station's distance to the centroid. This weighted mean was then attributed to the respective market. The same technique was applied to ascertain covariates such as rainfall, sunshine duration, and humidity. To ensure the robustness of the data quality, we employed gridded weather data products as robustness tests (Supplementary Fig. 4).

Another covariate examined in this study is air pollution. The pollution metrics were derived from remote sensing Aerosol Optical Depth (AOD) retrieval, which spanned our entire analysis period. AOD gauges the decrease in sunshine duration caused by the absorption, reflection, and scattering of sunlight by airborne particles, thus serving as an indirect indicator of particulate matter levels. We utilized AOD data from the M2TMNXAER version 5.12.4 product, part of NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). This pollution data was then aggregated from the grid level to the market level, capitalizing on the IDW method which is a standard approach in such analyses [1753].

Vegetable Wholesale Price and Wholesale Market Information

Our pricing and market information data are derived from the National Agricultural Products Price Database (https://pfsc.agri.cn/#/indexPage). Specifically, our dataset comprises daily transaction records from 265 wholesale markets, systematically selected from the Ministry of Agriculture and Rural Affairs (MARA) Designated Market System. These markets are rigorously accredited by the national government based on transaction volume, infrastructure capacity, and regional influence. Collectively, MARA-designated markets facilitate over 70% of China's inter-provincial agricultural trade.

To ensure data quality and relevance, we utilized the list from MARA's 2024 strict review process, further filtering this list to retain only markets specializing in vegetable distribution while excluding those focused solely on meat or aquatic products. This sampling strategy ensures that our analysis captures the "main arteries" of China's urban food supply network, thereby minimizing selection bias and ensuring the findings represent the systemic response of the national supply chain.

As shown in **Figure 1a**, our comprehensive dataset encompasses wholesale markets in 30 provincial-level administrative regions in mainland China (excluding the Tibet Autonomous Region), aligning with major population centers and agricultural logistics corridors. The data spans from January 1, 2012, to April 18, 2023, representing the most current data available. We collected daily price data on a wide variety of Chinese vegetables, including leafy greens, fruiting vegetables (e.g., eggplants), alliums (e.g., scallions and garlic), cabbages, tubers (e.g., potatoes and taro), root vegetables, melons, legumes, edible mushrooms, and other types. To account for inflation and ensure comparability, we adjusted the prices to correspond to the 2020 fiscal year. Summary statistics are presented in Supplementary Table 10.

Scenario Simulations: Climate, GDP, and Population

In the construction of our comprehensive dataset, we have integrated anticipated climate patterns, economic output (GDP), and demographic data. Our longitudinal weather forecasts and climatic projections are sourced from NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). Originating from the General Circulation Models (GCMs) of the Coupled Model Intercomparison Project Phase 6, the NEX-GDDP provides daily, high-resolution (0.25-degree spatial resolution) climate scenarios under SSP2-4.5 and SSP5-8.5 for the period 1950 to 2100 from 21 different GCMs[55]. These projections are congruent with our baseline model in terms of their analytical granularity, focusing on daily variations at the market level. We integrate market-centric vegetable wholesale price data with corresponding points on the NEX-GDDP's grid, ensuring locality-specific accuracy. Our primary findings are derived from the average of the projected temperatures and climate conditions as indicated by the consensus of the 21 GCMs.

Projections for GDP and population trends are from the long-term scenarios outlined by the Shared Socioeconomic Pathways (SSP) framework, which present credible narratives of socioeconomic evolution for the twenty-first century, relying on integrated assessment modeling frameworks. Within our analysis, we concentrated on two distinct SSPs: SSP2-4.5, emblematic of stringent regulations that enable sustainable development, and SSP5-8.5, indicative of a laissez-faire approach that could lead to unsustainable trajectories. Our research primarily utilized models incorporating China-specific data, including the OECD's (the Organization for Economic Co-operation and Development) Env-Growth model, the IIASA's (the International Institute for Applied Systems Analysis) GDP model, and the PIK's (Potsdam Institute for Climate Impact Research) climate projections[5658]. To calculate the future GDP per capita essential to our analysis, we adopted the methodology outlined by Lai et al. (2022)[21], which entails averaging projections across the SSP2, SSP3, and SSP4 scenarios, as provided by the OECD, IIASA and PIK. The original per capita GDP data were accessible at the national scale in five-year intervals. We interpolated these figures to derive annual growth rates, enabling us to ascertain yearly GDP per capita forecasts. Due to the lack of city-level future projections from the SSPs, we assigned the country-level growth rates uniformly to all counties, presupposing analogous growth patterns persisting from 2020 into subsequent years.

Data concerning historical climate variables (China Meteorological Data Service Center, which is an affiliate of the National Meteorological Information Center of China) and projected climate variables (https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6) as well as air pollution (https://gmao.gsfc.nasa.gov/gmao-products/merra-2/) metrics are available to the public. Researchers can access the source data for this article, excluding specific vegetable name information. The computational codes and an explanatory readme file necessary for replicating this study's analysis are publicly available via the Zenodo repository (https://zenodo.org/records/15236927).

Econometric Model

Short-term Temperature-price Relationship (Figs. 2-4)

Using the first difference of logarithmic wholesale prices as the dependent variable allows us to interpret this as a percentage change in wholesale prices during the collection dates. This approach helps eliminate differences in the overall price index across markets over official statistical cycles, making the price changes comparable across time periods and markets. To assess the vegetable wholesale price response to temperature, a parsimonious reduced-form model is employed:

$$dln(Y_{v,m,t}) = \sum_{j=0}^{J} \alpha T_{v,m,t}^{j} + \rho X_{v,m,t} + \theta_t + \varphi_{v,m} + \tau_{m,t,q} + \omega_{m,h} + \varepsilon_{v,m,t} \tag{1}$$

where $dln(Y_{v,m,t}) = ln(Y_{v,m,t}) - ln(Y_{v,m,t-1})$ denotes the change of logarithm price for vegetable *v* in market *m* on day *t*, relative to day *t-1*, $T^{j}_{v,c,t}$ is a categorical vector for temperature, consisting of 3°C bins; equals 1 if the average temperature over the preceding 6 days (*t*-5 to *t*) for vegetable *v* in market *c* falls within *j*-th temperature bin, and is 0 otherwise. We provide justification for the selection of this lag term later in this section (Extended Fig. 4). The variable set $X_{v,m,t}$ includes a range of climate controls including air pollution, rainfall, relative humidity, and sunshine duration along with their squared terms to capture potential nonlinear effects. To control time-varying unobservables common across all markets, which can exclude factors like national holidays and macroeconomic announcements, we include **day-of-the-sample fixed effects** in θ_t. We account for time-invariant factors by incorporating **fixed effects for each of the 386 vegetables within 265 vegetable markets** ($\varphi_{v,m}$), which absorb time-invariant heterogeneity in price-setting patterns specific to individual vegetable-market combinations (e.g., regional preferences for specific varieties). Additionally, fixed effects for **market-by-year-quarter** are introduced in $\tau_{m,t,q}$ to capture evolving market structures and policy impacts (e.g., infrastructure upgrades, trade policies) while preserving within-quarter variation. Fixed effects for **market-by-holiday** are also included in $\omega_{m,h}$ to isolate demand surges/shocks during China's statutory holidays (e.g., Spring Festival, Mid-Autumn Festival), which correlate with both consumption patterns and meteorological anomalies. We cluster standard errors at the market level, to allow for spatial correlation of food prices within a market as they may share the same supply chain. Finally, the error term is denoted by $\varepsilon_{v,m,t}$.

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[5960].

To consider the lagged effects, literature commonly employs regressions with a lag structure, known as distributed lag models[1,11,61], which is equivalent to our approach. For the temperature effects, scholars have revealed that short-term forecasted and lagged temperature effects, ranging from *t*-9 (prior 9 days) to *t*+5 (forecasted 5 days) could generate immediate effects on production and consumption[2161]. We incorporate lagged temperature effects to account for their influence on vegetable preservation during transportation and storage. Specifically, lagged cold/hot days may exacerbate spoilage risks in transit due to inadequate refrigeration or prolonged exposure to low/high temperatures, thereby increasing post-harvest losses. Conversely, anticipated temperature drops/surges incentivize consumers to adjust purchasing behavior: stockpiling vegetables in advance to mitigate future scarcity or quality degradation. We find no effects of forecasted temperature shocks; instead, we only observe lagged temperature effects within the prior five days at most (see Extended Fig. 4). Consequently, our collection dates span six days (from *t*-5 to *t*). In our study, incorporating five lagged temperature variables for each bin may lead to fluctuating and imprecise coefficient estimates due to substantial correlation. Rather than using a traditional distributed lag model, we define a five-day window prior to day *t* to account for delayed effects and temporal substitutions. The five-day analytical window is pivotal for quantifying these adaptive strategies, as it captures how temperature-induced delays in transit and strategic stockpiling in warehouses jointly reshape market supply-demand equilibria. This temporal lens allows us to isolate the propagation of weather shocks across logistics links and storage hubs, ultimately linking them to aggregate volatility in vegetable pricing and availability. For robustness, we discuss the choice of window length in Section Robustness.

Robustness: To ensure the reliability of temperature effects on vegetable wholesale prices in Eq. (1), we conducted nine complementary robustness tests: (1) **Alternative Econometric Specifications**: We employed county-level and city-level clustered standard errors to account for potential spatial correlations at these levels, added market-specific linear time trends to exclude other agricultural shocks (e.g., the Land Contracting Right Reform), and used a trimmed dataset to exclude potential outliers. Results are reported in Supplementary Part D.1. (2) **Reference Category Robustness**: In our baseline estimates, we identified the optimal vegetable comfort temperature range as 24°C to 27°C. For robustness, we also tested alternative omitted variable ranges—[15, 18°C), [18, 21°C), [21, 24°C) and [27, 30°C)—and found that these changes do not bias our conclusions. Results are reported in Supplementary Part D.2 (Supplementary Fig. 3). (3) **Satellite Temperature Measure Validation**: We performed cross-validation using the ERA-Interim atmospheric reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF). This global climate reanalysis system integrates satellite observations and conventional meteorological measurements through a 4D-Var assimilation framework, producing comprehensive atmospheric parameters, including surface temperature (2m), total precipitation, wind vectors (10m), and humidity fields. Operational since 1979, ERA-Interim provides gridded outputs at a 0.75°×0.75° spatial resolution (~79 km) and 6-hourly temporal resolution. Results are reported in Supplementary Fig. 4. (4) **Market Reporting Anomaly**: To mitigate potential market-level misreporting (Bao et al., 2023), we implemented two adjustments. First, unit-level aggregation: we converted daily vegetable wholesale prices from market-level observations to county-level averages (one price per vegetable per county). Second, price series harmonization: we transformed wholesale price changes into county-level time series (one composite price index per county). Results are reported in Supplementary Part D.4. (5) **Serial Correlation Check**: We plotted kernel density estimates, Q-Q plots, and residuals over seasons to assess serial correlation. Results are reported in Supplementary Part D.5 (Supplementary Fig. 5). (6) **Spatial Correlation Verification**: We computed Conley (1999)[62] standard errors with spatial bandwidths of 300 km and 500 km. Results are reported in Supplementary Part D.6 (Supplementary Table 1). (7) **Temperature Binning Sensitivity**: We validated our results using three temperature bins (<10°C, 10–30°C, >30°C) as an alternative baseline categorization. Results are reported in Supplementary Part D.7 (Supplementary Tables 2-5). All these tests cross-validate the robustness of our baseline estimates. (8) Weather, Soil, and Other Conditions During the Growing Season: To address potential confounding from agricultural production or urban demand shifts, we estimated models with additional structural controls. We incorporated supply-side variables including growing-season weather, water availability, and soil erosion severity, alongside demand-side factors such as CPI, city-level income, and population density. These comprehensive controls do not alter our baseline estimates (Supplementary Figs. 6 and 7), confirming that the observed price volatility is robustly driven by short-term distribution frictions rather than background agricultural conditions or macroeconomic demand dynamics. (9) **The COVID-19 Confounding Effect**: We conducted a sub-sample robustness check to isolate the potential confounding influence of the COVID-19 pandemic. While our baseline model incorporates day-of-the-sample and market-by-year-quarter fixed effects to absorb additive shifts in price levels, they may not fully account for multiplicative changes in climate sensitivity. Specifically, if the logistical frictions of the pandemic reduced overall supply chain resilience, the model risks misattributing pandemic-driven fragility to temperature sensitivity. To ensure our findings are not structurally biased, we performed a comparative analysis of the temperature-price coefficients for the pre-pandemic period (2012–2019) versus the pandemic and post-pandemic years (2020–2023).

The results demonstrate that the non-linear temperature sensitivities remain robust and highly consistent across both sub-samples (see Supplementary Part D.9 and Fig. 8), confirming that the identified distribution frictions are fundamentally driven by thermal stress rather than pandemic-era logistical anomalies.

Long-run scenario simulations (Fig. 5)

Climate change has increasingly influenced the economy, leading to an array of adaptive strategies in the supply chain of the agricultural sector[6364]. Over time, these adjustments by consumers and vegetable farmers are anticipated to yield notable effects. As such, we posit that the relationship between temperature and price will be dynamic, evolving in tandem with economic, social, and climatic changes. To explore the interplay between temperature and price, we employ a semi-parametric methodology that integrates daily climate and economic data, employing the projection methods established by Auffhammer (2022)[65], Carleton et al. (2022)[9], and Lai et al. (2022)[21]. Their research offers empirical evidence on the immediate and long-term consequences of temperature on mortality rates, energy consumption, and consumer total spending patterns. Central to our geographic analysis is the projection of how regions may adapt to temperature extremes, inferred from the historical adaptation patterns of areas with present-day climatic similarities.

Previous research has indicated that regions at various stages of economic development respond differently to temperature extremes[1,66] and that these differences extend to their adaptive capacities to climatic changes[967]. To explore the effect of income on the temperature-vegetable wholesale price relationship, our analysis employs a model that intersects temperature metrics with the log of GDP per capita. This method draws upon the approach proposed by Lai et al. (2022)[21]. According to the theoretical framework outlined by Carleton et al. (2022)[9], the term 'climate' covers the broad spectrum of possible adaptive strategies, while 'income' highlights the economic limitations that shape the extent of these adaptive capabilities. Below, we detail the unique aspects of our model examining the temperature-price dynamics:

$$dln(Y_{v,m,t}) = g\left([TP_{c,t}, TP(Mean)_c, \log\left(GDP_{pc}\right)_c, \theta]\right) + \rho X_{v,m,t} + \theta_t + \varphi_{v,m} + \tau_{v,m,s} + \omega_{m,h} + \varepsilon_{v,m,t} \tag{2.a}$$

where,

$$g\left(TP_{c,t}, TP(Mean)_c, \log(GDP\_pc)_c, \theta\right) = \alpha_0 TP_{ct} + \alpha_1 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [10,30)\right) + \alpha_2 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [30,+\infty)\right) + \left[\beta_0 + TP_{ct} + \beta_1 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [10,30)\right) + \beta_2 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [30,+\infty)\right)\right] \times TP(Mean)_c + \left[\gamma_0 TP_{ct} + \gamma_1 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [10,30)\right) + \gamma_2 TP_{ct} \times \mathbb{I}\left(TP_{ct} \in [30,+\infty)\right)\right] \times \log(GDP\_pc)_c \tag{2.b}$$

We define $TP_{c,t}$ as the daily maximum temperature for a 6-day span, involving the current day and the preceding five days for market *c* in period *t*. The climate conditions for market *c* in period *t* (specifically focusing on temperature) are represented by the 30-year maximum temperature from 1980-2010, denoted as $TP(Mean)_{ct}$. The logarithm of GDP per capita, $\log(GDP\_pc)_{c,t}$ is calculated for the year 2020, for the city in which market *c* is situated. To depict the temperature-price relationship effectively and adaptively, we introduce $g(\cdot)$ as a piecewise linear spline function of temperature, with breakpoints at 10°C and 30°C. This function $g(\cdot)$, is utilized in conjunction with CM_{ct} and GDP per capita to assess their interactive effects on the temperature-price relationship. Variables included in Equation (2) are conceptualized in a manner equivalent to their definitions in Equation (1). The coefficients derived from this analysis are reported in Supplementary Tables 8 and 9.

$$Adapt_{y^{\Delta}_{ct}} = g\left(TP_{c,t}, TP(Mean)_{c,t}, \log\left(GDP_{pc}\right)_{c,t}, \theta\right) - g\left(TP_{c,t0}, TP(Mean)_{c,t0}, \log(GDP)_{c,t}, \theta\right) \quad \text{(3.a, With adaptation)}$$

where $TP_{c,t}$, $TP(Mean)_{c,t}$, $\log(GDP\_pc)_{c,t}$ are projected future temperature (temperature range), climate condition (average temperature), and GDP per capita, respectively. In the projections without climate adaptation, the price change from t_0 (the base year) to *t* (a future year) can be expressed as:

$$Non\_adapt\_y^{\Delta}_{ct} = g\left(TP_{c,t}, TP(Mean)_{c,t0}, \log(GDP\_pc)_{c,t}, \theta\right) - g\left(TP_{c,t0}, TP(Mean)_{c,t0}, \log(GDP)_{c,t}, \theta\right) \quad \text{(3.b, Without adaptation)}$$

where $TP(Mean)_{c,t0}$ is held constant and represented by the historical average temperature across 1980-2010. The effectiveness of adaptation versus non-adaptation is discerned by comparing $Adapt\_y^{\Delta}_{ct}$ and $Non\_adapt\_y^{\Delta}_{ct}$. Importantly, the subscript *t* for $\log(GDP\_pc)_{c,t}$ signifies the logarithmically transformed per capita GDP in the forecasted year *t*.

Our analysis, however, does not fully incorporate the impact of increasing incomes on vegetable wholesale price patterns. We have specifically focused on how income variations modify the relationship between temperature and price, omitting its direct influence on total price levels. A detailed examination of this limitation is discussed in the Supplementary Information section. Supplementary Part K (Supplementary Tables 11-15) provides estimates of Figures presented in the article.

Data Availability

The weather and climate data supporting the findings of this study are publicly available, whereas the vegetable wholesale price data is confidential. We cannot disclose the data to the public under the nondisclosure agreement. However, the data for replication are uploaded to Zenodo after trimming sensitive data (https://zenodo.org/records/15236927).

Code Availability

The code used in this study is available via Zenodo at https://zenodo.org/records/15236927.

References

1. Dell, M., Jones, B. F., & Olken, B. A. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics* 4, 66–95 (2012).
2. Al-Qubati, A., Zhang, L. & Forkel, M. Urban and peri-urban agriculture under climate change: A review on carbon emissions and sequestration. *Sustain. Cities Soc.* 115, 105830 (2024).
3. Vermeulen, S. J., Campbell, B. M., & Ingram, J. S. I. Climate change and food systems. *Annual Review of Environment and Resources* 37, 195–222 (2012).
4. Hsiao, A., Moscona, J., & Sastry, K. A. (2025). *Food Policy in a Warming World*. NBER, Working Paper.
5. Zhu, P., Burney, J., Chang, J. et al. Warming reduces global agricultural production by decreasing cropping frequency and yields. *Nat. Clim. Chang.* 12, 1016 - 1023 (2022).
6. Aishwarya, Venkat., Masters, William A. Retail Food Price Vulnerability to Extreme Weather Events. *Working Paper.* (2022).
7. Bao, X., Sun, P., & Li, J. The impacts of tropical storms on food prices: Evidence from China. *Amer J Agr Econ* 105, 576–596 (2023).
8. Liu, Y., Yue, C. Investigating the impacts of time delays on trade. *Food Policy* 39, 108–114 (2013).
9. Carleton, T., et al. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics* 137, 2037–2105 (2022).
10. Ministry of Agriculture and Rural Affairs of People's Republic of China. China's Agricultural Products Origin Cold Chain Logistics Development Report (2024) http://www.moa.gov.cn/xw/zwdt/202411/t20241129_6467246.htm
11. Kotz, M., Levermann, A., & Wenz, L. The effect of rainfall changes on economic production. *Nature* 601, 223–227 (2022).
12. Chinese Nutrition Society. Chinese dietary guidelines 5th edn (China Nutrition Soc., 2022).
13. You, Z., Huang, C. L. & Epperson, J. E. Demand elasticities for fresh vegetables in the United States. *J. Int. Food Agribus. Mark.* 9, 57–71 (1997).
14. Kasteridis, P. & Yen, S. T. U.S. demand for organic and conventional vegetables: a Bayesian censored system approach. Aust. J. Agric. Resour. Econ. 56, 405–425 (2012).
15. Heinen , A., Khadan, J. & Strobl, E. The price impact of extreme weather in developing countries. *Econ. J.* 129, 1327–1342 (2019).

16. Zhang , X., Chen, X. & Zhang, X. Temperature and low-stakes cognitive performance. *J. Assoc. Environ. Resour. Econ.* 11, 75–96 (2024).
17. Deschênes, O., & Greenstone, M. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *Am. Econ. Rev.* 97, 354–385 (2007).
18. Burke, M., Hsiang, S., & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* 527, 235–239 (2015).
19. Lu, X., Chan, F., Chen, W., Chan, H., & Gu. An overview of flood-induced transport disruptions on urban streets and roads in Chinese megacities: Lessons and future agendas. *Journal of Environmental Management* 321, 115991 (2022).
20. Deschênes, O., & Moretti, E. Extreme weather events, mortality, and migration. *Rev. Econ. Stat.* 91, 659–681 (2009).
21. Lai, W., Li, S., Liu, Y. *et al.* Adaptation mitigates the negative effect of temperature shocks on household consumption. *Nat Hum Behav* 6, 837–846 (2022).
22. Zhang, H. (ed.) *Storage and Preservation Technologies of Fruit and Vegetable* (in Chinese) (Sichuan Sci. & Technol. Press, 2009).
23. Barwick, P. J. et al. Improved transportation networks facilitate adaptation to pollution and temperature extremes. NBER Working Paper No. 30462 (2022).
24. Deng, et al. Household income inequality aggravates high-temperature exposure inequality in urban China. *Journal of Environmental Management* 275, 111224 (2020).
25. Lambert, L. H., Schoeneman, J. P. Jr, Lambert, D. M. & Brienen, M. W. Road networks and food price volatility. *Glob. Food Secur.* 100884 (2025).
26. Wang, K. Y. & Yip, T. L. Cold-chain systems in China and value-chain analysis. in *Finance and Risk Management for International Logistics and the Supply Chain* (eds Gong, S. & Cullinane, K.) 217–241 (Elsevier, 2018).
27. Wang, J., Zhong, H., Yang, Z. et al. Exploring the trade-offs between electric heating policy and carbon mitigation in China. *Nat Commun* 11, 6054 (2020).
28. Krayenhoff, E. S., Moustaoui, M., Broadbent, A. M., et al. Diurnal interaction between urban expansion, climate change and adaptation in US cities. *Nature Clim Change* 8, 1097–1103 (2018).
29. Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proc Natl Acad Sci U S A* 110, 12936–12941 (2013).
30. Heutel Garth, Miller Nolan H. David Molitor. Adaptation and the Mortality Effects of Temperature across U.S. Climate Regions. *The Review of Economics and Statistics* 2021; 103 (4): 740–753.
31. IPCC. Climate Change 2013: The Physical Science Basis (eds Stocker, T. F. et al.) (Cambridge Univ. Press, 2013).
32. Attanasio, O., et al. Welfare consequences of food price increases: Evidence from rural Mexico. *Journal of Development Economics* 104, 136–151 (2013).
33. Hicks, J. R. Consumer surplus and index-numbers. *Rev Econ Stud* 9, 126–137 (1942).

34. Dercon, S. Growth and shocks: evidence from rural Ethiopia. *J. Dev. Econ*. 74, 309–329 (2004). https://doi.org/10.1016/j.jdeveco.2004.01.001
35. Crofils, C., Gallic, E., Vermandel, G. The dynamic effects of weather shocks on agricultural production. *J. Environ. Econ. Manag*. 130, 103078 (2025). https://doi.org/10.1016/j.jeem.2024.103078
36. Brown, M. E., Kshirsagar, V. Weather and international price shocks on food prices in the developing world. *Glob. Environ. Change*. 35, 31–40 (2015). https://doi.org/10.1016/j.gloenvcha.2015.08.002
37. Ma Meilin, Michael S. Delgado, H. Holly Wang. Risk, arbitrage, and spatial price relationships: Insights from China's hog market under the African Swine Fever. *Journal of Development Economics*. Volume 166, January 2024, 103200
38. Hadachek, J., Ma, M., Sexton, R. J. Market structure and resilience of food supply chains under extreme events. *Am. J. Agric. Econ*. 106, 21–44 (2024). https://doi.org/10.1111/ajae.12393
39. Piesse, J., Thirtle, C. Three bubbles and a panic: an explanatory review of recent food commodity price events. *Food Policy*. 34, 119–129 (2009). https://doi.org/10.1016/j.foodpol.2009.01.001
40. Maystadt, Jean-François, and Olivier Ecker. 2014. "Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks?" *American Journal of Agricultural Economics* 96: 1157–82.
41. Letta, M., Montalbano, P., Pierre, G. Weather shocks, traders' expectations, and food prices. *Am. J. Agric. Econ*. 104, 1100–1119 (2022). https://doi.org/10.1111/ajae.12260
42. Arellano Gonzalez, J., Juarez-Torres, M., & Zazueta Borboa, F. (2023). Weather shocks, prices and productivity: Evidence from staples in Mexico (Working Papers No. 2023-16). Banco de México.
43. FAO (Food and Agriculture Organisation of the United Nations). Post-harvest losses along value and supply chains in the Pacific Island Countries. http://www.fao.org/fileadmin/user_upload/sap/docs/Post-harvest losses along value and supply chains in the Pacific Island Countries.pdf (2015), Accessed 25th Jul 2023.
44. Lobell, D. B., et al. Climate trends and global crop production since 1980. *Science* 333, 616–620 (2011).
45. Iizumi, T., & Ramankutty, N. How do weather and climate influence cropping area and intensity? *Glob. Food Security* 4, 46–50 (2015).
46. Ruane, A. C., Phillips, M., Jägermeyr, J., & Müller, C. Non-linear climate change impacts on crop yields may mislead stakeholders. *Earth's Future* 12, e2023EF003842 (2024).
47. Cohn, A. S., VanWey, L. K., Spera, S. A., & Mustard, J. F. Cropping frequency and area response to climate variability can exceed yield response. *Nat. Clim. Change* 6, 601–604 (2016).
48. Tilman, D., Balzer, C., Hill, J. & Befort, B. L. Global food demand and the sustainable intensification of agriculture. *Proc. Natl Acad. Sci. USA* 108, 20260 - 20264 (2011).
49. Challinor, A. J., et al. A meta-analysis of crop yield under climate change and

adaptation. *Nat. Clim. Change* 4, 287–291 (2014).

50. Barreca, A. et al. Adapting to climate change: the remarkable decline in the US temperature–mortality relationship over the twentieth century. *J. Polit. Econ*. 124, 105–159 (2016).
51. Chen, X., Lin, Y., & Zhu, P. (2025). The impact of rainfall on productivity: Implications for Chinese manufacturing. *Journal of Comparative Economics*, *53*(2), 389-411.
52. Deschênes, O., & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *Am. Econ. J. Appl. Econ.* 3, 152–185 (2011).
53. Zhang P., Zhang, J. and Chen, M. Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other than Temperature and Precipitation. *Journal of Environmental Economics and Management* 83, 8 - 31 (2017).
54. Wang, D., Zhang, P., Chen, S., Zhang, N. Adaptation to temperature extremes in Chinese agriculture, 1981 to 2010. *Journal of Development Economics* 166, 103196 (2024).
55. Thrasher, B., Wang, W., Michaelis, A. et al. NASA Global Daily Downscaled Projections, CMIP6. Sci Data 9, 262 (2022).
56. Dellink, R., Chateau, J., Lanzi, E., & Magné, B. Long-term economic growth projections in the Shared Socioeconomic Pathways. *Glob. Environ. Change* 42, 200–214 (2017).
57. Leimbach, M., Kriegler, E., Roming, N., & Schwanitz, J. Future growth patterns of world regions—a GDP scenario approach. *Glob. Environ. Change* 42, 215–225 (2017).
58. Samir, K. & Lutz, W. The human core of the Shared Socioeconomic Pathways: population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Change* 42, 181 - 192 (2017).
59. Wien, H.C., Stutzel H. The Physiology of Vegetable Crops. Cab International, Oxon-New York (1997).
60. Bisbis, M. B., Gruda, N., & Blanke, M. (2018). Potential impacts of climate change on vegetable production and product quality – A review. Journal of Cleaner Production, 170, 1602–1620. https://doi.org/10.1016/j.jclepro.2017.09.224.
61. Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. *Journal of Political Economy* 129, 1797 - 1827 (2021).
62. Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0.
63. Wang, D., Zhang, P., Chen, S., Zhang, N. Adaptation to temperature extremes in Chinese agriculture, 1981 to 2010. *Journal of Development Economics* 166, 103196 (2024).
64. David, B., et al. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science* 344, 516–519 (2014).
65. Auffhammer, M. Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. *Journal of Environmental Economics and Management* 114, 102669 (2022).
66. Nguyen, H. Beyond the annual averages: Impact of seasonal temperature on employment growth in US counties. *Journal of Environmental Economics and Management*. Available online

28 February 2024, 102946.

67. Guimbeau, A., Xinde James Ji, Zi Long, Nidhiya Menon. Ocean salinity, early-life health, and adaptation. *Journal of Environmental Economics and Management*. Available online 6 March 2024, 102954.
68. Béné, C. et al. Resilience—and collapse—of local food systems in conflict-affected areas: reflections from Burkina Faso. *World Dev.* 176, 106521 (2024).
69. Kornher, L., Balezentis, T. & Santeramo, F. G. EU food price inflation amid global market turbulences during the COVID-19 pandemic and the Russia–Ukraine war. *Appl. Econ. Perspect. Policy* 46, 1563–1584 (2024).
70. Amiti, M., Redding, S. J. & Weinstein, D. E. The impact of the 2018 tariffs on prices and welfare. *J. Econ. Perspect.* 33, 187–210 (2019).
71. Adjemian, M. K., Smith, A. & He, W. Estimating the market effect of a trade war: the case of soybean tariffs. *Food Policy* 105, 102152 (2021).
72. Mahajan, K. and Tomar, S. (2021), COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India. *Amer. J. Agr. Econ.*, 103: 35-52. https://doi.org/10.1111/ajae.12158

Acknowledgements

We acknowledge Wangyang Lai and Zeng Li for providing guidance in methodology. We also acknowledge the financial support provided by Public Policy Research (PPR) Funding Scheme, Chief Executive's Policy Unit, Hong Kong Government (nos: 2021.A7.021.21C), Innovation and Technology Fund - General Support Programme, Hong Kong Government (nos: GSP/035/20), and Strategic Topics Grant, Research Grants Council, Hong Kong Government (nos: STG2/E-605/23-N). The work described in this paper was substantially supported by a fellowship award from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No.: HKUST RFS2425-6H03).

Author Contributions

Chen and Guo contributed to this work equally. X.C. launched this research. X.C., A.G. and P.Z contributed ideas. X.C. and A.G. performed data analysis. X.C. developed the theoretical model, wrote the manuscript. X. C. A.G. and P.Z revised the paper. X.C. led the overall project.

Corresponding authors

Correspondence to Xiaodong Chen and Pengyu Zhu

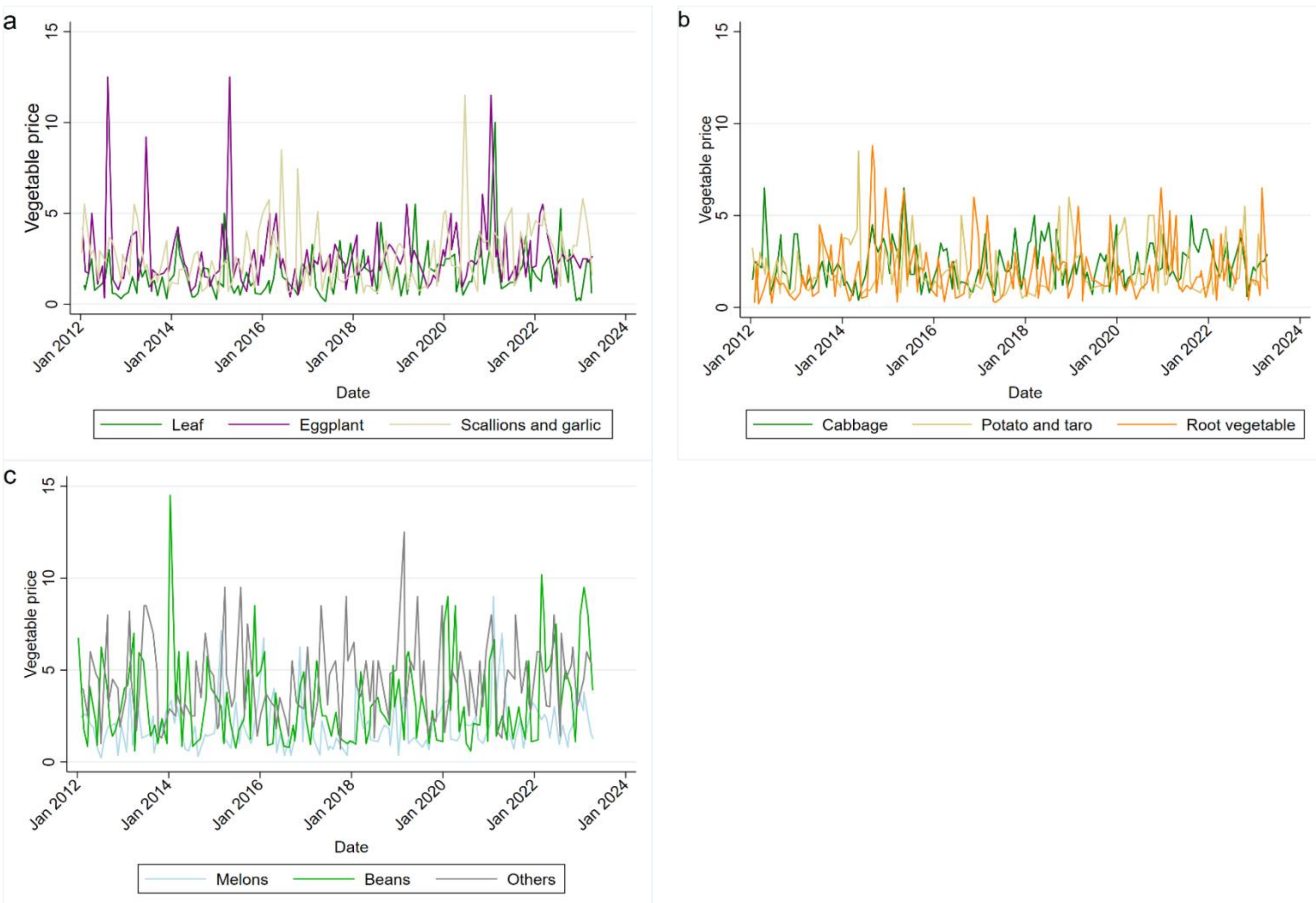
Ethics declarations

Competing interests

The authors declare no competing interests.

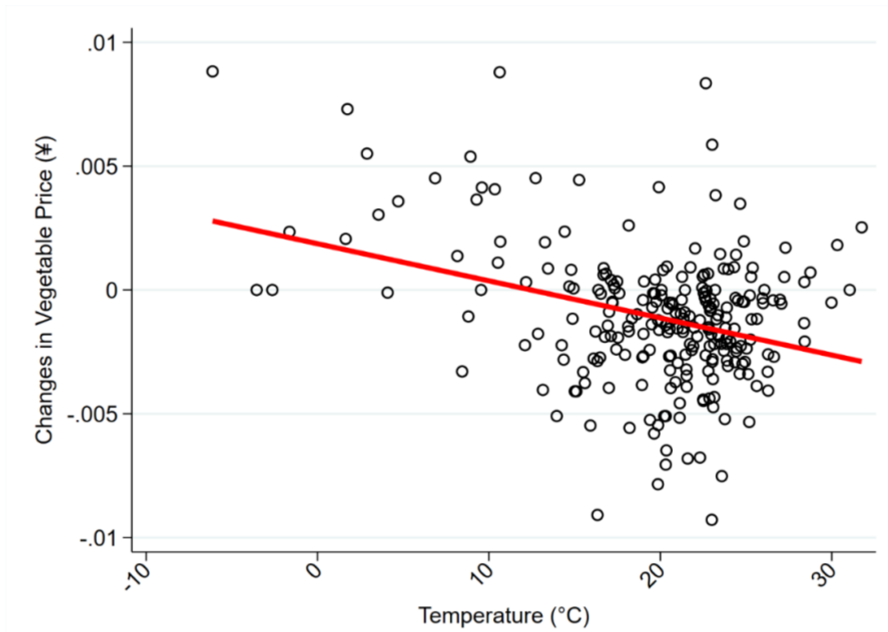
Extended Figures

Extended Fig. 1: Changing trend of wholesale vegetable prices



a, b, and c describe the changing trends of monthly vegetable wholesale prices from January 2012 to April 2023. Figure a includes leafy vegetables, eggplants, scallions, and garlic; figure b includes cabbage, potatoes, taro, and root vegetables; and figure c includes melons, beans, and other vegetables.

Extended Fig. 2: Correlation between temperature and changes in vegetable wholesale prices

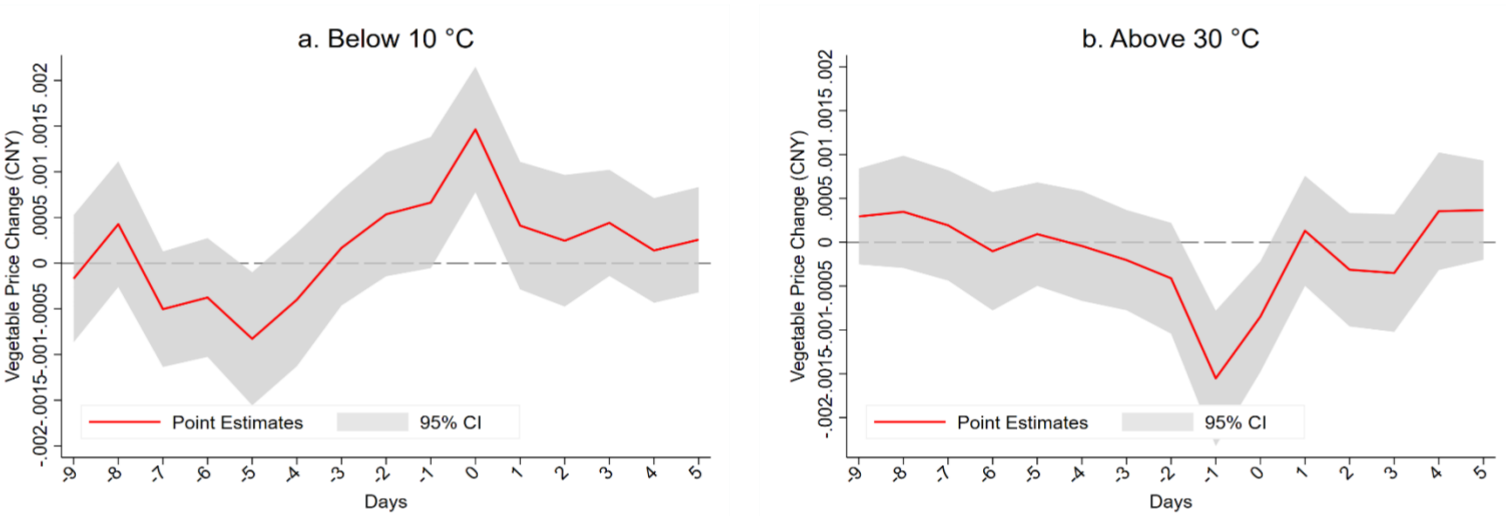


Note: each point represents the average price across 2012-2023 in one vegetable wholesale market with the average station-based temperature where the market is located. *N*=265.

Extended Fig. 3: The supply chain of vegetable in China.

Note: data are from Leadleo (2023) (see https://pdf.dfcfw.com/pdf/H3_AP202308161594849062_1.pdf). Icons are generated by doubao.ai.

Extended Fig. 4: Effects of Forecasted and Lagged Temperature Shocks on Vegetable Wholesale Price Change.



a,b detail 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 baseline for comparison. Our analysis calculates coefficient estimates for individual days (ranging from t = -9 to t = +5) by comparing them to the baseline temperature 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. Our controls include air pollution, rainfall, relative humidity, sunshine duration, temperature, and their square terms. In our model, we account for variables such as air pollution, rainfall, relative humidity, sunshine duration, and temperature, along with their squared terms to capture any non-linear effects these factors may have on the vegetable wholesale price change. Additionally, we apply market-level clustering to the standard errors to account for inter-market variability. Data are presented as point estimates (representing the mean marginal effects) with shaded regions indicating the 95% confidence intervals.

Supplementary information

Supplementary Figs. 1–12, Tables 1–15.

Supplementary files include Parts A-K. Part A presents the theoretical framework, which provides distribution-related explanations. Part B introduces the vegetable supply chain, as well as the production and consumption of vegetables in China. Part C provides estimates for vegetable subcategories. Part D incorporates various robustness checks, including checks of the econometric settings, alternative reference categories, the use of satellite-based temperature measure to cross-validate our station-based temperature measure, address price reporting issues, serial correlation, spatial correlation and the use of consistent three temperature bins. In Part E, we provide direct post-harvest explanations from the perspective of transportation and storage. In Part F, we examine whether the temperature effects between hot and cold regions are significantly different. Part G presents the coefficients for projection. In Part H, we provide summary statistics. In Part I, we discuss the generalizability of this study beyond China. In Part J, we provide detailed policy implications, supported by examples from the literature and relevant policies. In Part K, we provide source data for the estimates in the figures that appeared in the main text.