

NO. 54

AFFORDABLE FOOD SHOPS AND URBAN FOOD SECURITY IN CHINA

TAIYANG ZHONG,¹ JONATHAN CRUSH,² YAYA SONG,³ ZHENZHONG SI,⁴
STEFFANIE SCOTT⁵ AND YUXIN PENG⁶

SERIES EDITOR: JONATHAN CRUSH

¹ School of Geography and Ocean Science, Nanjing University, zty@nju.edu.cn

² Balsillie School of International Affairs, Canada, University of the Western Cape, South Africa, jcrush@balsillieschool.ca

³ School of Geography and Ocean Science, Nanjing University, songyy_nju@163.com

⁴ Balsillie School of International Affairs, Canada, sizhenzhong@gmail.com

⁵ Department of Geography and Environmental Management, University of Waterloo, Canada, sdscott@uwaterloo.ca

⁶ School of Geography and Ocean Science, Nanjing University, 1135983262@qq.com

Abstract

Food subsidies have been widely implemented as part of government policies to mitigate food insecurity among the urban poor. The effectiveness of supply and demand-side subsidies have been a source of debate in the literature. One form of supply-side subsidy designed to make food more affordable to low-income consumers is to offer subsidies to retail outlets. China's affordable food shop (AFS) program is one such example. The program was introduced by the central government in 2011 and implemented by municipal governments. Shops signing on to the program were required to sell a list of essential food items at a discount in exchange for a range of subsidies. To date, there has been no research examining the effectiveness of the AFS program despite more than a decade of implementation. This study focuses on a case study of Nanjing, one of the earliest Chinese to introduce an AFS program and which grew very quickly in the years that followed. In early 2020, however, the Nanjing program was closed down which raises important questions about its effectiveness and impact. Using household food security and consumption data, this paper uses logistic regression to examine the effectiveness of the AFS program in achieving its core goals. Our research indicates that the affordable-price food shop program has had a limited effect in reducing food insecurity and the failure of food retail subsidization is therefore unsurprising. Improving consumer income subsidies would be a better strategy for mitigating food insecurity among low-income households.

Keywords

food access, food security, retail subsidies, AFS Program, China

Suggested Citation

Zhong, T., Crush, J., Song, Y., Si, Z., Scott, S. and Peng, Y. (2022). *Affordable Food Shops and Urban Food Security in China* HCP Discussion Paper No. 54, Waterloo and Cape Town.

This is the 54th discussion paper in a series published by the Hungry Cities Partnership (HCP), an international research project examining food security and inclusive growth in cities in the Global South. The multi-year collaborative project aims to understand how cities in the Global South will manage the food security challenges arising from rapid urbanization and the transformation of urban food systems. The Partnership is funded by the Social Sciences and Humanities Research Council of Canada (SSHRC) and the International Development Research Centre (IDRC) through the International Partnerships for Sustainable Societies (IPaSS) Program.



© The authors

All HCP discussion papers and other publications are available for download from the Hungry Cities Partnership website: <http://hungrycities.net>.

Introduction

Food subsidies and price controls are widely used social protection policy tools to mitigate poverty and food insecurity, and to make staple foods and fresh produce more affordable to low-income households (Feltenstein, 2017). During periods of rapid food price increase and volatility, such as during the global economic crisis of 2007–2008, such measures take on added salience (Bakker, 2015; Bellemare, 2015; Smith, 2014). One analysis of food price policies in 14 countries in the Global South, for example, found extensive use of “bandage (sic) solutions” such as short-term subsidies for food as a response to price volatility and crisis (Pinstrup-Anderson, 2014, p. 481). As Ismail (2021, p. 3) notes in a review of the literature on the relationship between food prices and popular protest, food subsidies and price controls are “policy interventions that may address rising food prices and mitigate the rise of violent collective action.” Subsidies have also been deployed by governments during longer periods of disruptive social and economic transformation. The rapid urbanization of the Global South in recent decades and a growing crisis of urban food insecurity, for example, has unveiled many of the global and local drivers of food prices and food (un)affordability and prompted renewed interest in subsidies as a mitigation strategy (Clapp, 2009; Crush et al., 2012).

Food affordability is clearly crucial for the food security of urban populations and the maintenance of social order (Haug and Hella, 2013). Affordability generally refers to the food expenditure of a household relative to its income and the price of a basic basket of goods (Lee et al., 2013). Policies to ensure affordability involve measures on either the supply or the demand side or both. Demand-side interventions include price subsidies on essential foods, stabilizing or raising household income (through for example cash transfers, basic income grants or minimum wage legislation) and subsidizing other basic needs such as water, electricity, health care and education. Common supply-side interventions include guarantees for agricultural producers and subsidies for food marketers and retailers.

In China, considerable attention has been devoted to supply-side subsidies in the form of subsidization of agricultural production (Huang and Yang, 2017; Huang et al., 2013; Lopez et al., 2017; Meng, 2012; Shimokawa, 2010; Yi et al., 2012). While agricultural subsidies have been critical to increased production of grain and non-grain foodstuffs, less attention has been paid to how agricultural subsidies have impacted on food access and utilization in the cities. Similarly, the impact of other supply-side subsidies on urban food security have not yet been explored in systematic fashion. This paper focuses on the nature and impact of China’s affordable food shop (AFS) program which began in 2011. After nearly a decade of continuous expansion, the whole AFS program was abruptly shut down in early 2020. The termination of the program raises important questions about its effectiveness in achieving its core goals of making food more affordable and accessible and improving the food security situation of lower-income households. In this respect, we build on previous studies of the Nanjing food system to assess whether the affordable food shop program has had positive effect on levels of food security (Qi et al., 2019; Si et al., 2019; Zhong et al., 2018, 2019; Yuan, 2021).

Section 2 provides an overview of different forms of food price subsidization strategy in order to contextualize the AFS approach. This is followed in the next section by a description of the methodology and sources used for the Nanjing case study, one of the lead Chinese cities in AFS planning and implementation. Using primary data from a city-wide household food security survey, the paper then models the relationship between household characteristics and poverty and food insecurity in order to evaluate whether the program was achieving its stated aim of improving the food security of low-income households in the city. The results of the statistical analysis are presented in Section 4.

Food Retail Subsidization

Food retail subsidies have been implemented in various ways in different countries around the globe (Table 1). In Egypt, designated retail outlets sell food items such as cooking oil, sugar flour and baladi bread at subsidized prices (Ramadan and Thomas, 2011), while in the Philippines, the National Food Authority program provides credits to retailers selling rice at mandated prices (Jha and Ramaswami, 2010). In some countries, state-owned stores provide subsidized food. In India, for example, the Public Distribution System sells rice, wheat, sugar, and kerosene oil at subsidized prices through state-run fair-price shops (Chakrabarti et al., 2018), a model also used in Iraq (Krishnan et al., 2019).

In Canada, a retail subsidy program-- Nutrition North Canada -- has been implemented since 2012 to address remote northern communities' lack of access to perishable foods (Black et al., 2012). Subsidies paid to local retailers by the Nutrition North Canada program are expected to be fully passed on to consumers in the targeted communities (Naylor et al., 2020). In Greenland too, state-run Pilersuisoq stores provide food at regulated prices (Galloway, 2017). A different type of supply-side measures is New York City's Food Retail Expansion to Support Health (FRESH) Program with government-subsidized supermarkets aiming to improve the availability of fresh produce in urban food deserts (Elbel et al., 2015). Tax credits have also been used by the US federal government to encourage the entry of retail food establishment to low-income neighbourhood under the New Markets Tax Credit policy (Freedman and Kuhns, 2018).

Evidence on the positive impacts of subsidization on food consumption and security is mixed. The rising global tide of overnutrition and obesity has tended to elicit food taxes on unhealthy foods rather than subsidies on healthy food (Powell and Chaloupka, 2009). A recent study in New Zealand by Blakely et al (2020) found an increase in the healthiness of supermarket-purchased foods as a result of three

tax policies (on sugar, saturated fat, and salt), but not for a fruit and vegetable subsidy. Another study, however, indicated that 12.5% price discount (equivalent to the goods and services tax rate) significantly increased the purchase of healthier foods (Ni Mhurchu et al., 2009). This suggests that there could be a threshold above which price discount can result in a significant effect (Black et al., 2012; Blakely et al., 2020; Ni Mhurchu et al., 2009; Nnoaham et al., 2009; Powell and Chaloupka, 2009).

The introduction of new government-subsidized supermarkets in New York City did not significantly increase household purchase of healthier food types such as whole grains, fresh fruits, and vegetables (Elbel et al., 2015). In the Philippines, the National Food Authority Program has had limited impact mainly due to program waste (Jha and Ramaswami, 2010) and the targeted Public Distribution System in India led to an increase in the consumption of subsidized food, including pulses, but not overall calorie and protein intake (Chakrabarti et al., 2018; Kaushal and Muchomba, 2015). In Canada, the food subsidies of the Nutrition North Canada program succeeded in lowering food prices (Naylor et al., 2020), but some suggest that the program has failed to meet the goal of addressing lack of access to perishable foods (Galloway, 2014, 2017; St-Germain et al., 2019).

Some US programs were seemingly more successful (Jensen and Miller, 2015). Chang et al. (2015) report that the food price subsidies of the Supplemental Nutrition Assistance Program in the US did increase the consumption of fruits and vegetables. But while the New Markets Tax Credit Program encouraged supermarket entry into low-income communities it did not change household food purchasing patterns (Freedman and Kuhns, 2018). In urban Iran, the implementation of the Targeted Subsidies Policy positively affected the consumption of fish and red meat while having a negative effect on the consumption of cereal and poultry meat (Hosseini et al., 2017). By contrast, the subsidy programs in Egypt, India and Philippines all positively affected household access to food, increased food consumption by low-income households, and reduced the prevalence of underweight children

TABLE 1: Types of Food Subsidy Program

Program	Subsidy category	Subsidy allocation method	Subsidized/targeted food items
Public Distribution System, India (PDS) (George and McKay, 2019) Pulse subsidy program included in PDS, India (Chakrabarti et al., 2018)	Price subsidy	Fair-price shops owned and operated by government selling subsidized food; Identifying eligible families; Issuing ration cards; Two thirds of market price with quota (Kaushal and Muchomba, 2015)	Central government: Rice, wheat, sugar, and kerosene oil; State government: additional food items
Public distribution system (PDS), Iraq (Krishnan et al., 2019)	Price subsidy	Issuing ration cards; Partial rationing: food available at subsidized prices within ration quota and free-market price beyond ration quota	Rice, flour, oil, sugar
Public Food and Energy Subsidies, Iran (Hosseini et al., 2017)	Price subsidy	Equally distributed and untargeted income groups; Replaced by Targeted Subsidies Policy in 2020, which moved from food price subsidies to income supplements (Esmaeili et al., 2013)	Water, wheat, bread, rice, edible oil, milk and sugar
National Food Authority Program, Philippines (Jha and Ramaswami, 2010)	Price subsidy	National Food Authority selling rice to accredited retailers and requiring them to sell rice with mandated, below-market price (Jha and Ramaswami, 2010). Unlimited purchase (Jha and Ramaswami, 2010)	Rice
Food Subsidy Program, Egypt (Talaat, 2018)	Price subsidy	Licensed ration shops selling subsidized commodities; Beneficiaries holding ration card with quota of food (before 2014); Beneficiaries holding smart card with monthly allowance (since 2014)	<i>Baladi</i> bread, cooking oil, rice, sugar and macaroni (before 2014) more than 50 commodities (since 2014)
<i>Pilersuisoq</i> stores, Greenland (Galloway, 2017)	Price subsidy	State-owned stores regulated price	Wide variety of food items
Nutrition North Canada (St-Germain et al., 2019)	Retailer subsidy	Subsidizing food retailers, on a per kilogram basis with two levels (partial and full subsidy); No price caps; Grocery stores operated by companies (Galloway, 2017)	Perishable, nutritious foods in eligible food item list Retailing with eligible communities
New York City's Food Retail Expansion to Support Health (FRESH) Program, USA (Elbel et al., 2015)	Retailer subsidy	Financial and zoning incentives to decrease costs of food retailing; No requirements on food price	
New Markets Tax Credit Program, USA (Freedman and Kuhns, 2018)	Retailer subsidy	Providing investors with a tax credit; No requirements on food price	
Supplemental Nutrition Assistance Program (SNAP), US (Chang et al., 2015)	Consumer subsidy	Issuing Electronic Benefits Transfer card	Wide variety of food items such fruits, vegetable, meat, poultry, fish, cereals, dairy products, etc.
Affordable Food Shop Program, China	Retailer subsidy	Subsidizing food retailers; Business establishment subsidy per shop; Annual operation subsidy per shop; Selling food with regulated price	Vegetable: price 15% lower than mean price confirmed by price administration (Jiangsu Provincial Government, 2012); Grain, cooking oil, meat and eggs: price 5% lower than mean price

Source: Compiled by authors

(Anuradha and Raj, 2019). An's (2012) review of the literature on subsidies in seven countries including the USA, Canada, Germany and South Africa found that subsidies on healthier foods significantly increase the purchase and consumption of promoted products.

The AFS Program in China is a central government initiative aimed at stabilizing urban food prices through food retail shops that are financially subsidized by local government. The policy was first announced by the National Development and Reform Commission in May 2011 in an effort to stabilize rising vegetable prices (National Development and Reform Commission, 2011). In March 2012, the Commission expanded the program by enlarging the number of food items covered (National Development and Reform Commission, 2012). In exchange for various subsidies, the 2011 policy required AFS Program shops to sell vegetables and fruits at prices 15% lower than in other retail outlets, and grain, cooking oil, meat, poultry and egg at 5% lower than that in other retail outlets. To qualify for government subsidies, affordable food shops were required to sell prescribed food items at prices lower than that in other food retail outlets. In contrast to the Nutrition North Canada program which subsidizes private food retailers (without regulating food prices) and the Public Distribution System in India (where state-run food retailers sell subsidized food), the AFS program in China combines retailer subsidies and regulated selling prices.

Provincial and city governments were given some discretion over the elements of the program since they were primarily responsible for financing the subsidies. Due to the differing capacity and financial resources of local governments, the actual implementation of the program varied across the country. In some cities, shops were required by the municipal government to sell food at set prices every day, while in others they only had to do so when food prices significantly increased or during festivals such as the Spring Festival (Fuyang Municipal Government, 2021). Other variations include the particular food items on the lists and differences in the subsidy level. Central government monitoring of the program is reasonably pragmatic in the sense

that evaluation focuses more on the actual impacts on food affordability than the specific approach local governments choose to implement the program.

By 2013, there were 11,000 affordable food shops in Chinese cities, of which 20% were in Jiangsu Province, a leader in the implementation of the AFS Program. Shops in the province were required to sell local vegetables at prices 15% lower than in other retail outlets and to sell non-local vegetables at prices marginally lower than in other outlets (Jiangsu Provincial Government, 2011, 2012). Within Jiangsu, the capital Nanjing has been the lead city in the implementation of AFS program. Nanjing, launched its AFS Program in October 2011 (Nanjing Municipal Government, 2011) and the number of shops increased rapidly from 50 at the end of 2011 (Sun 2012) to over 200 in 2019. Some shops were established in response to the AFS program while others pre-dated the program and applied to join. In 2019, most shops were privately-owned (about 91%), although a small number were owned by the state. In addition, about 69% of shop owners were individual entrepreneurs while the rest were company-owned.

Funding for the Nanjing program came from two sources: the Nanjing Municipal Government and transfers from the Jiangsu Province Government. The Municipal Government was permitted to establish its own implementation policy provided that provincial government policies were incorporated. Subsidies to affordable food shops in Nanjing included tax and fee allowances or exemptions, favourable prices for water and electricity consumption, and subsidies for business establishment and operations. The business establishment subsidy was CNY100,000 (about USD15,000) per shop. The operations subsidy was paid quarterly based on a shop's performance as assessed by government. The average annual operations subsidy amounted to around CNY55,000 (about USD8,000) in 2017 (Nanjing Bureau of Administration for Commodity Prices, 2017). The food shops had to sell no fewer than ten types of fresh produce at a discount on a produce list compiled by the Municipal Government. All prices had to be 15% lower than the average food price determined by the Municipal

Price Administration based on a city-level food price monitoring system. Foods not on the produce list could also be sold but at prices no higher than those in nearby wet markets.

Between 2015 and 2019, annual fiscal expenditure on subsidizing the affordable food shops ranged from CNY8–11 million (about USD1.2–1.7 million). One report notes that about CNY0.42 billion was directly saved by consumers from 2011 to 2018, an annual saving of CNY50 million (about USD7.7 million) (Phoenix News Media Limited, 2018). However, if the total annual saving is divided by Nanjing's 8 million people, an average of USD1/person or USD3/household were saved, accounting for about 0.3% of annual urban household food expenditure in 2019.

Materials and Methods

Household Food Security Survey

The analysis in this paper uses data from a household food security survey in Nanjing conducted by Nanjing University and the Hungry Cities Partnership (Zhong et al., 2019). A total of 1,210 randomly-selected households across the city were interviewed on a wide range of issues including household characteristics, food consumption and sourcing behaviour, and levels of food security. Household food security was measured using the Household Food Insecurity Access Score (HFIAS) and the Household Food Insecurity Access Prevalence (HFIAP) classification. The HFIAP is a widely-used categorical indicator developed by the Food and Nutrition Technical Assistance (FANTA) Project, which classifies households food security into four categories based on responses to nine frequency-of occurrence over the previous six levels: food secure, mildly food insecure, moderately food insecure, and severely insecure (Coates et al., 2007, Swindale and Bilinsky, 2006).

Mapping Affordable Food Shops

A listing of affordable food shops was obtained from the Nanjing Municipal Commission of Development and Reform, which included information on the establishment and cessation of food shops between 2011 and 2019. The list of shops included the name, address and year of business establishment/closure. We geocoded the location of all listed shops based on BaiduMap (map.baidu.com) in order to generate locational maps and calculate the distance from a city-wide, representative sample of households to its nearest shop as well as the distance from each shop to its nearest wet market and supermarket which were also geocoded. We then calculated the Euclidean distance from the GPS location of all 1,210 households to their nearest affordable food shop.

Dependent Variables

To examine the relationship between food security and household characteristics, we conducted a binary logistic regression analysis of the survey data. Four measures of food security were selected as dependent variables. The binary dependent variables were created based on the answers to the nine HFIAS frequency-of-occurrence questions (see Coates et al., 2007, p. 5). Four dependent variables were selected to capture different aspects of household food insecurity (Table 2):

- Food Insecurity (*insecu*) was created by binning the four HFIAP categories into two: if a household was categorized as mildly, moderately or severely food insecure, *insecu* = 1, 0 for otherwise;
- Food Anxiety (*anxie*) captures the level of anxiety and uncertainty about the household food supply (Q1 of the HFIAS) where *anxie* = 1 if the response was rarely, sometimes or often, 0 for otherwise;
- Food Quality (*quali*) captures whether the food consumed was of adequate quality and desirability. The value of *quali* = 1 if the response to

Q2-4 of the HFIAS was rarely, sometimes or often; 0 for otherwise; and

- Food Quantity: (*quanti*) captures whether there was a sufficient quantity of food in the household. The value of *quanti* =1 if the response to Q5-9 of the HFIAS was rarely, sometimes or often; 0 for otherwise.

Independent Variables

Table 2 lists the nine independent variables selected for the analysis, together with the predicted coefficient signs and an explanation for the choice of variable. The variables included:

- Distance (*Distf*): represents the distance from a surveyed household to the nearest affordable food shop, as an increase in distance to food outlets often generally means reduced physical access to food. Because most households in Nanjing walk to shop for food, physical distance is an appropriate proxy measure of accessibility (Ma et al., 2016; Si et al., 2019). The coefficient

sign of the variable *distf* was expected to be positive, based on the expectation that an increase in distance to the nearest food shop would also increase the probability of a household being food insecure.

- Infrastructure Access (*Lpi*): Infrastructure access is increasingly seen as an important factor influencing household food security (Frayne and McCordic, 2015; Su et al., 2017). The Lived Poverty Index (LPI) is a common instrument used to measure household infrastructure access (Meyer and Keyser, 2016). The LPI score was calculated from household responses to five Likert scale consistency questions about infrastructure access. The variable represents a household’s LPI score, with an expected positive coefficient since an increase in the LPI (on a scale from 0 to 4) is an indicator of greater infrastructure access.
- Household Income (*HHIL* and *HHIM*). Household income is generally seen as a crucial factor influencing food security (Loopstra and Tarasuk, 2013). For this analysis, household income was

TABLE 2: Dependent and independent variables

Variable	Definition	Expected sign			
		<i>insecu</i>	<i>anxie</i>	<i>quali</i>	<i>quanti</i>
Dependent variables					
<i>Insecu</i>	Whether food insecure, 1 for insecure and 0 for otherwise				
<i>Anxie</i>	Whether anxious and uncertain about food supply, 1 for yes and 0 for otherwise				
<i>Quali</i>	Whether insufficient quality, 1 for yes and 0 for otherwise				
<i>Quanti</i>	Whether insufficient food intake, 1 for yes and 0 for otherwise				
Independent variables					
<i>Distf</i>	Distance to the nearest affordable food shop (100 metres)	+	+	+	+
<i>Lpi</i>	Value of household Lived Poverty Index	+	+	+	+
<i>HHIL</i>	Whether low-income household, 1 for yes and 0 for otherwise	+	+	+	+
<i>HHIM</i>	Whether middle-income household, 1 for yes and 0 for otherwise	+	+	+	+
<i>Reducedinco</i>	Whether reduced income for a household member, 1 for yes and 0 for otherwise	+	+	+	+
<i>Reduceem</i>	Whether loss/reduced employment for a household member, 1 for yes and 0 for otherwise	+	+	+	+
<i>Gendercent</i>	Whether a male-centred or female-centred household, 1 for yes and 0 for otherwise	+	+	+	+
<i>Headed</i>	Whether household head uneducated, 1 for yes and 0 for otherwise	+	+	+	+
<i>Headmale</i>	Whether a household head is male, 1 for yes and 0 for otherwise	+/-	+/-	+/-	+/-

first categorized into low, middle and high terciles. The variables *HHIL* and *HHIM* were used to represent low-income and middle-income terciles respectively. As households of lower income were more likely to be food insecure, and an improvement in household income can help decrease food insecurity, the coefficients of variable *HHIL* and *HHIM* were expected to be positive.

- Reduction in Household Income (*Reducedinco*) was used to represent a reduction in income of any household member in the six months prior to the survey. This variable was also expected to have a positive coefficient.
- Employment Status (*Reducedem*): In addition to household income, employment status is an important predictor of household food insecurity (Loopstra and Tarasuk, 2013). Increased employment generally leads to a decrease in household food insecurity, while unemployment can lead to an increase in food insecurity. The variable was used to reflect a loss of or reduced employment for any household member in the previous six months, and is also assumed to have positive coefficient.
- Household Structure (*Gendercent*): Type of household is another factor known to influence household food security (Balisteri, 2018; Drammeh et al., 2019). Female-headed households have been consistently shown to experience higher levels of food insecurity (Riley and Dodson, 2020). The household survey instrument classifies households into four categories: female-centred (with a female head and no spouse/partner), male-centred (with a male head and no spouse/partner), nuclear (with a household head and spouse/partner and their children); and extended (household head and spouse partner/ plus children any other relatives and non-relatives). The mean HFIAS value for female-centred and male-centred households was higher than that of nuclear and extended households. The variable *Gendercent* was used to represent male-centred and female-centred households with an assumed positive coefficient.

- Household Head (*Headmale* and *Headedu*). Various studies have drawn a link between household head characteristics and household food security (Mohamed et al., 2016; Obeyalu, 2018). Male headship (which includes most nuclear, extended and male-centred households) generally means a household is less vulnerable to food insecurity (McCordic et al., 2021). The variable *Headmale* was therefore used to represent whether a household head was male or not. Some studies have also found that the educational status of the household head is also positively related to food security (Mutisya et al., 2019; Tarasuk et al., 2019). The variable *Headedu* was used to capture whether the household head had any formal education.

Binary Logistic Regression

Binary logistic regression is the most appropriate analytical approach for a study with binary dependent variables (Long and Freese, 2001). The logistic regression model for general household food insecurity (*insecu*) is:

$$\text{logit}\{P(\text{insecu}=1) | X\} = a_1 + \beta_1 X$$

where a_1 is the constant term, X is the vector of independent variables in Table 1 and β_1 is their coefficients vector.

The regression model for whether a household was anxious and uncertain about its food supply (*anxie*) is:

$$\text{logit}\{P(\text{anxie}=1) | X\} = a_2 + \beta_2 X$$

where a_2 is the constant term, X is the vector of independent variables in Table 1 and β_2 is their coefficients vector.

The regression model for whether a household had insufficient quality food (*quali*) is:

$$\text{logit}\{P(\text{quali}=1) | X\} = a_3 + \beta_3 X$$

where a_3 is the constant term, X is the vector of independent variables in Table 1 and β_3 is their coefficients vector.

The regression model for whether a household had a sufficient food quantity (*quanti*) is:

$$\text{logit}\{P(\text{quanti}=1) | X\} = a_4 + \beta_4 X$$

where a_4 is the constant term, X is the vector of independent variables in Table 1 and β_4 is their coefficients vector.

Results

Spatial Distribution of AFS Program Shops

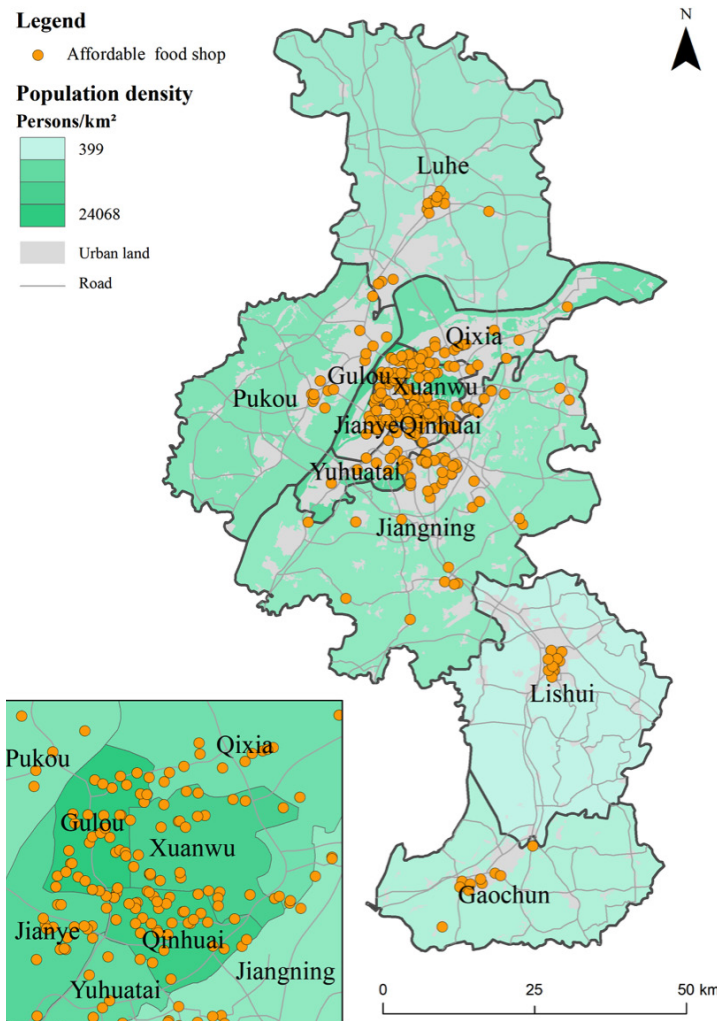
Figure 1 shows the spatial distribution of shops in Nanjing as of 2015. The shops were heavily concentrated in the downtown area of the city with the highest population density (the districts of Gulou,

Xuanwu and Qunhuai). There are also clusters of shops on urban land in the peri-urban areas of Luhe, Lishui and Gaochun. Most food shops were located near to wet markets or supermarkets. For example, some 30% of the shops shown in Figure 1 are located within 250 metres of a wet market or supermarket and 56% are within 500 metres of a wet market or supermarket. This was designed to ensure that consumers could easily comparison shop and shops would readily ensure that their prices were lower than in the other outlets.

Regression Models

Four regression models were calculated with *insecu*, *anxie*, *quali* and *quanti* respectively as the dependent variables (Tables 3-6). The tables also provide the tests for goodness of fit, including likelihood-ratio

FIGURE 1: Affordable food shops in Nanjing, 2015



chi-squared, log likelihood, pseudo R² and correctly classified rate. The values of AIC (Akaike information criterion) and BIC (Bayesian information criterion) are also provided for judging which model is superior to others, which can be used in models with the same dependent variables and whether they are nested or non-nested (Long and Freese, 2001).

Overall Food Insecurity

Table 3 provides three models with *insecu* as the dependent variable. Model IN1 includes the independent variables *HHIL* and *HHIM* that represent low-income and middle-income households respectively (while excluding the variables *reducedem* and *reducedinco* that represent loss/reduced employment or income). Models IN2 and IN3 exclude the variables *HHIL* and *HHIM* while including variables *reducedem* and *reducedinco* respectively. The estimated coefficients of all variables except *headedu* (education) are statistically significant and the signs of their coefficients are consistent with expectations. The model IN2 has the smallest AIC

and BIC while there is no notable difference in the value of AIC and BIC between all three models, which suggests that Model IN2 is slightly superior to the IN1 and IN3. Lived poverty (*Lpi*) and reduced employment (*reducedem*) have the strongest statistical relationship with the dependent variable for household food insecurity (*insecu*).

Anxiety About Household Food Supply

Table 4 provides three models with anxiety and uncertainty about the household food supply (*anxie*) as the dependent variable. Models AX1, AX2 and AX3 include different independent variables. Model AX3 has the largest Pseudo R² and the smallest value of AIC and BIC, suggesting model AX3 is statistically superior to AX1 and AX2. Although the estimated coefficients of most control variables are statistically significant, the estimated coefficient of the explanatory variable *distf* is not. Thus, proximity to affordable food shops does not appear to influence anxiety and uncertainty about household food supply. The estimated coefficients of variables for reduced household income (*reducedinco*) and

TABLE 3: Determinants of Overall Food Insecurity (*insecu* as a dependent variable)

Variable	IN1	IN2	IN3
Distance (Distf)	0.0043*	0.0039*	0.0046**
Lived Poverty (Lpi)	1.3513***	1.3668***	1.3340***
Low Income (HHIL)	0.4837**		
Middle Income (HHIM)	0.3681*		
Employment Reduction (Reducem)		1.9391***	
Income Reduction (Reducedinco)			1.0269**
Household Structure (Gendercent)	0.6024***	0.6971***	0.6767***
Education (Headedu)	-0.0706	-0.0833	-0.1055
Sex of Head (Headmale)	0.6199**	0.7678**	0.7180**
Constant	-1.9041***	-1.6839***	-1.6687***
N of observations	1,124	1,120	1,120
LR chi ²	62.5900***	62.4600***	58.4300***
Pseudo R ²	0.0542	0.0544	0.0509
Log likelihood	-546.3402	-542.8075	-544.8243
Correctly classified	79.7200	79.7300	79.5500
AIC	1108.6800	1099.6150	1103.6480
BIC	1148.8780	1134.7630	1138.7960

Note: * significant at 1%, ** significant at 5%, *** significant at 10%

lived poverty (*Lpi*) are statistically significant with the largest and second largest coefficient values respectively. This indicates that households with reduced income and higher levels of poverty are more likely to be anxious and uncertain about their food supply.

Insufficient Food Quality

Table 5 provides three estimated models with *quali* as the dependent variable. Model IQ1 includes the variable *HHIL* and *HHIM*, while IQ2 and IQ3 include variables *reducedem* and *reducedinco*, respectively, excluding *HHIL* and *HHIM*. Model IQ2 has the lowest value of AIC and BIC and the largest value of Pseudo R², suggesting it is statistically superior to IQ1 and IQ3. The estimated coefficient of the variable *distf* in model IQ1 and IQ3 are statistically significant at the 10%-level and is at the margin of statistical significance in model IQ2 (*p*=0.117). The other variables excluding the variable *headmale* are all statistically significant. The estimated coefficient of variable *Lpi* and *reducedinco* have the largest and second largest

coefficient values, which indicates that those households with higher Lived Poverty and low income are more likely to encounter the challenge of insufficient food quality.

Insufficient Food Quantity

Table 6 provides three estimated models with *quanti* as the dependent variable. Model IT1 includes variable *HHIL* and *HHIM*, model IT2 and IT3 includes the variable *reducedem* and *reducedinco*, respectively, excluding variable *HHIL* and *HHIM*. Model IT3 has the largest value of Pseudo R², and the smallest value of AIC and BIC, which suggests that IT3 is statistically superior to IT1 and IT2. The estimated coefficients of the variable *distf* are not statistically significant, which indicates that the AFS program had no statistically significant effect on reducing households' insufficient food intake. The estimated coefficients of the variables *Lpi* and *reducedinco* are most statistically significant, which indicates that households with higher Lived Poverty Index and reduced income and are more likely to experience insufficient food intake.

TABLE 4: Determinants of Anxiety About Food Supply (*anxie* as a dependent variable)

Variable	AX1	AX2	AX3
Distance (<i>Distf</i>)	-0.0048	-0.0041	-0.0061
Lived Poverty (<i>Lpi</i>)	2.1689***	2.2261***	2.0052***
Low Income (<i>HHIL</i>)	0.2867		
Middle Income (<i>HHIM</i>)	0.0456		
Employment Reduction (<i>Reducem</i>)		-0.2598	
Income Reduction (<i>Reducedinco</i>)		2.3061***	
Household Structure (<i>Gendercent</i>)	-0.1489	-0.0441	-0.4841
Education (<i>Headedu</i>)	-0.9136**	-0.9227**	-0.9800**
Sex of Head (<i>Headmale</i>)	1.4579***	1.5260***	1.5234***
Constant	-3.4077**	-3.3259***	-3.2833***
N of observations	1142	1138	1138
LR chi ²	40.4400***	39.9600***	50.6300***
Pseudo R ²	0.1292	0.1278	0.1619
Log likelihood	-136.2207	-136.3340	-131.0009
Correctly classified	96.8500	96.8400	97.0100
AIC	288.4414	286.6680	276.0018
BIC	328.7657	321.9272	311.2610

Note: * significant at 1%, ** significant at 5%, *** significant at 10%

TABLE 5: Determinants of Insufficient Quality of Food (*quali* as a dependent variable)

Variable	IQ1	IQ2	IQ3
Distance (Distf)	0.0044*	0.0038	0.0046**
Lived Poverty (Lpi)	1.3451***	1.3140***	1.3044***
Low Income (HHIL)	0.3958**		
Middle Income (HHIM)	0.3499*		
Employment Reduction (Reducem)		2.1123***	
Income Reduction (Reducedinco)		0.9586**	
Household Structure (Gendercent)	0.6230***	0.6893***	0.6705***
Education (Headedu)	-0.0600	-0.0680	-0.0894
Sex of Head (Headmale)	0.6198**	0.7562**	0.6994**
Constant	-1.9413***	-1.7490***	-1.7335***
N of observations	1131	1127	1127
LR chi ²	58.0500***	62.3000***	55.5800***
Pseudo R ²	0.0512	0.0553	0.0493
Log likelihood	-538.0388	-532.2510	-535.6107
Correctly classified	80.6400	81.0100	80.8300
AIC	1092.0780	1078.5020	1085.2210
BIC	1132.3240	1113.6930	1120.4130

Note: * refers to significant at 1%, ** refers to significant at 5%, *** refers to significant at 10%

TABLE 6: Determinants of Insufficient Quantity of Food (*quanti* as a dependent variable)

Variable	IT1	IT2	IT3
Distance (Distf)	0.0046	0.0038	0.0029
Lived Poverty (Lpi)	2.2556***	2.3698***	2.2558***
Low Income (HHIL)	0.4435		
Middle Income (HHIM)	-0.8075		
Employment Reduction (Reducem)		0.6390	
Income Reduction (Reducedinco)			2.1084***
Household Structure (Gendercent)	0.3424	0.5937	0.3648
Education (Headedu)	-0.9076***	-1.0124***	-1.0623***
Sex of Head (Headmale)	0.4820	0.6642	0.5366
Constant	-3.2398***	-3.2559***	-3.2186***
N of observations	1135	1131	1131
LR chi ²	58.9000***	54.2000***	63.7800***
Pseudo R ²	0.1530	0.1457	0.1715
Log likelihood	-163.0701	-158.8860	-154.0966
Correctly classified	95.8600	96.1100	96.3700
AIC	342.1403	331.7719	322.1933
BIC	382.4154	366.9879	357.4093

Note: * refers to significant at 1%, ** refers to significant at 5%, *** refers to significant at 10%

Discussion

In January 2020, the Nanjing Municipal Government closed the AFS Program in the city and stopped subsidizing the shops. Some shops in Nanjing closed while others continued to operate under the affordable shop banner but without the subsidies and directives about food pricing. The decision to stop the program after a decade of expansion raises the question of how effective it has been in meeting its primary goal of ensuring food security for lower-income residents of the city. This decision was reportedly a response to the provincial policy of reducing government intervention in the food value chain (Jiangsu Provincial Government, 2019). Local authorities in charge of the implementation of the AFS Program in Nanjing also expressed concern in interviews that its contribution to food security in the city was limited (NMCDDR, 2019). A related question is whether the cessation of the program in Nanjing is likely to impact negatively on access to affordable food by residents.

Proximity to AFS Program Shops

The household survey and mapping data help to answer the question of whether household food security is related to distance from the nearest affordable food shop. Table 7 summarizes the modelling results with the food security variables (*insecu*, *anxie*, *quali* and *quanti*) as dependent variables and distance (*distf*) as the independent variable. The estimated coefficients of *distf* are statistically significant with overall food security (*insecu*) and food quality (*quali*) as dependent variables, but not with anxiety about food (*anxie*) and food quantity (*quanti*) as dependent variables. These mixed results contrast with the strong relationship of all four dependent variables with independent variables such as the Lived Poverty Index (*Lpi*) and reduced income (*reducedinco*).

TABLE 7: Relationship between Dependent and Independent Variables

Independent Variables	Dependent Variables			
	<i>insecu</i>	<i>anxie</i>	<i>quali</i>	<i>quanti</i>
<i>Distf</i>	√		√	
<i>Lpi</i>	√	√	√	√
<i>HHIL</i>	√		√	
<i>HHIM</i>	√		√	
<i>Reducedem</i>	√		√	
<i>Reducedinco</i>	√	√	√	√
<i>Gendercent</i>	√		√	
<i>Headmale</i>	√	√		√
<i>Headedu</i>	√	√	√	

Note: √ denotes statistically significant

To assess the strength of the relationship between proximity to an affordable food shop and food security and quality, odds ratios (OR) were calculated (Long and Freese 2001). The coefficient of the distance variable *Distf* in model IN2 is 0.0039 and its estimated OR is 1.004. This indicates that an increase of one unit (100 metres) of distance from an affordable food shop increases the odds of a household being food insecure by a factor of only 1.004, holding all other variables constant. An increase of ten units in distance (1,000 metres) from an affordable food shop increases the odds of being food insecure by a factor of only 1.039. Similarly, an increase of 100 metres increases the odds of a household experiencing insufficient food quality by a factor of 1.0038 and an increase of 1,000 metres by 1.0387 respectively, holding all other independent variables constant. The OR results thus indicate that increasing distance from an affordable food shop actually has a very limited impact on household food insecurity and insufficient food quality.

Poor Targeting by the AFS Program

Inappropriate targeting is a common problem in food subsidy programs (Jha and Ramaswami, 2010). Ideally they should target low-income and food insecure communities and households, but they do not necessarily do so in practice (Esmaeili et al., 2013; Talaat, 2018). On the question of whether the Nanjing AFS program is appropriately targeted, Table 8 shows there are four possible combinations

of food and consumer targeting. In type I, both consumers and foods are targeted, while in type IV neither consumer nor food are targeted. In types II and III, one of either consumers or food is targeted.

TABLE 8: Food and Consumer Targeting

Consumer	Food		
		Targeted (+)	Non-targeted (-)
	Targeted (+)	I (+,+)	II (+,-)
Non-targeted (-)	III (-,+)	IV (-,-)	

The first question is whether the AFS Program was well targeted with regard to consumers. The distance to the nearest shop of surveyed low-income, middle-income and high-income households was 2.61km, 1.61km and 1.15 km respectively ($F=19.9420$ and significant at 1%-level) which is the opposite of optimal targeting. In other words, high income households had the greatest spatial access to affordable food shops and low-income households the least. The need for spatial targeting of low-income neighbourhoods and households was overlooked by all levels of government until the end of 2018, when the Lishui District Government within Nanjing intentionally began to direct affordable food shops towards low-income areas (Lishui District Government, 2018).

A second question is whether the right foods were targeted for subsidies. One survey of the diet of Nanjing consumers found that 71% of fish intake, 61% of fruit intake, and 47% of meat intake was lower than that recommended by Food Guide Pagoda (Wang et al., 2013). The household food security survey in Nanjing asked whether 12 common food items were affordable in the previous six months. Table 9 compares the proportion of households that found a food unaffordable and the proportion of affordable food shops selling each of the products. Vegetables were sold by 92% of shops but only 3% of surveyed households said that they were generally unaffordable. On the other hand, none of the shops sold fish or fruit, deemed unaffordable by 13% and 7% of households respectively. Although meat was deemed unaffordable by 20% of households and sold by over 80% of shops, only boneless leg of pork was included on the list of price subsidies. Other meat products such as beef, lamb, goat, chicken and duck were all excluded from subsidization.

Short Supply Chains

Besides offering subsidies to affordable food shops, the AFS Program expected the shops to buy direct from producers rather than intermediaries such as wholesale markets or wet markets. These direct supply-chains would supposedly allow the shops to decrease food prices for consumers. However, the ability of small food shop owners to purchase all

TABLE 9: Unaffordable Foods Sold by Affordable Food Shops

Food item	% of households finding food item unaffordable ¹	% of affordable food shops selling food item ²
Meat	20.2	83.4
Fish	13.1	0.0
Fruit	6.9	0.0
Vegetables	3.1	92.2
Milk	2.3	0.0
Beans	1.2	59.5
Grain	0.6	82.9
Eggs	0.5	85.9
Condiments	0.5	0.0
Oil	0.3	84.4
Roots or tubers	0.2	88.8
Sugar	0.2	0.0

Source: (1) calculated from household food security survey, (2) calculated from AFS Program monitoring results provided by Nanjing Municipal Reform and Development Commission

their subsidized products from a single producer or area was very limited because of the transportation costs involved (Lin, 2019). Most affordable food shops found that transportation costs to buy directly from farmers were significantly higher than from city wholesale markets. Farmers were also reluctant to sell produce to the shops at prices lower than those charged to wholesale dealers or supermarkets who purchase in bulk (Lin, 2019). Given the longer supply chains and cost reductions through bulk purchase of competitors, there was little room for affordable food shops to sell produce more cheaply without the subsidies. As a result, wholesale markets and not agricultural producers were the major source for food procurement. Another paper by the authors shows that the proportion of shops buying from wholesale markets was 84% for eggs, 83% for rice, pork, and roots and tubers, 82% for cooking oil and beans, and 80% for vegetables.

Missing Discounts

Another factor undermining the impact of affordable food shops is the “missing discount” problem. Shops were required to sell produce at a 15% discount, but this was calculated using the city-wide average price rather than prices at the nearest wet market or supermarket. While the shops sold food at 15% below the city average, their prices were often not 15% or more lower than those in the nearest wet market or supermarket. In some cases, food for sale at affordable food shops was equally priced or even less affordable than in other retail outlets. The missing discount problem thus reduced the incentive of consumers to shop at affordable food shops.

Program Redundancy

Nanjing has a highly competitive food retail market which helps keep food affordable. There are more than 300 wet markets and 170 supermarkets with fresh produce zones. The municipal policy of wet market development has ensured that the development of new wet markets has kept pace with population growth. The policy mandates that wet markets are constructed in all new residential developments (Zhong et al., 2018). There is also strong

competition within wet markets. There are an average of around 40 food stalls within a typical wet market and competition between vendors within a market is common. Supermarkets also compete with prices with each other and with wet markets. Competition avoids any chance of a monopoly over food sales and prices, thus contributing to food affordability. In a competitive environment, AFS shops became progressively redundant.

Monitoring Capacity

The municipal government encountered various challenges of field supervision and monitoring of the affordable food shops which intensified as the number of shops increased. At the beginning of the program, inspectors conducted field checks to monitor whether the food shops were complying with the required price discounts. Yet, as the program expanded, it was the municipal price administration department found it impossible to allocate enough staff to make intensive field checks. In recent years, an online monitoring system was introduced to inspect conformity by the shops, although extra staff were still needed to monitor these shops online.

Conclusion

To address the urban food security challenges accompanying rapid urbanization, China has made various efforts to develop and implement a series of city-focused food policies. Most of these policies emanate from the central government but implementation is often left to the discretion of provincial and city governments with central monitoring and oversight. Prominent among these initiatives is the strategy to facilitate greater access to healthy foods for lower-income urban households through retail subsidization. The main finding from the literature review on food subsidization is the considerable range of supply and demand-side subsidy programs across the Global North and Global South. Perhaps the closest program to that adopted in China is the Public Distribution System in India, with the

notable difference that subsidized shops in India are state-owned whereas in China they are largely in private hands. There is also no unanimity on which strategies are most effective in mitigating food insecurity and improving access to nutritious food. Against this backdrop, this paper focused on the development and implementation of China's Affordable Food Shop Program, using Nanjing as a case study. The AFS Program started in Nanjing in 2011 and aimed to foster food affordability and increased food security, particularly for lower-income households. However, data from a city-wide survey of Nanjing households indicates that as a food retail subsidy tool, the program has not had a significant impact on urban household food insecurity. The paper suggests various reasons for this including inappropriate targeting, program redundancy, and competition from supermarkets and wet markets.

While this analysis is independent of the city's decision to do away with the program, it provides confirmation that the AFS Program was failing to deliver on its initial promise. The food security policy of wet market development and access has been much more successful in ensuring even and equitable coverage and access to wet markets across the city, including for low-income households. However, while low-income and food insecure households may enjoy similar levels of physical access to food outlets as higher-income households, they pay the same set prices for food. Some households are able to take advantage of the Minimum Living Standard Assistance (MLSA) program (Hovhannisyian and Shanoyan, 2020) which was introduced in 2008 for low-income households when increases in the consumer price index exceed 3% (Yu, 2008). Although more research is needed on the effectiveness of this alternative program in Nanjing, an income subsidy may be more desirable for low-income households in the city than subsidized food prices. And some of the subsidy budget saved could potentially be redeployed to provide targeted income support for needy households and more directly mitigate food insecurity. In sum, the 'failed experiment' of AFS Program in Nanjing is unlikely to create a gap in access to food or an increase in household food insecurity across the city.

References

1. An, R. (2012). "Effectiveness of Subsidies in Promoting Healthy Food Purchases and Consumption: A Review of Field Experiments" *Public Health Nutrition* 16: 1215-1228.
2. Anuradha and Raj, T. (2019). "Enhancing Food Security Through Food Subsidy: An Economic Analysis" *IUP Journal of Business Strategy* 16: 27-36.
3. Bakker, R. (2015). "Let Them Eat Cake: Food Prices, Domestic Policy and Social Unrest" *Conflict Management and Peace Science* 32: 309-326.
4. Balistreri, K. (2018). "Family Structure and Child Food Insecurity: Evidence from the Current Population Survey" *Social Indicators Research* 138: 1171-1185.
5. Bellemare, M. (2015). "Rising Food Prices, Food Price Volatility, and Social Unrest" *American Journal of Agricultural Economics* 97: 1-21.
6. Black, A., Brimblecombe, J., Eyles, H., Morris, P., Vally, H. and O'Dea, K. (2012). "Food Subsidy Programs and the Health and Nutritional Status of Disadvantaged Families in High Income Countries: A Systematic Review" *BMC Public Health* 12: 1099.
7. Blakely, T., Cleghorn, C., Mizdrak, A., Waterlander, W. and Ngheim, N. (2020). "The Effect of Food Taxes and Subsidies on Population Health and Health Costs: A Modelling Study" *The Lancet Public Health* 5: E404-E413.
8. Clapp, J. (2009). "Food price Volatility and Vulnerability in the Global South: Considering the Global Economic Context" *Third World Quarterly* 30: 1183-1196.
9. Chakrabarti, S., Kishore, A. and Roy, D. (2018). "Effectiveness of Food Subsidies in Raising Healthy Food Consumption: Public Distribution of Pulses in India" *American Journal of Agricultural Economics* 100: 1427-1449.
10. Chang, K., Zastrow, M., Zdorovtsov, C., Quast, R., Skjonsberg, L. and Stluka, S. (2015). "Do SNAP and WIC Programs Encourage More Fruit and Vegetable Intake? A Household Survey in the Northern Great Plains" *Journal of Family and Economic Issues* 36: 477-490.
11. Coates, J., Swindale, A. and Bilinsky, P. (2007). *Household Food Insecurity Access Scale (HFIAS) for measurement of household food access: Indicator guide (V. 3)*. Washington, D.C.: FANTA.
12. Crush, J., Frayne, B. and Pendleton, W. (2012). "The Crisis of Food Insecurity in African Cities" *Journal of Hunger and Environmental Nutrition* 7: 271-292.
13. Drammeh, W., Hamid, N., and Rohana, A. (2019). "Determinants of Household Food Insecurity and Its

- Association with Child Malnutrition in Sub-Saharan Africa: A Review of the Literature” *Current Research in Nutrition and Food Science* 7: 610–623.
14. Elbel, B., Moran, A., Dixon, L., Kiszko, K., Cantor, J., Abrams, C. and Mijanovich, T. (2015). “Assessment of a Government-Subsidized Supermarket in a High-Need Area on Household Food Availability and Children’s Dietary Intakes” *Public Health Nutrition* 18: 2881–2890.
 15. Esmacili, A., Karami, A. and Najafi, B. (2013). “Welfare Effects of Alternative Targeted Food Subsidy Programs in Iran” *Food Security* 5: 451–456.
 16. George, N. and McKay, F. (2019). “The Public Distribution System and Food Security in India” *International Journal of Environmental Research and Public Health* 16: 3221.
 17. Lishui District Government (2018). “Announcement of New Establishment of An Affordable Food Shop” At: http://www.njls.gov.cn/lqrmzf/201811/t20181116_1227868.html
 18. Long, J. and Freese, J. (2001). *Regression Models for Categorical Dependent Variables Using Stata (3rd Ed.)* (College Station: Stata Press Publication).
 19. Frayne, B. and McCordic, C. (2015). “Planning for Food Secure Cities: Measuring the Influence of Infrastructure and Income on Household Food Security in Southern African cities” *Geoforum* 65: 1–11.
 20. Feltenstein, A. (2017). “Subsidy Reforms and Implications for Social Protection: An Analysis of IMF Advice on Food and Fuel Subsidies” Background Paper No. BP/17-01/02, International Monetary Fund, Washington, D.C.
 21. Freedman, M. and Kuhns, A. (2018). “Supply-Side Subsidies to Improve Food Access and Dietary Outcomes: Evidence from the New Markets Tax Credit” *Urban Studies* 55: 3234–3251.
 22. Fuyang Municipal Government (2021). “Notice of Keeping Affordable Food Shops in Operation During Spring Festival” At: www.fgw.fy.gov.cn/content/detail/60126aef7f8b9a3d118b4580.html
 23. Galloway, T. (2014). “Is the Nutrition North Canada Retail Subsidy Program Meeting the Goal of Making Nutritious and Perishable Food More Accessible and Affordable in the North?” *Canadian Journal of Public Health* 105: e395–e397.
 24. Galloway, T. (2017). “Canada’s Northern Food Subsidy Nutrition North Canada: A Comprehensive Program Evaluation” *International Journal of Circumpolar Health* 76: 1279451.
 25. Haug, R. and Hella, J. (2013). “The Art of Balancing Food Security: Securing Availability and Affordability of Food in Tanzania” *Food Security* 5: 415–426.
 26. Hosseini, S., Pakravan Charvadeh, M., Salami, H. and Flora, C. (2017). “The Impact of the Targeted Subsidies Policy on Household Food Security in Urban Areas in Iran” *Cities* 63: 110–117.
 27. Huang, J. and Yang, G. (2016). “Understanding Recent Challenges and New Food Policy in China” *Global Food Security* 12: 119–126.
 28. Huang, J., Wang, X. and Rozelle, S. (2013). “The Subsidization of Farming Households in China’s Agriculture” *Food Policy* 41: 124–132.
 29. Huang, C., Zhong, F. and He, J. (2013). “Income vs Price Subsidy: Policy Options to Help the Urban Poor Facing Food Price Surge” *China Agricultural Economic Review* 5: 89–99.
 30. Ismail, Z. (2021). “Interaction Between Food Prices and Political Instability” K4D Helpdesk Report, Institute of Development Studies, Brighton.
 31. Jensen, R. and Miller, N. (2011). “Do Consumer Price Subsidies Really Improve Nutrition?” *Review of Economics and Statistics* 93: 1205–1223.
 32. Jha, S. and Ramaswami, B. (2010). “How Can Food Subsidies Work Better? Answers from India and the Philippines” ADB Economics Working Paper Series No. 221, Asian Development Bank, Manila.
 33. Jiangsu Provincial Government (2011). “Opinion on Promoting Development of Affordable Food Shops and Stabilizing Food Prices” At: www.law020.com/fagui/public_dllgdv.html
 34. Jiangsu Provincial Government (2012). “Administrative Measures for Affordable Food Shop”. *Government Gazette of Jiangsu Province*, pp. 54–57.
 35. Jiangsu Province Government (2019). “Notice on Further Improving the Administration of the Non-Grain Food Price” At: http://jsdrc.jiangsu.gov.cn/art/2019/10/22/art_77150_8985982.html
 36. Kaushal, N. and Muchomba, F. (2015). “How Consumer Price Subsidies Affect Nutrition” *World Development* 74: 25–42.
 37. Krishnan, N., Olivieri, S. and Ramadan, R. (2019). “Estimating the Welfare Costs of Reforming the Iraq Public Distribution System: A Mixed Demand Approach” *Journal of Development Studies* 55: 91–106.
 38. Lee, A., Mhurchu, C., Sacks, G., Swinburn, B. et al. (2013). “Monitoring the Price and Affordability of Foods and Diets Globally” *Obesity Reviews* 14: 82–95.
 39. Lin, N. (2019). “The Operation Status of Affordable Food Shops Jiangsu Price” At: www.jsjgxxh.org/col21/index.php
 40. Loopstra, R. and Tarasuk, V. (2013). “Severity of Household Food Insecurity is Sensitive to Change in Household Income and Employment Status Among Low-Income Families” *Journal of Nutrition* 143: 1316–

- 1323.
41. Lopez, R., He, X. and De Falcis, E. (2017). "What Drives China's New Agricultural Subsidies?" *World Development* 93: 279-292.
 42. Ma, X., Liese, A., Bell, B., Martini, L., Hibbert, J., Draper, C., Burke, M. and Jones, S. (2016). "Perceived and Geographic Food Access and Food Security Status Among Households with Children" *Public Health Nutrition* 19: 2781-2788.
 43. McCordic, C., Riley, L. and Raimundo, I. (2021). "Household Food Security in Maputo: The Role of Gendered Access to Education and Employment" *Development Southern Africa* 38: 816-827.
 44. Meng, L. (2012). "Can Grain Subsidies Impede Rural-Urban Migration in Hinterland China? Evidence from Field Surveys" *China Economic Review* 23: 729-741.
 45. Meyer, D. and Keyser, E. (2015). "Validation and Testing of the Lived Poverty Index Scale (LPI) in a Poor South African Community" *Social Indicators Research* 129: 147-159.
 46. Mohamed, S., Mberu, B., Amendah, D., Kimani-Murage, E. et al. (2016). "Poverty and Uneven Food Security in Urban Slums" In J. Crush and J. Battersby (Eds.), *Rapid Urbanisation, Urban Food Deserts and Food Security in Africa* Cham: Springer Publishing, pp. 97-112.
 47. Mutisya, M., Ngware, M., Kabiru, C. and Kandala, N. (2016). "The Effect of Education on Household Food Security in Two Informal Urban Settlements in Kenya: A Longitudinal Analysis" *Food Security* 8: 743-756.
 48. Nanjing Bureau of Administration for Commodity Prices (2017). "Expenditure Budget of Special Fund and Recurrent Expenditures" At: www.wjj.nanjing.gov.cn/njswjj/201810/t20181021_549506.html
 49. Nanjing Municipal Government. (2011). "Opinion About Establishing Affordable Shops and Zone to Stabilize Food Prices" At: www.nanjing.gov.cn/zdgk/201202/t20120229_1055691.html
 50. National Development and Reform Commission. (2011). "Notice about Improving Price Policy to Promote Vegetable Production and Distribution" At: www.ndrc.gov.cn/fzgggz/jggg/zcfg/201105/t20110520_413159.html
 51. National Development and Reform Commission. (2012). "Opinion on Further Promoting Establishment of Affordable Food Shops" At: <http://law.esnai.com/mview/116586>
 52. Naylor, J., Deaton, B. and Ker, A. (2020). "Assessing the Effect of Food Retail Subsidies on the Price of Food in Remote Indigenous Communities in Canada" *Food Policy* 93: 101889.
 53. Ni Mhurchu, C., Blakely, T., Jiang, Y., Eyles, H. and Rodgers, A. (2009). "Effects of Price Discounts and Tailored Nutrition Education on Supermarket Purchases: A Randomized Controlled Trial" *American Journal of Clinical Nutrition* 91: 736-747.
 54. NMCDR (2019). "Interview with Government Official from Nanjing Municipal Commission of Development and Reform" August 13.
 55. Nnoaham, K., Sacks, G., Rayner, M., Mytton, O. and Gray, A. (2009). "Modelling Income Group Differences in the Health and Economic Impacts of Targeted Food Taxes and Subsidies" *International Journal of Epidemiology* 38: 1324-1333.
 56. Obayelu, O. (2018). "Food Security in Urban Slums: Evidence from Ibadan Metropolis, Southwest Nigeria" *Journal for the Advancement of Developing Economies* 7: 1-17.
 57. Phoenix New Media Limited. (2018). "Consumers Have Saved CNY0.42 Billion Yuan Due to Affordable Shops" At: www.js.ifeng.com/a/20180614/6655326_0.shtml
 58. Pinstrup-Andersen, P. (Ed.) (2014). *Food Price Policy in an Era of Market Instability: A Political Economy Analysis* (Oxford: Oxford University Press).
 59. Powell, L. and Chaloupka, F. (2009). "Food Prices and Obesity: Evidence and Policy Implications for Taxes and Subsidies" *Milbank Quarterly* 97: 229-257.
 60. Qi, X., Si, Z., Zhong, T., Huang, X. and Crush, J. (2019). "Spatial Determinants of Urban Wet Market Vendor Profit in Nanjing, China" *Habitat International* 94: 102064.
 61. Ramadan, R. and Thomas, A. (2011). "Evaluating the Impact of Reforming the Food Subsidy Program in Egypt: A Mixed Demand Approach" *Food Policy* 36: 638-646.
 62. Riley, L. and Dodson, B. (2020). "The Gender-Urban-Food Interface in the Global South" In J. Crush, B. Frayne and G. Haysom (Eds.), *Handbook on Urban Food Security in the Global South* (Cheltenham: Edward Elgar), pp. 218-232.
 63. Shimokawa, S. (2010). "Nutrient Intake of the Poor and Its Implications for the Nutritional Effect of Cereal Price Subsidies: Evidence from China" *World Development* 38: 1001-1011.
 64. Si, Z., Scott, S. and McCordic, C. (2019). "Wet Markets, Supermarkets and Alternative Food Sources: Consumers' Food Access in Nanjing, China" *Canadian Journal of Development Studies* 40: 79-86.
 65. Smith, T. (2014). "Feeding Unrest: Disentangling the Causal Relationship Between Food Price Shocks and Sociopolitical Conflict in Urban Africa" *Journal of Peace Research* 51: 679-695.
 66. St-Germain, A., Galloway, T. and Tarasuk, V. (2019). "Food Insecurity in Nunavut Following the

- Introduction of Nutrition North Canada” *Canadian Medical Association Journal* 19 : E552-E558.
67. Su, S., Li, Z., Xu, M., Cai, Z. and Weng, M. (2017). “A Geo-Big Data Approach to Intra-Urban Food Deserts: Transit-Varying Accessibility, Social Inequalities, and Implications for Urban Planning” *Habitat International* 64: 22-40.
 68. Sun, J. (2012). “Newly Established 53 Affordable Food Shops” At: www.news.sina.com.cn/o/2012-07-17/064424787955.shtml
 69. Swindale, A. and Bilinsky, P. (2006). “Development of a Universally Applicable Household Food Insecurity Measurement Tool: Process, Current Status, and Outstanding Issues” *Journal of Nutrition* 136: 1449-1452.
 70. Talaat, W. (2018). “The Targeting Effectiveness of Egypt’s Food Subsidy Programme: Reaching the Poor?” *International Social Security Review* 71: 103-123.
 71. Tarasuk, V., St-Germain, A. and Mitchell, A. (2019). “Geographic and Socio-Demographic Predictors of Household Food Insecurity in Canada, 2011-12” *BMC Public Health* 19: 12.
 72. Wang, S., Lu, X., Wang, G., Yang, L., Lu, Y. and Sun, G. (2013). “A Survey of Dietary Patterns and Health Status of Residents in Nanjing City” *Chongqing Medicine* 42: 320-322.
 73. Yi, F., Sun, D., Zhou, Y., Lopez, R., He, X. and De Falcis, E. (2015). “Grain Subsidy, Liquidity Constraints and Food Security: Impact of the Grain Subsidy Program on the Grain-Sown Areas in China” *Food Policy* 50: 114-124.
 74. Yu, Q. (2008). “Nanjing Mechanism Coupling Price Increase and Income Subsidy to Low-income Households” At: www.gov.cn/govweb/fwxx/sh/2008-04/23/content_952056.htm
 75. Yuan, Y., Si, Z., Zhong, T., Huang, X. and Crush, J. (2021). “Revisiting China’s Supermarket Revolution: Complementarity and Co-Evolution Between Traditional and Modern Food Outlets” *World Development* 147: 105631.
 76. Zhong, T., Si, Z., Crush, J., Xu, Z., Huang, X., Scott, S., Tang, S. and Zhang, X. (2018). “The Impact of Proximity to Wet Markets and Supermarkets on Household Dietary Diversity in Nanjing City, China” *Sustainability* 10: 1465.
 77. Zhong, T., Si, Z., Crush, J., Scott, S., and Huang, X. (2019). “Achieving Urban Food Security Through a Hybrid Public-Private Food Provisioning System: The Case of Nanjing, China” *Food Security* 11: 1071-1086.