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Air pollution and food prices: evidence from China

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Air pollution is one of the top environmental concerns in China. On days with severe air pollution, people (both consumers and producers) often reduce outdoor economic activities in order to avoid possible health damages. This impacts the market trade of fresh food products, at least in a short run. This empirical study sheds light on the impact of air pollution on the short run prices of three major fresh food products (Chinese cabbage, tomatoes and pork) using daily data from the largest outdoor wholesale market in Beijing. With an increase in AQI (Air Quality Index) by 100 units, prices for Chinese cabbage and tomatoes decrease by 1.19 and 0.89 per cent. With an increase in PM2.5 concentration by 100 μg/m^3, prices for Chinese cabbage and tomatoes decrease by 0.64 and 0.55 per cent. Air pollution affects vegetable prices, but has no significant impact on prices of pork products.

Key words: air pollution, air quality index, Beijing, food price, PM2.5.

1. Introduction

In developing countries, rapid economic growth and drastic urbanisation are usually accompanied by increasing environmental pollution, and China is no exception (Yu and Abler 2010; Zheng and Kahn 2013). Particularly, air pollution is a top environmental concern in urban China, and the major pollutants include nitrous oxides (NOx), carbon monoxide (CO) and atmospheric particulate matters. Smog outbreaks are frequently observed in China. According to the official data published by the Ministry of Environmental Protection, the proportion of haze-fog[1] days in 2013 was 35.9 per cent, and the annual average PM2.5 (particles less than 2.5 micrometres in aerodynamic diameter) concentration was 26–160 μg/m^3, far above the safety standard set by the World Health Organization (10 μg/m^3).

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[1] Haze-fog is the result of constant interaction between specific climatic conditions and human activities. When PM2.5 emissions exceed the environmental capacity, the sunlight, high relative humidity and stagnant air flow, make it is very easy for haze and fog to form.

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Air pollution can lead to severe health damages. It is linked to increases in mortality rate, incidences of cancers, visits to physicians, low birthweight and significantly shortens life expectancy (Seaton *et al.* 1995; Künzli *et al.* 2000; Brunekreef and Holgate 2002; Hoek *et al.* 2002; Yu and Abler 2010; Chen *et al.* 2013). On days with heavy air pollution, people often reduce outdoor activities in order to avoid health damages.

During Chinese public holidays in October 2016, Beijing, one of the most popular tourist destinations in China, suffered from very heavy hazes, which directly led to an 11.2 per cent decrease in the number of tourists compared to the previous year.[2] Poor visibility due to fog, mist and haze can easily cause road traffic accidents, cancellation of flights and closedown of highways.

In December 2013, we conducted a household survey in Beijing of people's behaviour on pollution days. Amongst our 624 respondents, 43.15 per cent stated that their daily life has been 'severely affected', 52.39 per cent 'somewhat affected', and only 4.46 per cent stated 'not affected' in pollution days. In sum, more than 95 per cent of people have their daily life affected by air pollution.

We conjecture that these daily activity changes could alter both supply and demand conditions, which consequently shifts market equilibrium. Thus, air pollution could increase the volatility of commodity prices, which is particularly true for some fresh food products. However, this phenomenon is not well studied in the literature.

An enormous body of the literature shows that the social and economic impact of air pollution could be colossal, diverse, and long lasting. For example, part of this literature sheds light on the effect of air pollution on property values with use of the hedonic price techniques (Ridker and Henning 1967; Smith and Deyak 1975; Harrison and Rubinfeld 1978; Smith and Huang 1995; Brasington and Hite 2005). Some other studies have empirically investigated the influence of air pollution on labour efficiency and firm productivity. For instance, Zivin and Neidell (2011) find that a 10 ppb decrease in ozone concentrations increases agricultural worker productivity by 4.2 per cent. Similarly, Chang *et al.* (2014) reveal a significant negative impact of PM2.5 on the productivity of indoor workers and find that reductions in PM2.5 in the U.S. during 1999–2008 generated $19.5 billion in labour cost savings, accounting for nearly one-third of the total estimated welfare benefits. Cui *et al.* (2016) find an inverse relationship between firm productivity and pollution emission per unit output, and exporting firms have lower emission per unit output.

In the agricultural sector, the literature finds that air pollution can stunt plant growth (Emberson *et al.* 2003; Heck *et al.* 1988), thereby reducing crop yield. A number of studies have evaluated the impact of some common air

[2] See http://env.people.com.cn/n1/2016/1003/c1010-28755747.html.

pollutants (e.g. SO_2, NO_x and O_3) on agricultural crop growth (e.g. Voutsa *et al.* 1996; Agrawal *et al.* 2003).

Food prices are strongly connected with both consumer and producer welfare (Yu 2014a,b). The current literature mainly attributes domestic food price volatility to the international food market, unpredictable weather shocks, petroleum/energy prices and government policies (Gerrard and Roe 1983; Ramaswami and Balakrishnan 2002; Clapp 2009; Yu and Zhao 2009; Mueller *et al.* 2011; Anderson and Nelgen 2012; Gardebroek and Hernandez 2013; Meyer and Yu 2013; Yu 2014a; Catão and Chang 2015; Yu and Abler 2016). However, examining the effect of air pollution on food price volatility has largely been neglected in the current literature.

To fill in the research gap, we evaluate the effects of air pollution on food prices in Beijing (city), using the wholesale market prices for three major fresh food products consumed in China: Chinese cabbage, tomatoes and pork. To do this, we develop a theoretical model based on the market equilibrium and employ the autoregressive distributed lag (ARDL) model.. As the capital and second largest city in China, for years Beijing has been well known to have serious air pollution problems. Such a study could also have significant policy impacts.

The study is organised as follows. Section 2 presents a theoretical framework for modelling the effects of air pollution on food prices. Section 3 discusses our empirical strategy, which is followed by a description of the data in Section 4. Section 5 presents the estimation results and the discussion. Finally, we conclude in Section 6.

2. Theoretical framework

Air pollution could affect commodity prices through the channels of both supply and demand. On the one hand, the fall in labour productivity (Zivin and Neidell 2011; Chang *et al.* 2014), or decline in crop yields (Agrawal *et al.* 2003; Emberson *et al.* 2003; Heck *et al.* 1988), or the decrease in outdoor activities of farmers or traders, could lead to a decrease in supply, which could push up food prices. On the other hand, based on the weather forecast, consumers may adjust shopping times and store some shelf-stable food to avoid exposure to harmful air pollution (Wen *et al.* 2009), which would eventually shift demand and would affect commodity prices. The final effect of air pollution on commodity prices depends on the aggregate effects of demand and supply in response to air pollution. This study formalises ideas and adopts a similar theoretical framework as proposed by Yu (2014a).

Assume both demand D_{it} and supply S_{it} of food i at time t are determined by food price P_{it} and air quality A_t,

$$\begin{aligned} D_{it} &= D(A_t, P_{it}) \\ S_{it} &= S(A_t, P_{it}) \end{aligned} \tag{1}$$

Taking a total derivative,

$$\begin{aligned} \mathrm{d}D_{it} &= \frac{\partial D_{it}}{\partial A_t}\mathrm{d}A_t + \frac{\partial D_{it}}{\partial P_{it}}\mathrm{d}P_{it} \\ \mathrm{d}S_{it} &= \frac{\partial S_{it}}{\partial A_t}\mathrm{d}A_t + \frac{\partial S_{it}}{\partial P_{it}}\mathrm{d}P_{it} \end{aligned} \tag{2}$$

Based on the market equilibrium condition, $\mathrm{d}D_{it} = \mathrm{d}S_{it}$ and,

$$\frac{\mathrm{d}P_{it}}{\mathrm{d}A_t} = \frac{\frac{\partial D_{it}}{\partial A_t} - \frac{\partial S_{it}}{\partial A_t}}{\frac{\partial S_{it}}{\partial P_{it}} - \frac{\partial D_{it}}{\partial P_{it}}} \tag{3}$$

By first rewriting Equation (3), we can then obtain the food price elasticity $\eta_{P_i,A}$ with respect to air quality for food i.

$$\eta_{P_i,A} = \frac{\mathrm{d}P_{it}}{\mathrm{d}A_t} \cdot \frac{A_t}{P_{it}} = \frac{\frac{\partial D_{it}}{\partial A_t} \cdot \frac{A_t}{D_{it}} - \frac{\partial S_{it}}{\partial A_t} \cdot \frac{A_t}{S_{it}}}{\frac{\partial S_{it}}{\partial P_{it}} \cdot \frac{P_{it}}{S_{it}} - \frac{\partial D_{it}}{\partial P_{it}} \cdot \frac{P_{it}}{D_{it}}} = \frac{\varepsilon_{D_i,A} - \varepsilon_{S_i,A}}{\varepsilon_{S_i,P_i} - \varepsilon_{D_i,P_i}} \tag{4}$$

where $\varepsilon_{D_i,A}$ and $\varepsilon_{S_i,A}$ are, respectively, demand and supply elasticities with respect to air quality for food i. ε_{D_i,P_i} and ε_{S_i,P_i} are the price elasticities of demand and supply, respectively.

Economic theory indicates that for a normal good, the sign of price elasticity of demand ε_{D_i,P_i} is negative, while the price elasticity of supply ε_{S_i,P_i} is positive. Therefore, the denominator of Equation (4) is always positive. Notably, we presume that the denominator is a positive constant, because the price elasticities of demand and supply are independent of air quality.

However, the sign of the numerator of Equation (4) is difficult to infer. As aforementioned, both consumers and suppliers tend to reduce their outdoor activities on heavy pollution days to avoid health damage, which simultaneously pushes down both demand and supply in the short run. Both the signs of $\varepsilon_{D_i,A}$ and $\varepsilon_{S_i,A}$ are positive, although their magnitudes are different depending on the properties of the food (e.g. storability). Finally, the aggregate effect of air quality on food prices depends on the relative scales of demand and supply elasticities with respect to air quality.

1. If the stimulating effect of air quality on demand is larger than that on supply, then $\varepsilon_{D_i,A} > \varepsilon_{S_i,A}$, we have $\eta_{P_i,A} > 0$, implying that the food price increases with the improvement of air quality.
2. If the stimulating effect on demand is offset by that on supply, then $\varepsilon_{D_i,A} = \varepsilon_{S_i,A}$, that is $\eta_{P_i,A} = 0$, implying that air quality has no significant effect on food price.

3. If the stimulating effect on demand is smaller than that on supply ($0 < \varepsilon_{D_i,A} < \varepsilon_{S_i,A}$), or air pollution stimulates demand for some special foods ($\varepsilon_{D_i,A} < 0$), then $\eta_{P_i,A} < 0$ implying that the food price increases with the deterioration of air quality.

The demand and supply elasticities with respect to air quality and the final aggregate effect on prices may differ for each product. For instance, vegetables may be different from meat products due to a different demand and supply structure. In this study, we shed light on three specific fresh food products: Chinese cabbage, tomatoes and pork products, which are all staple daily foods for Chinese consumers (Yu and Abler 2014; Zhou *et al.* 2015).

3. Econometric model

Food price determination is a dynamic process, which could be modelled by many different econometric models. However, finite lag models often impose very strong restrictions on the lagged response of the dependent variable to a change in independent variables. As a general compromise, the autoregressive distributed lag (ARDL) model provides a more flexible platform to model time series (Greene 2007, pp. 681). Particularly, the ARDL(1, 1) model has become the most frequently used in modern time series analysis (Greene 2007, pp. 689). The model is specified as:

$$\ln P_t = \alpha_0 + \sum_{i=1}^{p} \delta_i \ln P_{t-i} + \sum_{j=1}^{n} \sum_{i=0}^{q} \omega_{j,i} X_{j,t-i} + \rho \text{Holiday}_t + \sum_{k=1}^{6} \gamma_k \text{Week}_{tk} + \sum_{l=1}^{11} \theta_l \text{Month}_{tl} + \sum_{m=1}^{1\text{or}2} \varphi_m \text{Year}_{tm} + \varepsilon_{it} \tag{5}$$

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where P_t is the food price at time t, δ_i is the coefficient for the lag of food prices. $X_{j,t}$ is a vector of exogenous variables, including air pollution levels, daily temperature and 24-h precipitation. $\omega_{j,i}$ captures their effects on food prices at different times. Severe weather condition, as well as pollution, may have both influences on consumer behaviour (Agnew and Thornes 1995; Murray *et al.* 2010) and commodity supply (Olesen & Bindi, 2002; Zhang & Carter, 1997), so it is reasonable to add these variables into regression. Additionally, food prices tend to increase during traditional festivals, so we add a dummy variable Holiday_t in the baseline model. We also include dummies for each day in a week (with Sunday as the omitted category) Week_{tk}, for each month of the year (with December as the omitted category) Month_{tl}, and year dummies Year_{tm} to net out potential seasonality effects. α_0 is a constant, ε_t is the error term, and p and q are maximum lag orders.

The ARDL model provides a general form for us to test the dynamic impact of air pollution on food prices. When ω_i = 0, the ARDL(1, 1) model degenerates to an AR(1) model.

Notably, ARDL model requires that the dependent variable does not have a unit root. Hence, a test of unit roots for ln P_{it} is a precondition for conducting these econometric exercises. In addition, there may exist serial correlation in the error terms, which may lead to incorrect standard errors. Hence, we use the Newey–West method to correct the standard errors (Newey and West 1987). Greene (2007, PP.643) proposes the lags in Newey–West could be $N^{1/4}$ where N is the sample size.

4. Data sources and descriptive statistics

4.1 Data sources

Beijing is the capital and second largest city in China. It has been well known for its severe air pollution for many years, due to its basin geographic location, increasing population, limited resources and heavy pollution in neighbouring regions. In order to carry out the abovementioned research, we collected daily food prices, daily AQI numbers and daily PM2.5 concentration from various sources.

4.1.1 Air quality measures

There are many ways to measure air quality. In general, air pollutants are subdivided into criteria and non-criteria air pollutants. The former group includes particulate matter (PM2.5 and PM10), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2) and carbon monoxide (CO), and most countries have regulated the maximum amount of each criteria pollutant in ambient air. On the other hand, non-criteria air pollutants are much more numerous, but no general maximum levels exist.

The Ministry of Environmental Protection (MEP) in China is responsible for monitoring the level of air pollution. Based on the content of criteria air pollutants, the MEP then calculates the air quality index (AQI), ranging from 0 to 500, and categorises air quality into six levels: Grade I (Excellent, AQI $\leq$ 50), Grade II (Good, 50 < AQI $\leq$ 100), Grade III (Light Pollution, 100 < AQI $\leq$ 150), Grade IV (Medium Pollution, 150 < AQI $\leq$ 200), Grade V (Heavy Pollution, 200 < AQI $\leq$ 300) and Grade VI (Extremely Heavy Pollution, 300 < AQI). If air quality is worse than Grade II, it may be harmful to health. The statistics from the National Bureau of Statistics of China show that more than half of the days in Beijing were in fact polluted in recently years.

As the AQI is the most prevalent index used for measuring air quality in China, we take the daily AQI published by the MEP to measure air quality. As these data have been published since 2014, the time frame is from 1 January 2014 to 31 December 2015.

However, for the general public, the AQI calculation is often not understandable, and the accuracy of AQI is frequently questioned by researchers (Ghanem and Zhang 2014). In addition, the AQI is capped at 500, so that the extreme pollution cases, which could significantly affect human behaviour, may not be correctly mirrored by this index.

As a comparison, we also use PM2.5 concentration data published by the U.S. Embassy in Beijing[3] to measure air quality. PM2.5 is a particularly harmful pollutant particle, as it can penetrate deep into the lungs and blood streams, causing severe health damages. The PM2.5 concentration data of the U.S. Embassy in Beijing are an independent measure of air quality and are believed to be less manipulated. The U.S. Embassy reports hourly air pollution information, so we use the 24-hour average to obtain daily PM2.5 concentrations. To match the daily prices data, the PM2.5 data we used spans three years, from 1 January 2013 to 31 December 2015. However, we find that the trends between AQI and PM2.5 are basically consistent.

4.1.2 Food prices

We collect daily food prices from Beijing Xinfadi Agricultural Products Wholesale Market.[4] This market is located in southern Beijing, between the 4th and 5th Ring Roads and much of the fresh food supply comes from Hebei and Shandong Province,[5] which are also highly air polluted areas in northern China. This outdoor food market is able to satisfy over 90 per cent of food demand in the city. It bears 70 per cent of the vegetable supply and 80 per cent of super market fruit supply in Beijing. Therefore, the daily commodity trading prices published by Xinfadi is a good reflection of the city's food prices. As Chinese cabbage and tomatoes are particularly popular vegetables in northern China, we specifically shed light on these two products. For comparison, pork (mainly the carcass meat) is also included in the analysis, as more than 60 per cent of consumed meat products in China are made from pork (Yu and Abler 2014). Although Xinfadi Wholesale Market also sporadically reports the prices of other products, they cannot be used in this study due to many missing observations. The trends of the three food prices are presented in Figure 1.

4.1.3 Other variables

Except for pollution, the weather conditions also affect people's outdoor activities. In order to control for these variables, we include temperature (maximum temperature) and precipitation conditions in the regression.[6] Data on minimum daily temperature show similar temporal patterns as the

[3] Source: http://www.stateair.net/web/historical/1/1.html.

[4] Beijing Xinfadi Agricultural Products Wholesale Market was established in 1988 and has become the largest professional agri-products wholesale market in Asia. It can handle up to 16000 tons of vegetables, 16,000 tons of fruit, more than 3000 pigs, 3000 sheep, 500 cattle and 1800 tons of aquatic products every day.

[5] In 2014, 20.5 per cent vegetables sold in Xinfadi came from Hebei province and 19.0 per cent vegetables were coming from Shandong province. Source: http://www.xinfadi.com.cn/company/cintros.shtml.

[6] Source: http://www.tianqihoubao.com/lishi/beijing.html.

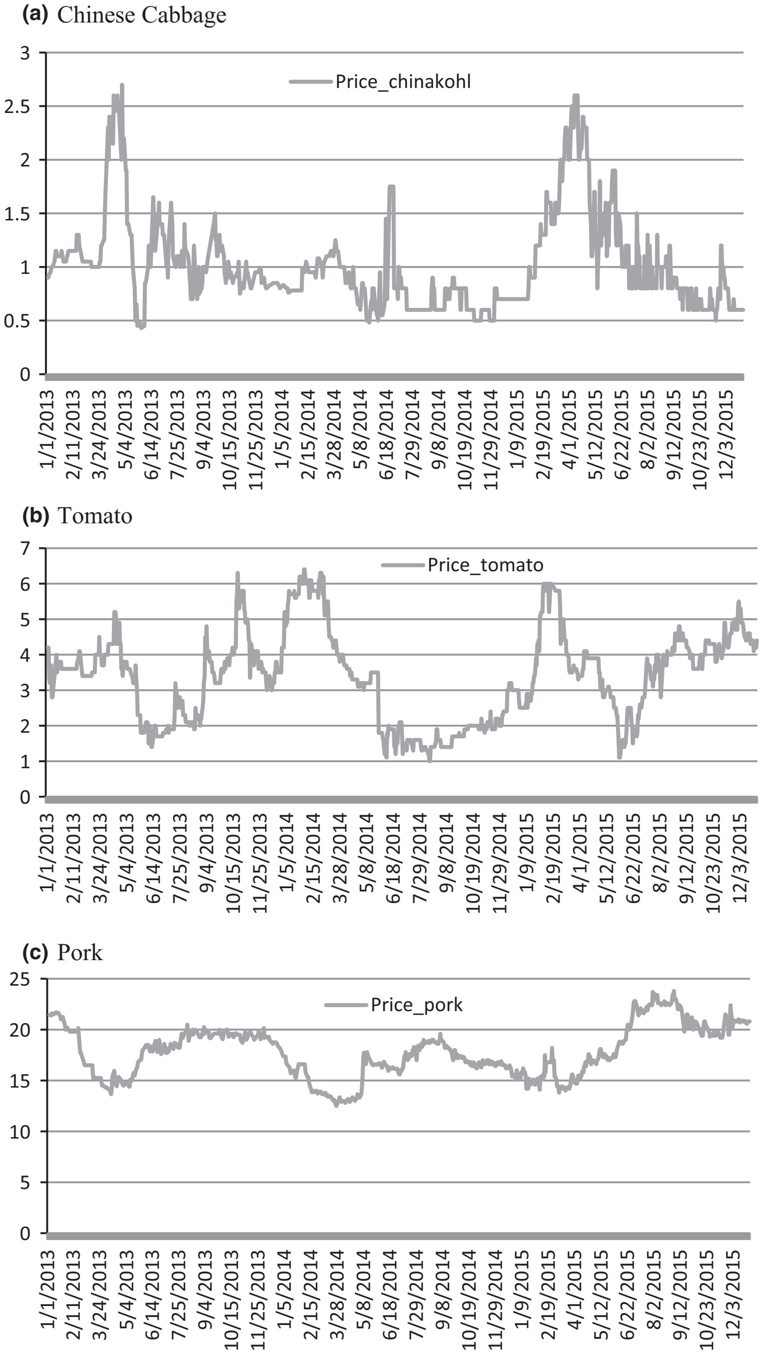

Figure 1 The trends in food prices Source: Beijing Xinfadi Agricultural Products Wholesale Market.

Table 1 Descriptive analysis of variables

Variable	Obs.	Mean	SD	Min	Max	Units/definition
Dependent variable						
Price_cabbage	1092	1.02	0.44	0.43	2.70	Chinese cabbage price, yuan/kg
Price_tomato	1092	3.38	1.28	1.00	6.40	Tomato price, yuan/kg
Price_pork	1092	17.77	2.51	12.50	23.80	Pork price, yuan/kg
Independent variable						
AQI	730	125.38	76.60	23.00	485.00	Daily Air Quality Index
pm2.5	1095	94.00	80.43	6.08	557.31	Daily PM2.5 Concentrations, $\mu g/m^3$
Temperature_max	1095	18.72	11.14	−6.00	39.00	Daily maximum temperature, °C
Rain	1095	0.24	0.43	0	1	Dummy for whether it rains or not
Holiday	1095	0.08	0.26	0	1	Dummy for whether it is a public holiday or not

Notes: The price of tomato is taken from the database of Beijing Xinfadi Agricultural Products Wholesale Market,[8] and the prices of Chinese cabbage and pork are taken from Chinese Agricultural Information Network.[9] Overall, the time frame is from 4 January 2013 to 31 December 2015. The 'AQI' is taken from the Ministry of Environmental Protection. The 'pm2.5′' is taken from the U.S. Embassy in Beijing. The weather variables, 'temax', and 'rain' are taken from the network.

maximum temperature series and yield similar results to what we find with the maximum temperature, so we do not report these.[7]

Figure 1 has demonstrated that food prices show strong seasonality, so do the air pollution indicators. Usually, air pollution reaches high levels in winter seasons due to coal burning for heating and cool weather condition. In order to control for seasonality, we include weekday, month and year dummies in the econometric models.

It is known that holidays may affect food prices. Hence, a dummy for national holiday is also included.

4.2 Descriptive statistics

Table 1 presents the definitions and descriptive statistics of the variables. The average price of Chinese cabbage was 1.02 yuan/kg, with a standard deviation of 0.44. Tomatoes had an average price of 3.38 yuan/kg and a standard deviation of 1.28. The pork price was 17.77 yuan/kg on average, with a standard deviation of 2.51. The relatively large deviations show the high volatilities of food prices in Beijing.

During 2014–2015, the average daily AQI was 125.38, with a standard deviation of 76.60. As the national standard for good air quality is an AQI of 100 or less, this reaffirms the severity of air pollution in Beijing.

[7] Source: http://ccm.ytally.com/fileadmin/user_upload/downloads/publications_5th_workshop/Wang_paper.pdf.

[8] Source: http://www.xinfadi.com.cn/marketanalysis/0/list/1.shtml.

[9] This network is hosted by the Ministry of Agriculture of the P.R. China. Source: http://www.agri.cn/.

Moreover, the average daily PM2.5 concentration was 94.00 $\mu g/m^3$ (standard deviation 80.43) over three years, with highs usually occurring in winter seasons. Given that the national safety standard for PM2.5 is 75 $\mu g/m^3$, this is also evidence for the severe air pollution in Beijing.

4.3 Test for unit roots

If the dependent variables in the ARDL or AR model have unit roots, it would make the model unstable. The augmented Dicky-Fuller test (ADF) is the most prevalent approach in the literature (Dickey and Fuller 1979, 1981; Elliott *et al*. 1996). Table 2 reports the unit root test for Chinese cabbage price, tomato price, pork price, AQI and PM2.5 concentration. The results rejected the null hypothesis of existence of unit roots for all variables. Hence, both the ARDL and AR model are legitimate here.

5 Estimation results and discussions

Tables 3–5 present the estimated results of the ARDL and AR models for Chinese cabbage, tomatoes and pork, respectively. The coefficients for time dummies (week, month and year) are not reported due to space limit.

Generally, the AR(1) model performs better in estimating the effects of air pollution on food prices, as all lagged terms for air pollution are not statistically significant. Air pollution has immediate negative effects on Chinese cabbage price and tomato price, but has no significant effects on pork price. Moreover, the results between AR(1) and ARDL model are very similar, which mirrors the robustness of our results. The following discussions are based on the results of the AR(1) model.

5.1 Chinese cabbage

Column 2 of Table 3 reports the estimation results of the AR(1) model for Chinese cabbages with AQI data. Compared with column 1, the coefficients of all variables are very close, which shows that our results are robust. The

Table 2 Unit roots test

	Augmented Dicky-Fuller test H_0: existence of unit roots			
	Z(t)	1% Critical Value	5% Critical Value	10% Critical Value
Ln(price_cabbage)	−4.70***	−2.33	−1.65	−1.28
Ln(price_tomato)	−2.81***	−2.33	−1.65	−1.28
Ln(price_pork)	−2.08**	−2.33	−1.65	−1.28
AQI/100	−14.26***	−2.33	−1.65	−1.28
pm2.5/100	−17.37***	−2.33	−1.65	−1.28

Notes: Above tests aim at level variables and include drift term in regression. AQI and PM2.5 have been rescaled by a factor of 1/100 for better readability. ***, **, and * the significant levels of 1%, 5%, and 10%, respectively.

Table 3 Empirical results for Chinese cabbage price

	AQI		PM2.5	
	ARDL(1, 1)	AR(1)	ARDL(1, 1)	AR(1)
L1.(Ln(price_cabbage))	0.8621**	0.8621**	0.9001**	0.9000**
	(0.0247)	(0.0247)	(0.0178)	(0.0178)
AQI/100 or pm2.5/100	−0.0130**	−0.0119**	−0.0070*	−0.0064*
	(0.0044)	(0.0035)	(0.003)	(0.0026)
L1.(AQI/100) or L1.(pm2.5/100)	0.0023		0.0012	
	(0.0055)		(0.0033)	
Temperature_max	−0.0007	−0.0007	−0.0012	−0.0012
	(0.0011)	(0.0011)	(0.0008)	(0.0008)
Rain	0.0148	0.015	0.0156	0.0156
	(0.0121)	(0.0121)	(0.0093)	(0.0093)
Holiday	−0.0195	−0.019	−0.0044	−0.0046
	(0.0163)	(0.016)	(0.0116)	(0.0116)
Observations	729	730	1091	1091
F-test for Model Specification	*F*(24, 704) = 382.71**	*F*(23, 706) = 398.72**	*F*(25, 1065) = 747.18**	*F*(24, 1066) = 775.52**
Included other explanatory variables				
Each day in a week	√	√	√	√
Month	√	√	√	√
Year	√	√	√	√

Notes: The value in brackets is the Newey–West standard error with lag = 6. **, and * the significant levels of 1% and 5%. We only display the regression output of main variables.

price of one-day lag has significant positive effects on present price and the effect is quantitatively large, implying strong price stickiness. Notably, an increase in AQI by 100 units would lead to a 1.19 per cent decrease in Chinese cabbage price. We interpret this as the aggregate effect of air pollution on food demand and supply. Looking back at our theoretical framework, we can infer that the stimulating effect of air pollution on demand is larger than that on supply, so that the price decreases as the severity of air pollution increases. Although the magnitude of the coefficients for air pollution measure does not seem large, the extremely heavy pollution with AQI > 300 could lower vegetable price by 3–5 per cent. This could substantially reduce net income or profit margins of these farmers by 8–13 per cent, as the profit margins of vegetable farmers are around 40 per cent (National Development and Reform Commission 2015, Table 1-21-1). It could also bias CPI statistics and lead to incorrect macroeconomic policies as food expenditure share still remains about 30 per cent in total household expenditure in China (Yu and Abler 2014, 2016; Zhou *et al*. 2015).

As for the weather condition variables (maximum temperature and precipitation dummy) and the holiday variable, their coefficients are all not statistically significant. We attribute this to the seasonal dummy variables.

For comparison, in columns 3 and 4 of Table 3, we replace the AQI with the PM2.5 concentration and estimate the ARDL(1, 1) model and the AR(1) model again, respectively. Consistent with the results of the AQI, the PM2.5

Table 4 Empirical results for tomato price

	AQI		PM2.5	
	ARDL(1, 1)	AR(1)	ARDL(1, 1)	AR(1)
L1.(Ln(price_tomato))	0.9667**	0.9666**	0.9695**	0.9695**
	(0.0072)	(0.0072)	(0.0088)	(0.0088)
AQI/100 or pm2.5/100	−0.0068*	−0.0055*	−0.00926*	−0.0089**
	(0.0030)	(0.0025)	(0.0037)	(0.0028)
L1.(AQI/100) or L1.(pm2.5/100)	0.0027		0.0008	
	(0.0032)		(0.0038)	
Temperature_max	2.65E-05	3.03E-05	0.0003	0.0003
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Rain	0.0017	0.0018	0.0004	0.0005
	(0.0052)	(0.0052)	(0.0067)	(0.0067)
Holiday	−0.0099	−0.0102	−0.0094	−0.0094
	(0.0068)	(0.0069)	(0.0067)	(0.0066)
Observations	729	730	1091	1091
F-test for Model Specification	*F*(24, 704) = 2387.61**	*F*(23, 706) = 2463.00**	*F*(25, 1065) = 2156.49**	*F*(24, 1066) = 2226.23**
Included other explanatory variables				
Each day in a week	√	√	√	√
Month	√	√	√	√
Year	√	√	√	√

Notes: The value in brackets is the Newey–West standard error with lag = 6. **, and * the significant levels of 1% and 5%. We only display the regression output of main variables.

concentration of one period lag does not have a significant effect on Chinese cabbage price, so the AR(1) model is still the best choice.

Additionally, the outcome of column 4 is very close to that of column 2, reaffirming our abovementioned conclusion. Column 4 shows that an increase in PM2.5 concentration by 100 μg/m^3 would lead to 0.64 per cent decreases in Chinese cabbage price, and the effect is significant. Consistent with our theory, air pollution could push down both demand and supply, but the plunge of demand is larger than the supply. It eventually pushes down the equilibrium market price.

5.2 Tomatoes

Table 4 reports the estimation results for tomatoes. As expected, the AR(1) model performs better in estimating the effects of air pollution on tomato price, because the coefficients on A_{t-1} are insignificant in both columns 1 and 3. Both coefficients for A_t in the AR(1) model (columns 2 and 4) are negative and statistically significant. That is, an increase in AQI by 100 units would lead to a 0.89 per cent decrease in tomato price, while an increase in the PM2.5 concentration by 100 μg/m^3 would lead to a 0.55 per cent decrease. This implies that air pollution has a similar effect on the price of the tomato as on the Chinese cabbage. The explanation is also similar. Air pollution could plunge both demand and supply of tomato, but the magnitude of plunge for demand is larger than supply. Eventually, the market prices go down.

Table 5 Empirical results for pork price

	AQI		PM2.5	
	ARDL(1, 1)	AR(1)	ARDL(1, 1)	AR(1)
L1.(Ln(price_pork))	0.9444**	0.9448**	0.9649**	0.9647**
	(0.0128)	(0.0127)	(0.0085)	(0.0085)
AQI/100 or pm2.5/100	0.0012	0.0003	0.0009	0.0004
	(0.0015)	(0.0014)	(0.0011)	(0.0010)
L1.(AQI/100) or L1.(pm2.5/100)	−0.00159		−0.0010	
	(0.0010)		(0.0007)	
Temperature_max	0.0002	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Rain	0.0001	0.0000	0.0003	0.0003
	(0.0018)	(0.0018)	(0.0013)	(0.0013)
Holiday	−0.0005	−0.0002	0.0009	0.0010
	(0.0024)	(0.0024)	(0.0018)	(0.0018)
Observations	729	730	1091	1091
F-test for Model Specification	*F*(24, 704) = 4073.16**	*F*(23, 706) = 4211.16**	*F*(25, 1065) = 4307.40**	*F*(24, 1066) = 4486.56**
Included other explanatory variables				
Each day in a week	√	√	√	√
Month	√	√	√	√
Year	√	√	√	√

Note The value in brackets is the Newey–West standard error with lag = 6. **, and * the significant levels of 1% and 5%. We only display the regression output of main variables.

5.3 Pork

Table 5 reports the effects of air pollution on pork price. Unlike the situation of Chinese cabbage and tomatoes, air pollution seems to have no significant effects on pork price, regardless of the model used. We attribute this difference to the property of meat. First of all, pork can be frozen for future sale, and China's cold storage capacity for meat reached 7 million tons in 2008, with more than 10,000 cold storage units across the country . This could imply that air pollution might have negligible effects on pork supply in the short term, due to a flexible cold storage control system. Second, pork has a relatively longer shelf life, and consumer can chill or freeze pork for future consumption, so the effect of air pollution on daily pork demand is also negligible.

6 Conclusion

In recent years, air pollution has become one of the top environmental concerns in China. In this study, we first develop a theoretical model based on market equilibrium and then employ econometric tools to evaluate the effects of air pollution on food prices in Beijing, using the wholesale market prices for three major fresh food products consumed in China (Chinese cabbage, tomatoes and pork). We find that air pollution has negative effects on the price of Chinese cabbage and tomatoes, but has no significant effects on pork price in the short term. Specifically, with an increase in AQI by 100 units, the prices for Chinese cabbage and tomatoes decrease by 1.19 and 0.89 per cent, respectively; with an increase in PM2.5 concentration by 100 $\mu g/m^3$, the prices for Chinese cabbage and tomatoes decrease by 0.64 and 0.55 per cent, respectively.

We interpret these results as the aggregate effect of food demand and supply in response to air pollution, while the stimulating effects on demand and supply are, respectively, determined by natural properties of fresh products, such as shelf life and storability. For instance, fresh vegetables perish relatively quickly and are difficult to preserve, so the supply does not shrink much in the short run. However, when consumers reduce their outdoor activities, the impact on demand could be larger, eventually pushing down their market prices. On the contrary, pork has a longer shelf life and can be frozen for future sale, so the impact of air pollution on the price is insignificant in the short run.

Air pollution can affect social welfares in many dimensions. This study indicates that air pollution decreases prices of fresh vegetables in the short run. Food price volatility is linked to the welfare of both consumers and producers. Even though the magnitude of the coefficients for air pollution measure does not seem substantial, extremely heavy pollution with AQI > 300 still could lower vegetable prices by 2–5 per cent compared to excellent air quality. This could shrink profit margin or net income of vegetable farmers by 5–13 per cent, which is a sizable number, as the profit margin for Chinese vegetable farms is 41 per cent in 2014 (National Development and Reform Commission 2015, Table 1-21-1). It could also alternate CPI statistics and lead to incorrect macroeconomic policies as food expenditure share still remains about 30 per cent in total household expenditure in China (Yu and Abler 2014, 2016; Zhou *et al.* 2015). Chinese governments are taking different measures to mitigate air pollution and stabilise food prices.

Our main research purpose is to use the market price data to estimate the impact of air pollution. We unfortunately have no household level data to match the time series data, to understand specific behaviours of consumers and suppliers in response to air pollution. It is well known that storage plays important role in food consumption and could mitigate the impacts (Gibson and Kim 2012). We find that the impact of air pollution could differ for different products due to their shelf life length and storability. For instance, there is no significant impact of air pollution on pork price. Our study is to measure the aggregate effect of air pollution, rather than to identify the channels. Air pollution has many channels to affect food prices, which will be our future research.

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