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Review

Macro-Impacts of Air Quality on Property Values in China—A Meta-Regression Analysis of the Literature

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Abstract: Air pollution has received increasing attention in recent years, particularly in China, due to the rapid industrialisation that has wrought intense levels of air pollution. A number of studies, therefore, have been devoted to quantifying the impacts of air pollution on property value in China. However, the empirical results are somewhat mixed. This naturally raises questions of whether there is a significant relationship between air quality and housing prices and the plausible reasons for the mixed results in previous studies. This study aims to fill this gap by explaining the variations in the findings by a meta-regression analysis. To control for heterogeneity, a weighted least square model was used to explore the factors influencing the magnitude and significance of the air quality effect based on empirical estimates from 117 observations. This study confirms that air quality does have a discernible impact on housing prices beyond the publication bias. Besides, the types of air quality indicator and the air data source do significantly influence estimates through affecting both the magnitude of the elasticity and the partial correlation coefficient (PCC). Further, the selections of control variables and estimation approaches also have significant impacts on estimates. This study also finds that published papers tend to be biased towards more economically significant estimates. The implications of the findings have also been discussed.

Keywords: air pollution; housing prices; meta-regression analysis; China

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1. Introduction

Megacities all around the world have struggled with severe air pollution in recent decades [1], especially cities in developing countries [2]. China is one of the developing countries that has been experiencing severe air pollution due to its rapid economic growth in which it heavily relies on coal burning to meet the energy demand from the manufacturing industry.

Since China's economic reform in the 1980s, China has been keeping a relatively fast speed of economic growth, with an annual average rate of over 7% in the last decade [3]. China's Gross Domestic Product (GDP) accounts for 16% of the world's GDP in 2018, which makes China the engine of economic growth, the largest industrial country and the largest trader of goods across the globe [4]. However, those great achievements are accomplished based on substantial energy consumption and at the sacrifice of the environment, which consequently results in the hover of notorious ambient air pollution over the majority of the urban areas in China. The air pollution problem in China has become worse and has raised the attention of the public since 2005, whilst it has deteriorated continuously over time [5].

Although China's central and local governments have introduced numerous relevant policies and regulations to combat the ambient air pollution, such as the Air Pollution Prevention and Control Action Plan, traffic restriction and environmental tax, etc., no noticeable improvement in air quality is evident [6]. Approximately over half of China's urban population are under severe pernicious air pollution with the concentrations of $PM_{2.5}$ and

PM_{10} five times exceeding the guideline set by the World Health Organisation (WHO) [7]. The air quality in some specific areas is even worse. For example, the air pollution index in Beijing was beyond the measurable capacities in 2013, and the $PM_{2.5}$ concentration reached the level of over 1000 $\mu g/m^3$ in 2015 [6], while the standard concentration of $PM_{2.5}$ that affects human health is 10 $\mu g/m^3$ set by the WHO.

According to the previous literature, air pollution has substantial effects on the rise in mortality rate and the decline of average lifespan [8,9]; respiratory diseases and cardiovascular diseases including lung cancer, asthma, respiratory allergy, inflammation, heart disease, thromboembolic and sclerosis [10–14]. Due to the significant adverse impacts of air pollution on human health and lifespan [9,11,12,14], it has received increasing attention from scholars and governments as well as residents. Many scholars have assessed the influences of air pollution on various aspects, including climates [15], the health of plants and animals [16–18], telecommunication and traffic [19–21] and buildings [22]. These studies generally found that ambient air pollution threatens the suitability of habitats and breaks the balance of healthy ecosystems [23]. It also causes decreases in the biodiversity of plants and animals and reduces crop yield [16–18,24,25]. The pollutants in the air restrict the transmission of telecommunication signals and traffic and decrease the sustainability of buildings [19,21,26–28].

Given the significant multidimensional adverse effects of air pollution and the increasing public awareness of a better living environment [29], the demand for clean air has also increased over time. The residents are willing to pay for a reduction in air pollution level and move to a place with better air quality if they can afford it [30–32]. Such demand has resulted in emerging studies to explore the relationship between air quality and housing prices. The impacts of air quality on housing prices are commonly addressed with a hedonic price model (HPM), which considers air quality as one of the environmental attributes of the property and calculates the price of air quality based on the observations of real estate values [33].

Following the pioneering work of Ridker and Henning [34] on the influences of air quality on housing value, scholars continue to contribute to this topic by introducing extra key variables, comparing different function forms, applying spatial econometric approaches, using instrument variables, testing the theory with macro-housing data and micro-housing data as well as subjective and objective indicators for air quality [35–37]. Most of the studies confirm that air quality is significantly associated with housing values, and the improvement of air quality would lead to an increase in local housing prices.

In recent years, the association between air quality and real estate values has attracted close attention from Chinese scholars with respect to the heightened level of air pollution in China. Several attempts have been conducted to assess the relationship between air quality and housing prices, applying both micro and macro hedonic empirical studies. However, the empirical results from these Chinese studies are somewhat mixed in that some studies indicate a weak relationship between air quality and housing prices [38] and other studies document the strong impact of air quality on housing values [6,39,40]. Further, there are huge variations among the results reported by studies, which find significant impacts of air quality on housing prices and that the percentage change in housing value caused by a 1% change in air quality ranges from 0.0365 to 1.3% [6,41].

Some researchers attempted to identify influential factors to explain the variations among environmental hedonic empirical studies [42,43]. Nevertheless, it is difficult to distinguish the influential factors only relying on a systematic review with respect to descriptive analyses, which could be subjective in study selection and result interpretation [44]. To offer objective and persuasive explanations about the mixed results among empirical studies, quantitative approaches are needed. In this case, a meta-regression analysis can be a powerful tool to identify influential factors and to extract additional information on how those influential factors affect the results of the estimates. By employing econometric specifications, a meta-regression analysis can objectively and accurately estimate the real effects of air quality on macro housing prices and enhance our understanding of why the impacts of air quality vary across the previous studies [44].

Several meta-regression analyses [45–48] have been conducted, exploring the relationship between housing price and environmental contamination including air pollution, landfills, underground water contaminant, pipeline, nuclear power plant and airborne radioactive release. However, previous meta-regression analyses focused on exploring the critical factors in micro-level hedonic studies, which quantify the impacts of air quality on housing prices based on the housing price data of individual properties and largely ignore macro variables. Compared with micro-level studies, macro studies tend to apply a panel dataset. Besides, the influential factors affecting micro and macro housing prices are different; therefore, the control variables in micro and macro studies are considerably different. Instead of employing housing characteristics such as locational and structural characteristics as control variables, macro studies apply macroeconomic features, demographic characteristics, housing supply, infrastructure and public service level to control the influences on macro housing prices. As macro hedonic air quality studies are significantly different from micro hedonic air quality studies, whether the results of the macro-level meta-regression analysis are consistent with the previous findings of micro-level studies is still an open question.

This study aims to explore the factors affecting the impacts of air quality on macro housing prices with a focus on the Chinese context. We confined our study to China as it offers a unique dataset for a number of reasons. Firstly, the majority of Chinese cities have suffered from severe air pollution in the last decade. Given the high level of air pollution in China, a dedicated study of China is required to offer a comprehensive explanation of the impact of air quality in China. Secondly, China has experienced a rapid industrialisation and urbanisation process in the last three decades, and the development is based on substantial energy consumption and the sacrifice of the environment. Thus, a dedicated study of China would provide some empirical evidence of how the environment will be priced by households. Further, almost all macro hedonic air pollution studies selected China as a study case. The relatively small sample size for studies conducted in other regions might lack the explanatory ability for the variations among studies. Therefore, a dedicated meta-regression analysis study of air pollution on Chinese housing prices is more capable of delivering a comprehensive explanation of the fluctuations of the estimates in the Chinese context. Finally, the macro analysis of air quality on property value only commenced in 2000. This reduces the potential bias of the time, as most studies were conducted since 2000.

This study contributes to the literature in a number of ways. Firstly, to the best of our knowledge, this is the first meta-regression analysis focusing on air pollution impacts on macro-level housing markets. This study provides a systematic review of the macro hedonic air quality studies in China. This may guide policymakers to have a complete understanding of the effects of air quality and to make a more balanced policy in terms of economic growth and air quality. Secondly, the publication bias conducted in this meta-regression analysis confirms that air quality does have a noticeable impact on housing prices, excluding the influence of publication bias. This assists policymakers and homeowners in making a more informed decision. Thirdly, this meta-regression analysis also provides us with a fuller understanding of the reasons for the variations of previous studies, which help scholars on data, estimation methods and control variables selections. Further, it can be referred to as a benchmark for researchers to understand how their results fit with others. Fourthly, as previous meta-regression analyses use samples before 2000, this study will supplement previous research by applying a more recent dataset. Finally, through identifying critical factors affecting estimates of macro hedonic air quality studies, this study enables a comparison between macro and micro hedonic studies. This is expected to offer a complete understanding of the impact of air quality from both macro and micro perspectives.

This paper is structured as follows. Section 2 presents the literature review about previous meta-regression analyses in the topic of environmental impacts on housing prices. Section 3 demonstrates our method of data collection and the design for the meta-regression analysis. The publication bias test is also reported in this section. Section 4 reports the regression results of the meta-regression analysis, and Section 5 discusses the strength and weakness of the study. Finally, Section 6 draws the conclusion of the overall study.

2. Literature Review

Hedonic price model (HPM) was first formally coined by Court in 1941 [49] to report the price index for automotive and investigate the link between functions and prices by employing regression models [50]. Then, the theory of HPM was developed by the two major approaches: utility theory and revealed preference theory [34,51]. These two methods aim to quantify the implicit prices of attributes through empirical studies based on the products' characteristics and prices [52]. The modern HPM is based on the assumptions that the property is a set of goods, and individuals are free to move according to their demands [53]. A house is considered as a set of immovable and local attributes, including the conditions of the entire urban area where it is located [54], the accessibility to other facilities and travel convenience and the quality of the neighbourhood [55–57] such as the quality of public services, the quality of the residents and the quality of the neighbourhood environment [58–60]. HPM is commonly applied to understand the real estate price dynamics in general or to estimate the variation caused by a specific factor [61]. Estimating neighbourhood characteristics' impacts on housing prices has always been a popular topic among HPM studies [61]. Among neighbourhood characteristics, there are three categories including social factors (race and crime rate), infrastructure (school, park and public goods) and environmental factors (air pollution, forest and wetlands). Recently, with the rise in the public awareness of the importance of the environment, the effects of environmental externalities arouse more extensive attention from scholars. A number of environmental factors, both amenities and disamenities, have been investigated, including landscape and urban water bodies [62,63], urban trees [64], noise [65], hazardous waste site [66], wildfire risk [67], flood risk [68,69], etc.

Ridker and Henning [34] carried out probably the first empirical study to investigate the influence of air pollution on housing prices; afterwards, scholars continue to explore the variations in housing values caused by the changes in air quality. A number of studies have been devoted to gauging the linkage between air pollution and housing prices in China. The results have frequently observed that the interlinkage is mixed and dependent on the markets examined. Wang and Cai [70] found a negative and statistically significant association between air pollution and housing prices; reflecting that homebuyers are willing to pay a premium for better air quality. Comparable evidence is also documented by Kong [41], Dong, Zeng [71], Chen and Jin [72], Chen [73], Zou [74], Shen [75] and Dong, Zeng [76]. Chen and Chen [6] and Sun and Yang [77] suggested that the findings are intuitively appealing, as the demand for clean air has increased over time in China with respect to the heightened level of air pollution and the increasing awareness on the importance of air quality.

However, a number of empirical studies found contradictory results. Chen and Chen [6], Zheng, Kahn [37], Jia [39], Wang and Shi [40], Sun and Yang [77], Zhang and Huang [78], Huang and Lanz [79] and Yu [80] found mixed results in that they did not find a strong relationship between air quality and Chinese housing prices in some specific cases, for example, study period, submarket, etc. Further, Chen and Chen [6] and Wang and Shi [40] indicated that air pollution had been paid more attention by residents who lived in developed regions or high-ranking cities than homebuyers who reside in less developed areas or low-ranking cities. In fact, the documented positive and statistically insignificant association could be attributed to omitted variable bias [6,40,79,80]. This is further exacerbated by the fact that there is no consensus on the magnitude of air pollution's impact on housing price. The elasticity (the change in housing price with one percentage change in air quality) varies across these studies, ranging from 0.3679 (a premium for air pollution) to −1.3038 (a discount for air pollution). To sum up, the empirical evidence on the interlinkage between air quality and Chinese housing prices are mixed. This naturally raises questions of whether air quality is priced by home buyers and what are the plausible reasons for the mixed results that have been documented by previous studies.

Several scholars had conducted research by reviewing the literature to identify the influential factors and to explore further and explain the reasons why different environmental hedonic studies come up with different results with the focus on US studies. These include two review papers concerning the broad areas of environmental contamination conducted by Jackson [42] and Boyle and Kiel [43]. Jackson [42] reviewed 21 papers focusing on the impacts of environmental factors (including landfills, underground water contaminant, pipeline, nuclear power plant and airborne radioactive release) on housing prices and found that the impacts on residential and commercial housing are stronger in urban areas and the regions with greater market demands. Boyle and Kiel [43] compared the empirical results of the impacts of environmental pollutants on residential property value based on 39 studies, which pay attention to several different pollutants, including air and water quality, undesirable land use, neighbourhood variables and multiple pollutants. The author suggested that the coefficients of air pollution impacts are influenced by the control variables included in the models. In terms of water contamination, water measurements are crucial to the results of the estimates. The measurement, which can be easily observed, results in the best estimate, while multiple measurements are problematic because of the multicollinearity between different measurements.

Considering these two review papers compare the empirical results through simple descriptive methods; the results might by subjective and inadequate for identifying the influential factors resulting in the mixed regression results. In this case, the approach of meta-regression analysis can be applied to provide objective and persuasive explanations about the variations among empirical studies. The term “meta-analysis” was coined by Glass [81] and was defined as a statistical analysis method with the purpose of synthesising existing findings based on individual studies. Glass [81] conducted the first meta-analysis in the area of psychology and first proposed the term “effect sizes”—the dependent variable in meta-analysis. Meta-analysis is a commonly applied review method in medicine and social science; then, given the difference between economic research and medicine studies, Stanley and Jarrell [44] came up with the concept of “meta-regression analysis”, which is developed based on meta-analysis and enabled the application of meta-regression analysis in other study areas such as business and economics. Stanley and Jarrell [44] introduced different possible effect sizes (including elasticity, t-value, partial correlation coefficient, F-value, etc.) in meta-regression analysis to replace the odds ratio and risk ratio, which are commonly applied in psychological and clinical studies. Meta-regression analysis was defined by Stanley and Doucouliagos [82] as an evidence-based multivariate investigation, exploring the influential factors affecting the estimates reported by previous studies.

Following Stanley’s work, meta-regression analysis had been applied on business and economics [83–85], and it has become increasingly popular in environmental economics recently [86]. Some researchers applied the approach of meta-regression analysis to understand the factors affecting estimates of environmental hedonic studies comprehensively [45–48]. Smith and Huang [45] conducted a meta-analysis to estimate how data and model specification influence the results of Hedonic price model regression and air pollution with the data collected from 37 studies with overall 167 observations from 1976 to 1990 with the focus on major American cities; the author found that the impact of air pollution on housing price is influenced by modelling decision, air pollution measurements and the condition of the local housing market. Specifically, using sales prices reduces the significant effects of air pollution compared with census data, and the linear model also reduces the significance of air pollution. Moreover, the number of air pollution measurements in models reduces the prospects for finding a significant relationship. Then, Smith and Huang [46] further analysed some of those studies (with 86 observations) through applying the following two approaches: minimum absolute deviation and ordinary least square. After reconstructing the data, this study draws the following conclusion that 1 unit reduction in PM_{10} concentration is related to a USD 110 increase in property value, which equals to 0.1% of the property value.

Simons and Saginor [47] addressed the effects of several environmental contamination sources on housing prices in the United States. This study estimates the effects of the contextual and methodological variables; the regression results show that contamination type, amenities, region, distance from the contamination source, information of announcement and research methods are significantly associated with regression results of the reduction on property value.

Chen, Li [48] identified the influential scenario, modelling and contextual variables that affect the impacts of urban rivers on residential property values through conducting a meta-analysis with 30 studies (with 53 observations). Employing the random-effect model with the data of contextual variables, scenario variables and modelling variables, estimate results indicate that the effect size is affected by the abovementioned three types of variables. Specifically, in terms of environmental amenity scenarios, the view of the river is the most significant factor, while the proximity that received the widest attention in previous studies has the lowest relative value. As for modelling variables, the study year and whether the result is significant shows significant positive influences on effect size; however, whether the model considers spatial factors is not statistically significant to effect size. Among contextual factors, GDP per capita and the average housing price, which reflect the income level of the case, have significant positive influences on willingness to pay for river amenity. Moreover, the population density is negatively related to the impact of urban river impacts, and the regional difference shows insignificant effects.

However, previous literature only paid attention to micro-hedonic studies which focus on the influences of environmental factors on individual housing prices, while the critical factors in macro-level studies have been neglected. Therefore, this paper looks into macro-scale hedonic price model and environmental contamination of air pollution, filling the gap of meta-regression analysis and macro-hedonic price studies.

3. Method

Meta-regression analysis serves as an important tool for a systematic explanation of differences in the previous empirical findings [46,82]. The meta-regression analysis involves three major stages. The first stage is to identify the related studies in the literature. One of the primary tasks for identifying relevant studies is to move out systematic biases by conducting searches comprehensively [87]. To be more specific, we need to include as many of the relevant studies in the meta-regression analysis, instead of only covering some of the seminal studies. All studies, including unpublished papers, can be valuable for identifying influential factors affecting the estimates [88]; a more inclusive sample of a paper can also address publication bias in the analysis [89]. In addition, to explain the variations in some specific context, it is of great importance to access non-English studies to get a more thorough overview of the studies in this area. After identifying the relevant literature, the second stage involves identifying and coding differences as the critical groups of factors among selected studies. In general, according to the previous meta-regression analyses about environmental impacts on housing prices [47,48], three factor groups, including scenario, methodology and context factors, were identified and used in the meta-regression. Lastly, through undertaking an econometric model to estimate the impacts of each factor, influential factors explaining the variations among empirical studies were finally identified. Except for the abovementioned three steps, we also conducted a publication bias test as suggested by Stanley and Doucouliagos [82] to test whether air quality has genuine effects on real estate price beyond the publication bias. The specific methodology strategies of data searching, publication bias test, factors identification, effect size and econometric method selection will be elaborated on in the following subsections.

3.1. Data

To comprehensively identify the studies investigating the impacts of air quality on macro housing prices, this study applies the following processes (the specific procedures are presented in Figure 1): Firstly, in the stage of identification, the original case study data are assembled through searching in the online bibliographical database—Scopus—and utilising Google Scholar and the reference of the returned studies as a complimentary. Given that the scope of this study is macro-level hedonic price method empirical studies exploring the relationships between the residential property market and air quality level in China, the keywords employed for searching are the most representative keywords: "air pollution" or "air quality" or "environmental quality" or "environmental pollution" or "environmental factor" or "living environment" or "soft power" or habitability or competitiveness and "housing price" or "housing value" or "property price" or "property value" or "real estate price" or "real estate value" and China or Chinese. This meta-regression analysis covers papers within all types to reduce the effects of publication bias, including journal articles, conference articles, book chapters, books, dissertations, conference proceedings, the essays in press and business articles. To further reduce the language bias and to have a more comprehensive understanding of the Chinese context, this research also includes studies written in Chinese. These studies are collected from a Chinese online bibliographical database—Chinese National Knowledge Infrastructure (CNKI). The total number of 65 papers (from Scopus) and 633 studies (from CNKI) were returned (the search was conducted on 4 December 2020).

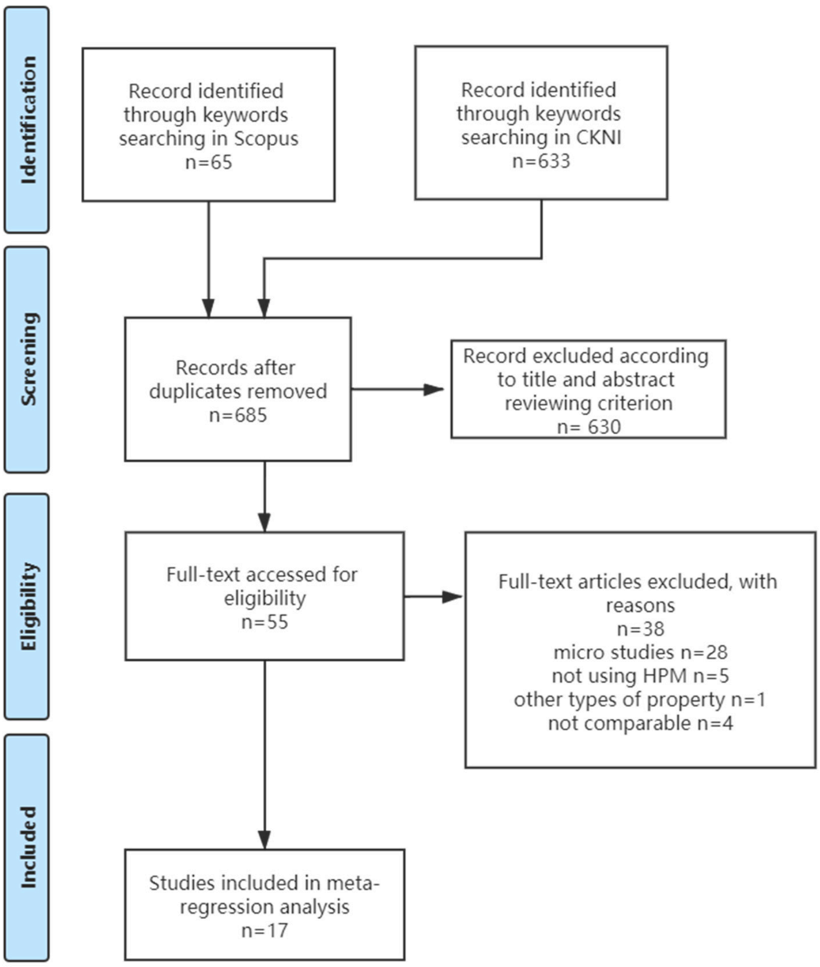

Figure 1. Prisma flow diagram [90].

Secondly, in the screening stage, the returned studies were first screened to remove repeated literature. Thirteen repeated papers were removed, and 685 papers remained to be evaluated by title and abstract reviewing following the criterion: the study must have a focus on understanding the impacts of air quality on the housing market. Specifically, studies focussing on the following topics were identified as irrelevant studies and were removed: indoor air quality; cause of air pollution; the tendency of air pollution in a particular region; air pollution improvement and control strategies; air pollution and policy-making; predicting, detecting, processing and recovering air quality data; air pollution caused by construction; air pollution's impacts on house materials; the relationship between air quality and health risk and life quality; factors affecting real estate market or property value; household energy's influence on housing price; factors impacting both air quality and real estate market; the relationships between air pollution and aerosol optical properties.

Thirdly, 55 studies moved to the next stage of eligibility to be further filtered through full-text reviewing, and only studies that satisfied the following criteria were finally included as the meta-sample: (1) The study must be a macro-level study instead of micro-level study applying individual housing transactions as the dependent variable. (2) The impacts of air quality in the study must be quantified based on the hedonic price method. Studies that use other econometric approaches such as the travel cost method and contingent valuation method are excluded, as their studies focus on the willingness to pay for air pollution, but their willingness to pay might not necessarily be reflected on housing prices. Although the results that are estimated by different approaches can also reflect the associations between air quality and housing markets, herein, we only focus on the HPM to build the consistency that the estimates are based on the same theory and methodology. (3) The research must focus on the residential property market (housing price, rental price and land price are included), and cases that pay attention to the commercial property or other types of property are excluded. This criterion is another strategy employed in this study to satisfy the commodity consistency of the meta-regression analysis [91]. (4) The study must report the primary estimations, and the estimates must be capable of being expressed and compared (after standardisation). Specifically, the study must report the sample size and t-value or standard error of the coefficient.

Finally, there were 17 papers looking into the relationship between air quality and hosing prices from a macro perspective. The specific list of the dataset is shown in Table 1; Figure 2 maps the cities covered by previous studies. Given some of the studies do not provide the detailed information about the cities covered by their studies, the map presented in Figure 2 only shows the cities included in [6,37,39,71,72,74,77,78].

Table 1. The list of meta-samples.

Reference	Air pollution Indicator	Study Year	Number of Cities	Sign and Significance	Elasticity
[70]	$PM_{2.5}$	2006–2016	70	−; sig	−0.187 to −0.881%
[77]	$PM_{2.5}$	2005, 2009 and 2013	286	−; mixed	−0.0245 to −0.1986%
[76]	AQI	2013–2015	74	−; sig	−0.209%
[71]	$PM_{2.5}$	2002–2016	280	−; sig	−0.109 to −0.134%
[72]	$PM_{2.5}$	2005–2013	286	−; sig	−0.0612 to −0.2416%
[40]	PM_{10}	2005–2017	30	− and +; mixed	0.3679 to −0.5806%
[73]	$PM_{2.5}$	2009–2017	62	−; sig	−0.0612 to −0.1217%
[74]	$PM_{2.5}$	2015	282	−; sig	−0.2759%
[41]	SO_2	2003–2011	104	−; sig	−0.0365%
[80]	SO_2 and PM_{10}	2010–2012	74	− and +; mixed	0.025 to −0.35078%
[75]	Index (SO_2, NO_2 and PM)	2013	31	−; sig	−0.142 to −0.217%
[79]	PM_{10}	2011	288	− and +; mixed	−0.71 to −1.09%
[6]	$PM_{2.5}$	2004–2013	286	− and +; mixed	0.34443 to −1.3038%
[38]	SO_2	2003–2015	283	− and +; insig	0.00336 to −0.00117%
[78]	PM_{10} and SO_2	2015	288	−; mixed	−0.09 to −0.68%
[39]	API	2009–2012	35	−; mixed	−0.1918 to −0.7826%
[37]	PM_{10}	2003–2006	30	−; mixed	−0.167 to 0.388%

Notes: AQI refers to air quality index. API refers to air pollution index. − and + refer to whether the study reports that air quality has a negative and a positive effect on housing prices, respectively. Mixed refers to the mixed results reported in which the results are either statistically significant and insignificant.

Figure 2. The map of the cities covered by sample studies (notes: Yellow dots refer to cities covered by less than 4 studies; green dots denote cities explored by 4 to 6 studies; black dots are cities investigated by more than 6 studies.).

Then, all relevant estimates reported in the selected studies that satisfy the standardisation criterion were included in the dataset, providing 117 observations in total. The reasons for applying all-set are [82]: Firstly, it greatly expands the sample size for the meta-regression analysis, which helps to explore the explanations for the heterogeneity between studies and within studies. Furthermore, it is sometimes not appropriate or unavailable to apply the best set, which only consists of the key regression result reported by the author, because not all studies present clear view about the best estimate. In this case, we need to make some judgements based on personal preferences, which might result in bias of the meta-regression analysis.

3.2. Publication Bias Test

Publication selection is the process of selecting and reporting statistically significant results, and it is a commonly known fact in social science, natural science, political science and medical research [92–94]. Publication selection can be found between both researchers and reviewers [92]. For researchers, they tend to report the models with expected results; for reviewers, they are more likely to accept studies reporting statistically significant results and confirming conventional theories. As the majority of the studies tend to choose for statistical significance, the effects are overstated with larger and more significant estimates. Neglecting the publication selection bias will distort the literature review, including meta-regression analyses [95]. Therefore, a publication bias test is conducted to test whether publication bias exists in the empirical studies exploring the macro-impacts of air quality on housing prices.

To test for publication selection bias, a funnel plot is presented in Figure 3. The funnel plot is a scatter diagram, depicting the relationship between estimates and the precision of the estimates, which is commonly used for publication bias detection [96]. Then, a funnel asymmetry test (FAT) is performed through a regression model to further test for publication bias. Stanley and Doucouliagos [82] suggested that FAT, which reflects the relationship between t-statistics and the standard error reported by the studies, can be applied to test the publication bias. The specification of FAT is shown in Equation (1):

$$t_i = \beta_0 + \beta_1\left(\frac{1}{SE_i}\right) + \mu_i, \quad (1)$$

where t_i is the t-statistics, and SE_i refers to the standard error. Evidence for publication bias will be judged by the value of β_0. If β_0 is significantly not 0, there exists publication bias; otherwise, publication bias does not exist. Additionally, β_1 provides an estimate of whether there is a genuine effect beyond the potential distortion caused by publication selection bias [87,88].

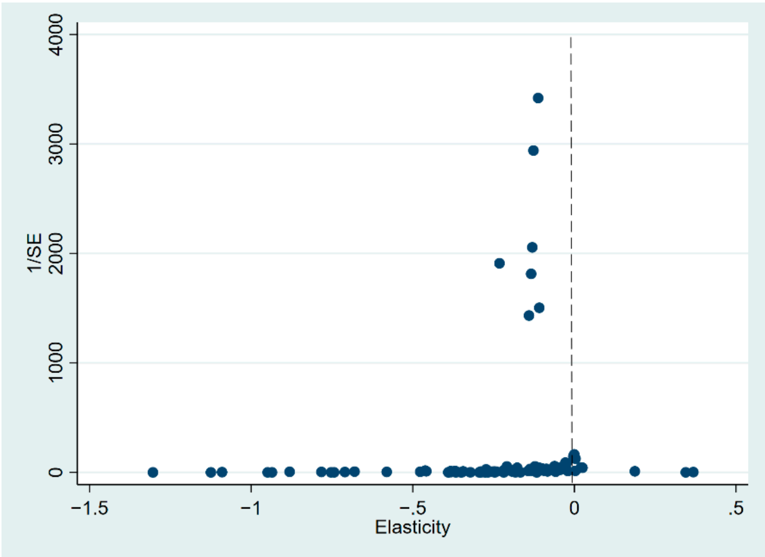

Figure 3. Funnel plot.

Figure 3 plots the estimated elasticities for air quality impacts on housing prices. As shown in Figure 3, the funnel plot is asymmetric, suggesting that there exists publication bias towards negative elasticities. The results of FAT are shown in Table 2. According to the estimation presented in Table 2, although FAT has limited power to reflect the existence of publication bias [88,97], β_0 estimation value rejects the null hypothesis ($\beta_0 = 0$) at 1% significance level, suggesting that publication bias in the effects of air quality on housing prices exists. This result further confirms the interpretation of the funnel plot. With regards to β_1, the result also indicates that β_1 is significantly not zero, demonstrating that air quality does affect the property value beyond the publication selection bias.

Table 2. Results of the funnel asymmetry test (FAT).

Variables	t
1/SE	−0.00224 ***
	(−6.33)
Constant	−2.395 ***
	(−12.19)
Observations	117
R-squared	0.258

Notes: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

3.3. Effect Sizes of the Impacts of Air Quality on Housing Prices

There are two types of effect size commonly used in the meta-regression analysis in economics and business studies; they are elasticity and partial correlation coefficient (PCC). Each type of the abovementioned effect size has its strength and weakness. PCC refers to the coefficient between two variables in the multivariate regression model after eliminating the effects of other variables [98]. The advantages of applying PCC as the effect size in meta-regression analysis are shown as following [82]: Firstly, PCC is a unitless measure, and it reflects the direction and strength of the relationship between two variables. Therefore, it enables the comparison between different results in various units. Besides, it can be accessed easily and is more capable of compiling a comprehensive dataset into comparable data, because most of the studies report the t-value or standard error, which enables the calculation of PCC. However, as PCC cannot measure the economic effect between two variables, it is inappropriate to employ PCC in benefit transfer meta-regression analyses [82]. Elasticity means the percentage change in the dependent variable when the independent variable change in 1%, and it measures the economic effects of two variables. As no standard for functional form selection exists, different estimates might apply different functional forms including linear, semi-log and double-log. To transform all the estimates into elasticity, the mean value of housing data and air quality data are needed. However, not all researchers report those mean values in their paper, and this will significantly decrease the sample size for meta-regression analysis [82].

In this study, both PCC and elasticity are employed as the effect sizes to identify influential factors affecting statistical significance and economic significance between air quality and housing prices. Although PCC is not always directly reported in the research, it can be easily calculated [82] through Equation (2):

$$\mathrm{PCC} = \frac{\mathrm{t}}{\sqrt{\mathrm{t}^2 + \mathrm{df}}} \tag{2}$$

PCC is the partial correlation coefficient; t refers to the t-statistics of regression coefficient reported in the original study; df denotes the degree of freedom of the t-statistics. The descriptive statistics of elasticity and PCC are shown in Table 3.

Table 3. The descriptive statistics of the two effect sizes.

Variables	Obs	Mean	Std. Dev.	Min	Max
Elasticity	117	−0.2289675	0.2697816	−1.303818	0.3679
Partial correlation coefficient	117	−0.1383982	0.1448643	−0.8152795	0.1669264

3.4. Independent Variables

According to the three examples of literature reviewed and the consideration of the concept of the effects of air pollution on real estate market, several factors can pose impacts on the final regression results, these including the elements in the two broad categories: scenario variables and methodological variables [48,99]. In this meta-analysis, we try to identify and code any of the possible influential factors, which might have effects on regression results to explain the heterogeneity among estimates. We introduce two additional types of factors, namely, data source factors and modelling factors, to obtain a more comprehensive understanding of the influence of those factors on the empirical values. In this study, three groups of variables including scenario and data variables (the combination of scenario variables and data variables), methodology variables and modelling variables will be considered to identify influential factors for the mixed results. The contextual variable of average housing price is initially considered. As suggested by Stanley and Doucouliagos [82], we applied a general-to-specific approach to identify influential factors. However, the average housing price was found to be insignificant. Further, when employing the stepwise method to introduce each group of factors, adding the variable of housing price results in inconsistency among models; dropping this variable will lead to a more robust result. This could also be attributed to the high correlation of housing supply in which this is intuitively appealing, as higher supply might lead to a lower housing price [59,60]. Table 4 shows the definition of each variable, and the results of the variance inflation factor (VIF) test of these variables are shown in Appendix A. The variables included in the abovementioned three groups will be explained below.

Table 4. The definition of meta-variables.

Variables	Dimension	Definition	Reference Case
		Scenario and data factors	
D_ai	Air index	= 1 if the study using air index as air quality indicator	The study using single air pollutant as air quality indicator
D_ie	Industrial_emission	= 1 if the air pollution data are based on industrial emission	The air pollution data are based on monitoring station reading
D_sp	Source_published	= 1 if the sample is a published academical article	The sample is an unpublished dissertation
		Methodological factors	
D_p	Panel	= 1 if the data type is panel data	The data type is cross-sectional data
D_s	Spatial	= 1 if the spatial effects are controlled in the regression model	Spatial effects are not considered in the study
D_iv	IV	= 1 if the estimate introduces instrument variable	The study does not include instrument variable
		Modelling factors	
D_i	Infrastructure	= 1 if the model applies infrastructure variable(s) as the independent variable(s)	-
D_hs	Housing_supply	= 1 if the model applies housing supply variable(s) as the independent variable(s)	-
D_oe	Other environmental	= 1 if the model applies other environment variable(s) as the independent variable(s)	-

3.4.1. Scenario and Data Factors

Scenario and data factors consist of variables related to the scenario of air quality indicator and the source of the data. In terms of the air quality indicators, there are two broad categories included in our dataset: single air pollutant and the index of several combined air pollutants. Compared with the level of a single air pollutant, air indexes can reflect the air quality level more comprehensively with respect to it measures the air quality by considering the level of all six types of the major air pollutants. It should be noted that studies that consider the concentration of a single air pollutant as air quality indicators usually select the major source of air pollution, such as $PM_{2.5}$, PM_{10}, SO_2, and these air pollutants might be more sensible and noticeable compared with the air indexes and might receive closer attention from the residents. In this study, we introduce a dummy variable of "air index", which represents the studies applying air indexes as air quality indicators to test the impacts of different scenarios on estimates.

Two data factors are considered in this study: the source of air quality data and the source of the original case studies. According to the selected studies, most of them utilise the readings from the monitoring stations to measure the air quality level, while others take the industrial emission data from city-level official census tracts as the city air quality indicators. Monitoring station readings, which reflect the air quality in specific locations, might be biased in representing the air quality of the entire city. Fortunately, most of the cities in China have several monitoring stations in different districts and counties. It is appropriate to apply the average value of the readings of all monitoring stations in a specific region to reflect the air quality condition for the entire region. Compared with monitoring station readings, industrial emission data only measure the air pollutant generated by factories and ignore the air pollutant emitted by other sources such as transportation emission. Therefore, monitoring station readings are capable of representing the actual air quality level for the city. "Industrial_emission" is added as a dummy variable in the meta-variable to test whether different air pollution data sources have influences on estimates.

As for the source of the original case studies, the sample cases are a mix of published journals and unpublished dissertations. Undoubtedly, papers published in the peer-reviewed journal are mostly of a high quality but tend to report significant results. The unpublished dissertations are theses to fulfil the requirement of completing a Master degree or a Doctoral degree; therefore, we just assume that these dissertations are also of a high quality. To test whether published papers tend to report more meaningful results, we introduce the variable of "source-published" in this meta-regression analysis. To measure and control the quality of the study, precision (inverse of standard error) is applied as the weight of the model to control the influence of the study quality.

3.4.2. Methodological Factors

Methodological factors refer to the variables related to the methodology of the original empirical studies, including the type of data used and the estimation approaches applied. There are two types of data included in the meta-sample—panel data and cross-sectional data. To testify impacts of data type on regression results, a dummy variable of "panel" is set.

As researchers continue contributing to investigate the relationship between air quality and housing prices, some studies apply advanced approaches to come up with more comprehensive explanations about air quality and property value. Some studies apply spatial econometrics to control the effects of spatial factors (spatial dependence, spatial heterogeneity or both), while some studies apply instrument variables with a two-stage method to address the endogenous problem. Overlooking spatial or endogenous factors might affect the estimates or result in biased estimates. Two dummy variables are set as "spatial" and "IV" in this study to understand the effects of using spatial econometrics and instrument variable on estimates.

3.4.3. Modelling Factors

Modelling factors reflect the selections of control variables included in hedonic models. Undoubtedly, the selection of independent variables is critical to the regression results and the goodness-of-fit of the model. There are four types of control variables included in the selected studies, including infrastructure characteristics, housing supply characteristics, demography and socioeconomics characteristics and other environmental characteristics. These factors have been widely seen as a key factor in explaining housing markets as documented by Liang, Koo [56], Lee and Locke [57], Bangura and Lee [59], Bangura and Lee [60], Bangura and Lee [100] and Shih, Li [101]. Infrastructure characteristics reflect the infrastructural level of the region, such as the number of universities, hospitals, libraries, road area, etc. Housing supply characteristics represent the supply of the property through the supply of residential land, the total area for sale, etc. Other environmental characteristics refer to other neighbourhood and environmental factors except for air quality, such as green land area, rainfall, temperature, etc. All studies include demographic and socioeconomic factors in their models; therefore, we focus on the influences of the other three types of variables, which are not included in all studies, on the regression results. A set of the modelling variables are introduced to examine the role of controlling different types of variables in the hedonic model specifications.

3.5. Meta-Regression Analysis Model Specification

As mentioned above, we introduce three groups of the factors, which might affect the estimate in this meta-regression analysis as the meta-regressors to systematically address the heterogeneity. A typical meta-regression analysis model is shown in Equation (3): [82]

$$p_i = \alpha_0 + \sum_k \alpha_k D_{ik} + \mu_i \tag{3}$$

where i refers to the individual estimate(s), p_i is the dependent variable, which refers to the effect size of observation i, D_{ik} is the meta-regressor k of the observation i, α_k refers to the model parameter related to meta-regressor k. α_0 is the constant of the model, and μ_i is the residual.

However, μ_i in different estimates are significantly different; this results in the dissatisfaction of the independent distribution condition. Therefore, it is inappropriate to apply ordinary least square. In this case, the random-effect model is a popular approach for meta-regression analyses and widely used in previous studies [48,99]. Compared with the random-effect model, the fixed-effect model only allows for within-study variations, which is likely to neglect the characteristics of different studies [102], for example, the differences between housing markets. Further, Braden, Feng [103] argued that the fixed-effect models generate inefficient results in meta-regression analyses. Therefore, it is more appropriate to employ the random-effect model. However, Stanley and Doucouliagos [82] stated that using random-effect models in meta-regression analyses increases bias, because it is likely to reintroduce the publication bias into the models. To filter the publication selection bias, it is more appropriate to apply a weighted least square (WLS) method to identify influential factors in this meta-regression analysis [82]. When publication selection bias is detected, the publication selection effects are correlated with the standard errors [82]. Thus, the inverse of the standard error is employed as the analytic weight to correct for the detected publication bias; the model can be expressed as Equations (4) and (5). To ensure the robustness of our baseline results, we re-ran our PCC model by fixing market levels as suggested by Lee, Stevenson and Lee [104]. The results are fairly robust in which we found that scenario and data factors, methodological factors and modelling factors have significant effects on estimates. In other words, the results did not alter the conclusion.

$$PCC_i/se_i = \alpha_0/se_i + \sum_k \alpha_k D_{ik}/se_i + \epsilon_i \tag{4}$$

$$E_i/SE_i = \alpha_0/SE_i + \sum_k \alpha_k D_{ik}/SE_i + \epsilon_i \tag{5}$$

where PCC_i and E_i refer to the effect size PCC and elasticity of observation i; se_i and SE_i are the standard error of PCC_i and E_i; D_{ik} is the meta-regressor k; α_k refers to the model parameter related to meta-regressor k; α_0 is the constant of the model.

4. Results

The correlation coefficient of each meta-variable is reported in Table 5. According to the results reported in Table 5 and the VIF value (reported in Appendix A), there is no multicollinearity issue among the variables. The results of the meta-regression analysis are shown in Tables 6 and 7.

Table 5. Correlation coefficient matrix.

	D_ai	D_ie	D_sp	D_i	D_hs	D_oe	D_p	D_s	D_iv
D_ai	1.0000	-	-	-	-	-	-	-	-
D_ie	−0.1526	1.0000	-	-	-	-	-	-	-
D_sp	−0.3039	0.1254	1.0000	-	-	-	-	-	-
D_i	−0.4705	−0.2910	0.0244	1.0000	-	-	-	-	-
D_hs	0.4208	−0.1526	−0.1161	−0.1094	1.0000	-	-	-	-
D_oe	−0.2495	−0.2404	0.3100	0.3202	0.1928	1.0000	-	-	-
D_p	−0.2676	0.0461	−0.2314	−0.0332	−0.5269	−0.1523	1.0000	-	-
D_s	−0.086	−0.1526	−0.4291	0.3034	−0.1584	−0.2495	0.1862	1.0000	-
D_iv	−0.1282	−0.1235	0.1593	0.0633	0.0423	−0.0718	−0.0020	−0.1282	1.0000

Table 6. Meta-regression analysis results (elasticity).

	(1)	(2)	(3)
Variables	**E**	**E**	**E**
	Scenario and data factors		
D_ai	−0.107 ***	−0.105 ***	−0.128 ***
	(−2.909)	(−2.630)	(−2.836)
D_ie	0.121 ***	0.101 ***	0.0832 ***
	(9.067)	(4.735)	(3.278)
D_sp	0.0612 ***	0.0623 ***	0.0643 ***
	(6.007)	(6.179)	(6.495)
	Methodological factors		
D_p	-	0.0389	0.0469
	-	(1.330)	(1.406)
D_s	-	−0.0237	−0.0598 **
	-	(−1.280)	(−2.566)
D_iv	-	−0.136 **	−0.153 **
	-	(−2.040)	(−2.308)
	Modelling factors		
D_i	-	-	0.0238
	-	-	(0.950)
D_hs	-	-	0.0440
	-	-	(0.836)
D_oe	-	-	−0.108 ***
	-	-	(−2.751)
Constant	−0.184 ***	−0.201 ***	−0.198 ***
	(−20.46)	(−6.443)	(−4.433)
Observations	117	117	117
R-squared	0.569	0.592	0.620
F test	0	0	0
F	49.7	26.65	19.38

Note: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 7. Meta-regression analysis results (PCC).

	(1)	(2)	(3)
Variables	**PCC**	**PCC**	**PCC**
	Scenario and data factors		
D_ai	−0.222 ***	−0.202 ***	−0.238 ***
	(−5.769)	(−5.707)	(−6.068)
D_ie	0.0951 ***	0.0837 ***	0.0765 ***
	(5.102)	(4.738)	(3.867)
D_sp	0.00223	−0.0117	−0.00269
	(0.104)	(−0.550)	(−0.125)
	Methodological factors		
D_p	-	0.120 ***	0.153 ***
	-	(4.837)	(4.868)
D_s	-	−0.0585 ***	−0.0609 ***
	-	(−2.967)	(−2.835)
D_iv	-	0.0285	0.0183
	-	(1.379)	(0.854)
	Modelling factors		
D_i	-	-	−0.00226
	-	-	(−0.127)
D_hs	-	-	0.0890 **
	-	-	(2.263)
D_oe	-	-	−0.0287
	-	-	(−1.269)
Constant	−0.107 ***	−0.197 ***	−0.229 ***
	(−5.372)	(−6.008)	(−5.264)
Observations	117	117	117
R-squared	0.381	0.529	0.554
F test	0	0	0
F	23.18	20.63	14.74

Note: t-statistics in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Tables 6 and 7 report the meta-regression results based on the effect size of elasticity and PCC, respectively. As mentioned in Section 3, we consider three groups of factors in the meta-regression analysis. Therefore, three models are reported in Tables 6 and 7, stepwise introducing scenario and data factors, methodology factors and modelling factors into Models 1, 2 and 3. The R-squared of Models 1, 2 and 3 increases gradually; the R-squared of Model 3 in Tables 6 and 7 is 0.62 and 0.554, suggesting that it is able to explain 62% and 55.4% of the variation in elasticity or PCC. Further, the results of the F test indicate that all six models reject the null hypothesis; all six models are significant. Considering the results of elasticity and PCC are robust, and Model 3 in both Tables 6 and 7 has the highest R-squared, the results will be explained and discussed based on Model 3 in the following part.

4.1. Influences of Scenario and Data Variables

For scenario and data factors, “air index” and “industrial_emission” are significant in both models, while “source_published” is found to be significant only in elasticity. The negative and statistically significant coefficients of “air index” indicate that using air index as an air quality indicator has negative effects on the percentage change in housing prices and the strength of the correlation between air quality and property values that “air index” is found to be significant at the 1% in both elasticity and PCC. This confirms that air quality, in general, is priced by households in China. These results are intuitively appealing in which the rapid industrialisation has wrought intense levels of air pollution in China; thereby, it is reasonable to document that Chinese households are willing to pay a premium for clean air. Compared with applying the level of a single air pollutant as air quality indicator, utilising the air index leads to a more significant result in both elasticity and PCC with a 0.128 and 0.238 increase in the absolute value of elasticity and PCC, respectively. This result is in line with the finding of Smith and Huang [45] in that air quality measurement can affect the estimated results. Jackson [42] also found that the measurement, which is easier for residents to notice and distinguish, changes to best estimates with higher statistic and economic significance. Our finding further compliments Jackson’s finding that the measurement, which can reflect residents’ subjective sense comprehensively, generates best estimates. Although studies quantifying a single air pollutant’s impact on housing price tend to apply $PM_{2.5}$, PM_{10}, SO_2, which are more sensible either visually or olfactory, air indexes are more capable of reflecting the residents’ perceptions of the air quality in both the visual sense and olfaction.

Different from the air index, “industrial emission” shows significant positive signs for both elasticity and PCC with the significances both at 1%. Instead of applying the data collected from the real-time readings of the monitoring stations, using the data of total industrial emission results in smaller elasticity with lower statistical significance. Specifically, compared with the model using monitoring station readings, the model employing industrial emission generates results with a 0.0832 decrease in the absolute value of elasticity and a 0.0765 decrease in the absolute value of PCC. Industrial emission is the primary source of air pollutants in China and can partly reflect the total air quality level. However, compared with the actual readings represent the air pollution level in no matter what sources. Therefore, monitoring station readings can better reflect the actual air pollution level and the residents’ perceptions about air quality.

In terms of the last variable in scenario and data factors, different from “air index” and “industrial emission”, “source_published” demonstrates significant effects on elasticity but shows the insignificant influence on PCC. This finding suggests that the estimates from published samples are 0.0643 higher in the absolute value of elasticity than the estimates of unpublished observations. It indicates that published papers tend to report the studies finding more significant impacts of air quality on housing prices to show their research significance, and it is also the source of publication bias [89]. However, no remarkable difference in PCC is identified between published and unpublished samples.

4.2. Influences of Methodological Variables

Finally, as for methodological factors, each variable shows different impacts on effect sizes of elasticity and PCC. "Spatial" demonstrates significant influences on both elasticity and PCC, while "panel" and "IV" are found to be significant to PCC and elasticity, respectively. Controlling spatial effects of air pollution impacts result in larger coefficients with higher statistical significance in hedonic models that the estimates would be 0.06 larger in the absolute value of elasticity and 0.06 larger in the absolute value of PCC. This finding reconfirms that ignoring spatial effects might generate biased or even inconsistent estimates argued by Anselin and Lesage [105,106]. Therefore, spatial effects should be considered when quantifying the impacts of air quality on real estate values.

In addition, utilising panel data versus cross-sectional data generates estimates with lower statistical significance that the PCC for models applying panel data present a 0.153 decrease in PCC (absolute value). It might be because panel data are able to reduce the omitted variable bias. In this case, this finding can be interpreted as failing to control the effects of omitted variables through applying panel data, which will lead to biased estimates when quantifying the price of air quality based on housing prices. Furthermore, the application of the instrument variable poses a negative impact on elasticity that the estimates generated by models utilising instrument variable present a 0.153 increase in percentage change (absolute value) in housing prices. Applying instrument variables is also helpful for control-omitted variable bias, and this finding suggests that overlooking the bias caused by omitted variables will lead to a decrease in percentage change but will not make remarkable differences in statistical significance.

4.3. Influences of Modelling Variables

With regard to modelling factors, different results can be found in "housing_supply" and "other_enviromental". "Housing_supply" has a significant positive impact on PCC and an insignificant effect on elasticity, while "other_enviromental" has a significant negative influence on elasticity and an insignificant impact on PCC. For models introducing housing supply characteristics as control variables, the results of the impacts of air quality on property values are less significant, with a 0.089 reduction in the absolute value of PCC. For models applying other environmental factors as control variables, the estimates of the effects of air pollution on housing prices are 0.108 larger in the magnitude of the elasticity. However, "infrastructure" demonstrates insignificant influences on both models. It is consistent with Smith and Huang [45] that the model selection will affect estimates. Therefore, to come to results with less bias, other environmental characteristics and housing supply characteristics are important control variables and need to be controlled in quantifying the impacts of air quality based on housing prices.

5. Discussion

This study attempts to explain the variation of the statistical significance and economic significance of air quality impacts on macro housing prices across the previous literature. It is the first study to examine macro-level hedonic air quality studies and compares two types of effect sizes of the effects of air pollution on housing prices. Applying the quantitative method of meta-regression analysis, this study provides a comprehensive understanding of how empirical estimates are influenced by study-design factors. Further, the findings of this study also provide researchers who try to quantify the price of air based on HPM with some suggestions on how to generate less biased estimates. With two types of effect sizes reflecting the statistical and economic significance of the relationship between air quality and housing prices, this study offers a more comprehensive explanation of the mixed results of previous empirical studies in two perspectives and enables comparisons between them.

In terms of the finding of this study, given the differences between micro and macro hedonic air quality studies, the influential factors for micro studies and macro studies are heterogeneous. Based on the results reported in Section 4, we find that factors, including scenario and data factor, modelling factor and methodology factor, significantly influence the estimates on the magnitude and the significance of air quality impacts on property values. With regard to scenario and data factors, different sources of air quality data significantly influence the estimates that applying monitoring station data leads to a 36.3% and a 55.3% (calculated based on the mean value of elasticity and PCC) increase in the absolute value of elasticity and PCC. Compared with the source of air quality data, the selection of air quality measurement has even more noticeable effects. Employing the air index instead of a single air pollutant as an air quality indicator will result in a more significant regression result, which is 55.9% higher in the magnitude of elasticity and 172% larger in the PCC. These influences can be interpreted as the measurements and data sources, which can more comprehensively represent the actual air quality level to generate best estimates. In addition, the modelling selection does have an impact on the estimates. These findings are consistent with previous literature [42,45]. To be specific, controlling the effects of environmental factors (except for air quality) when estimating the impacts of air quality on housing prices leads to estimates of 47.2% higher in the absolute value of elasticity, while controlling housing supply results in estimates of 64.3% lower in the absolute value of PCC.

However, some divergence between our findings and previous meta-analysis findings on micro analyses have been documented. Specifically controlling spatial effects emerged to have significant impacts on the effects of air quality on property values. Employing spatial econometric approaches for estimation significantly affects the economic significance and statistical significance of the results. The results will witness a 26.1% increase in elasticity (absolute value) and a 44% increase in PCC (absolute value). These findings are inconsistent with the findings reported in Chen's work [48], and this inconsistency might be because of the differences between micro and macro hedonic studies. Moreover, this study identifies some new critical factors and further supplements previous meta-regression analysis on environmental factors and housing prices, explaining the effects of methodological factors on estimates. Results reported in this study indicate whether panel data are utilised and whether instrument variables are introduced in hedonic models would have significant influences on PCC and elasticity of the estimates of air quality effects, respectively.

This meta-regression analysis is also the first study employing two effect sizes to allow comparisons between the variations in economic significance and statistical significance. Elasticity is the effect size representing the economic meaning of the effects of air quality on housing prices; while the partial correlation coefficient is selected as the effect size to reflect the statistical relationship between air quality and property prices. Surprisingly, almost half of the factors identified in this study show similar impacts on both effect sizes. Another five factors demonstrate different or opposite influences on the two effect sizes. The first factor is "source_published"; the regression results suggest that this factor only significantly affects the magnitude of the elasticity but presents insignificant influences on PCC. The factor of "other_environmental" and "IV" demonstrates similar influences on the two effect sizes and that it has significant impacts on elasticity but insignificant effects on PCC. In contrast with the three abovementioned factors, "housing _supply" and "panel" present insignificant impacts on elasticity but significant effects on PCC. The comparison provides evidence that although some critical factors influence the economic meanings and statistical meanings of the effect of air quality simultaneously, economic significance and statistical significance are sensitive to different factors. To come up with a more comprehensive explanation in the variations in the effect of a phenomenon, it is better to employ two effect sizes in the meta-regression to represent the economic meaning and statistical meaning, respectively.

This research fills the gap of air-quality-hedonic-study-based meta-regression analysis by focusing on macro residential housing prices; there are still some questions that remain to be explored, including the influential factors for the estimates of both micro and macro hedonic air quality studies on rental prices of residential housing and the selling prices as well as rental prices of commercial property. Further, given the relatively severe air pollution in China, this study focuses on the impacts of air quality on housing prices in China. Researchers who are interested in this topic can expand the study scope to a global scale and testify whether some country-level factors such as socioeconomic condition and air pollution condition affect the estimates of the impacts of air quality on housing prices.

6. Conclusions

Given the mixed empirical results concerning the impacts of air pollution on housing value in China, this study investigates whether air quality significantly affects housing prices in China with a meta-regression analysis. Further, this study explores the variation in the estimated effects of air quality on property values and provides a comprehensive explanation of the mixed results in previous studies by identifying and comparing influential factors, which significantly affect the magnitude of the elasticity and the strength of the correlation coefficient.

The study found several important findings. Firstly, the study found that air quality does have a profound impact on housing prices. This suggests that air pollution is priced by Chinese households. Secondly, the impact of air quality is diverse in the following aspects: scenario and data factors, modelling factors and methodology factors. Half of the variables show significant influences on both effect sizes, including two scenario and data variables, one modelling variables and a methodology variable. With regard to the scenario variable, the selection of the type of air pollution and the source of air pollution data negatively and positively affects both elasticity and PCC, separately.

This finding suggests that the air pollutant and data source, which is more capable of comprehensively reflecting the residents' real perceptions, lead to more significant estimates. Moreover, addressing spatial effects using spatial econometric approaches results in more accurate regression estimates, which is higher in both economic and statistical meanings. Thus, to come up with less biased estimates, spatial econometric approaches can be helpful tools. The modelling factor of "infrastructure" demonstrates insignificant effects on both elasticity and PCC.

Except for the four abovementioned variables, there are five factors that only present significant impacts on either elasticity or PCC. This meta-regression analysis finds that published studies included in the meta-sample tend to report estimates with higher economic meaning. In terms of modelling variables, applying housing supply characteristics and other environmental factors as control variables in the hedonic models will lead to estimates with smaller elasticity and higher statistical significance, respectively. In other words, housing supply characteristics and other environmental characteristics are important control variables in hedonic models when quantifying macro impacts of air quality, and the ignorance of these two types of control variables will lead to biased estimates. Besides, utilising panel data and instrument variables, helping to reduce omitted variable bias, decreases the strength of the correlation between air pollution and property values. Therefore, in macro-level hedonic air quality studies, employing panel data and instrument variables can significantly reduce estimated biases.

The above-listed findings of this study have several profound implications and can be of interest to not only researchers but also policymakers. Firstly, this study provides a systematic review of the macro hedonic air quality studies in China, so policymakers and researchers would have an enhanced understanding of the impacts of air quality. This offers a rigorous foundation for policy formulation; thereby, Chinese and international policymakers, particularly in cities or countries where no empirical evidence is available for the effect of air quality on housing values, are able to formulate a better policy in relation to air quality and economic development.

In addition, the significant results in the meta-regression analysis might guide scholars on the choice of control variables for their analyses, such as infrastructure characteristics and housing supply characteristics. This study also gives some suggestions on the choice of data type and estimation approaches. For example, applying spatial econometric methods generates more significant results with higher statistical significance; introducing the instrument variable leads to larger coefficients. These suggest that the ignorance of spatial effects and endogeneity will lead to biased estimates. Furthermore, this study can be referred to as a benchmark for scholars who would like to find how their results fit with other studies; the results may also be used to explain different estimates obtained from different research.

Recognising the uniqueness of the Chinese market (e.g., the imperfections of the Chinese financial market [107] and the high level of air pollution in China), the abovementioned contributions can, to a certain extent, be limited to China. To better understand the variations among the impacts of air quality on property prices globally or in other markets, future studies of air pollution impacts on other housing markets are necessary. However, this study also helps scholars (not restricted to Chinese researchers) to get a comprehensive overview of the variations in how the air quality impacts in the following two perspectives. Firstly, different findings in elasticity and PCC models give reasonable suggestions on effect size selection in meta-regression analysis. Although half of the factors in this study have comparable effects on both elasticity and PCC, elasticity and PCC are still sensitive to some of the different factors. Therefore, to better understand the relationship between air quality and housing prices, we need to understand the critical factors for economic significance and statistical significance, respectively. Additionally, some of the inconsistent findings with previous micro-level studies demonstrate that the macro hedonic air quality studies are affected by different factors (e.g., spatial effects). Given most previous literature focused on the meta-regression analysis with micro-hedonic studies, further meta-regression analyses considering macro studies and comparisons are of great importance to understand the mixed results of air quality impacts.

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Appendix A

Table A1. Variance inflation factor (VIF) of meta-variables.

Variable	VIF	1/VIF
D_ai	2.21	0.452671
D_i	1.90	0.527032
D_hs	1.88	0.530586
D_sp	1.77	0.564519
D_p	1.75	0.571473
D_oe	1.73	0.578003
D_s	1.63	0.618269
D_ie	1.42	0.703426
D_iv	1.19	0.843061
Mean VIF	1.72	

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