Environ Resource Econ
DOI 10.1007/s10640-017-0186-8

The Value of Air Quality in Chinese Cities: Evidence from Labor and Property Market Outcomes

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Accepted: 9 October 2017

Abstract Using a dual-market sorting model of workers' location decisions, this paper studies the capitalization of air pollution in wages and property prices across Chinese cities. To account for endogeneity of air pollution in the determination of wages and property prices, we exploit quasi-experimental variation in air quality induced by a policy subsidizing coal-based winter heating in northern China, and document a discontinuity in average air quality for cities located north and south of the policy boundary. Using data for all 288 Chinese cities in 2011, we estimate an equilibrium relationship between wages and house prices for the entire system of Chinese cities, and specify a regression discontinuity design to quantify how variation in air quality induced by the policy affects this relationship locally. Our preferred estimates of the elasticity of wages and house prices with respect to PM_{10} concentration are 0.53 and −0.71 respectively. At the average of our sample, the willingness to pay for a unit reduction in PM_{10} concentration is CNY 261.28 ($\simeq$USD 40.50), with a significant share reflected in labor market outcomes.

Keywords Hedonic model · Air pollution · Labor market · House prices · Local public goods · Regression discontinuity

JEL Classification H41 · J31 · R31 · Q53

We would like to thank Souvik Datta, David Good, and Wei Hu, as well as participants at the 2015 EAERE meeting in Helsinki for useful comments and discussions. Funding from the China Scholarship Council is gratefully acknowledged. Any remaining errors are ours.

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Published online: 13 November 2017

1 Introduction

Along with the rapid industrialization and urbanization of China in the past decades, severely polluted air is now smothering most Chinese cities. In 2011, seven of the world's ten cities with worse air quality were located in China (Zhang and Crooks 2012), and daily concentration of suspended particulate matter (PM_{10}) in 84 major Chinese cities averaged 118 $\mu g/m^3$ (MEP 2012), more than five times the level at which mortality risks have been shown to increase (20 $\mu g/m^3$).[1] In spite of that, commonly proposed measures to mitigate air pollution involve reshaping the composition of primary energy use and sectoral economic activities (Guan and Liu 2014), which are associated with concerns about high costs and adverse effects on economic growth. Providing evidence about the economic value of air quality improvements is thus of great importance.

Since the partial liberalization of the Chinese economy in the 1990s, and in particular that of the labor and property markets (see Zheng et al. 2006, for a review), many workers have swarmed into more developed regions and cities. Labor mobility and the associated location decisions are directly related to the emergence of a system of open cities (Zheng et al. 2010), and in turn to spatially differentiated demand for housing across Chinese cities (Zheng and Kahn 2013). Given this, a number of empirical studies have applied the hedonic property value model of Rosen (1974) to measure the capitalization of local amenities in house prices, including air pollution. For example, in a study covering 35 major Chinese cities from 2003 to 2006, Zheng et al. (2010) show that house prices are lower in cities with higher levels of PM_{10}. This is confirmed by Zheng et al. (2014) using data for 85 large Chinese cities from 2006 to 2009, and a study of house prices across neighborhoods in Beijing by Zheng and Kahn (2008). These papers provide supporting evidence that residents 'vote with their feet' (Tiebout 1956), with market prices adjusting to reflect the prevailing supply of local amenities in different urban areas.

In a system of cities in which individuals and firms are mobile, however, location decisions will affect both labor and property market outcomes. Relative to existing studies focusing on how the housing market respond to differentials in air quality, the main contribution of this paper is to consider the joint determination of wages and property prices, and in this setting assess how variation in air quality affects market outcomes. We use a standard dual-market sorting model developed by Rosen (1979) and Roback (1982), in which labor and property markets clear simultaneously. Intuitively, cities that offer relatively high levels of amenities will attract both firms and workers, creating three-way interactions between property prices, wages, and the provision of local amenities. In the case of air quality, workers locating in cities with relatively high pollution will command higher wages or face lower housing prices, ceteris paribus, to compensate for the welfare cost associated with air pollution. Moreover, if polluting emissions have a cost-reducing effect on firms (e.g. emissions do not require mitigation expenditures), then through equilibrium sorting firms will be willing to spend more on wages and/or house prices in cities with relatively low air quality. In turn, regional differences in air quality will be compensated by variations in both wages and house prices.

[1] See World Health Organization (WHO 2006). PM_{10} represents the part of suspended particles with a diameter smaller than 10 μm. These particles can enter the lungs which, among other things, can cause an increase in the prevalence of cardiovascular diseases (e.g. D'Ippoliti et al. 2003; Tsai et al. 2003). More generally, empirical evidence has shown that air pollution, and in particular PM_{10}, has significant welfare consequences, among which a negative impact on the overall level of public health (e.g. Chay and Greenstone 2003; Pope and Dockery 2006; Chen et al. 2013; Qiao et al. 2014). Growing evidence also suggests that air pollution affects wider economic outcomes such as worker productivity (Graff Zivin and Neidell 2012), labor supply (Hanna and Oliva 2015), as well as school attendance (Currie et al. 2009).

Incorporating evidence from the labor market is a priori important, as existing applications of the Rosen–Roback approach have generally shown that a large share of amenity values are accounted for by variation in wages (e.g. Hoehn et al. 1987; Blomquist et al. 1988; Graves and Waldman 1991; Albouy 2016). In the case of China, a study using data for a subset of 85 large Chinese cities (Zheng et al. 2009) finds that compensating differentials for wages and property prices have increased markedly from 1998 to 2004, that is, early in the liberalization process of the Chinese economy. However, Zheng et al. (2009) do not report evidence about air quality among the set of local amenities they consider, whereas the more recent studies focusing on house prices suggest that air quality is a relevant determinant of spatial differentials in house prices. Furthermore, as the population grows richer and more educated, demand for environmental quality in general and air quality in particular is expected to increase. This suggests that market capitalization effects would tend to increase with time.

To estimate spatially compensating wages and property prices differentials, we use a unique dataset that includes the full set of Chinese prefectural-level cities (MEP 2012).[2] More specifically, while existing studies employ a subsample of "large" cities, which experience on average higher air pollution, wages and house prices, we assemble 2011 data for all 288 cities on PM_{10} concentration (MEP 2012), wages and house prices (NBSC 2012a), and use data from the 2010 census (NBSC 2010) to obtain information about local labor and property markets. This extensive geographical scope allows us to generate a comprehensive picture of inter-city differences in China, providing a counterpart to the use of metropolitan statistical area (MSA) in US studies (e.g. Glaeser and Tobio 2008; Gyourko et al. 2010; Albouy 2016). While our main focus is on annual PM_{10} concentrations, which would capture visual air quality problems, we also consider an Air Pollution Index (API) which captures a border set of airborne pollutants.

In this setting, one empirical challenge is the potential endogeneity of air pollution. First, local amenities are not randomly assigned across location, but are themselves the outcome of equilibrium sorting mechanisms (see Kuminoff et al. 2013, for a review). For example, if households have heterogeneous preferences for air quality, and they spatially sort according to their preferences, then capitalization of air quality in market outcomes is an endogenous outcome of the sorting process. In turn, standard OLS estimates of implicit prices are likely to be severely biased towards zero (Chay and Greenstone 2005). Second, it is practically impossible to control for all possible determinants of wages and house prices, giving rise to a risk of an omitted variable bias whenever air pollution is correlated with unobserved characteristics of different locations (Cropper et al. 1988; Kuminoff et al. 2010).

As an attempt to address these endogeneity concerns, we build on a growing hedonic pricing literature that uses quasi-experimental sources of variations to motivate instrumental variable (IV) strategies.[3] Our research design exploits variation in air pollution induced by the River Huai policy, which subsidizes winter heating in cities that are located in northern China. Because heating systems are, for a large part, inefficient and predominantly use coal as a fuel source, the policy heavily contributes to air pollution in the northern part of China. Therefore, as initially suggested by Almond et al. (2009), the River Huai policy provides a setting to implement a regression discontinuity design based on a discrete change in air

[2] In China's administrative structure, a prefectural city is an administrative division ranking below a province and above a county/town. A prefectural city emerges if the administrative subdivision meets the following three criteria: (i) the non-agricultural population in the central urban area is over 250 thousand; (ii) the gross value of industrial output is more than CNY 200 million (around USD 31 million); (iii) tertiary industry's share is higher than that of the primary industry, and accounts for over 35% of the gross regional production.

[3] See for example Black (1999), Epple and Sieg (1999), Davis (2004), Chay and Greenstone (2005), Linden and Rockoff (2008), and Pope (2008).

quality for cities on each side of the policy boundary. A similar strategy is used in Chen et al. (2013) to document a causal impact of total suspended particles on health outcomes.

Given our focus on the equilibrium relationship between labor and property market outcomes for the full set of Chinese cities, our estimation strategy effectively quantifies how the discontinuity created by the River Huai policy locally affects the country-wide relationship between wages and property prices. In other words, our strategy identifies the *local* impact of changes in air quality near the policy boundary on the equilibrium sorting relationship that emerges across the full system of Chinese cities.[4]

Our main results confirm the existence of compensating differentials in both labor and property markets across Chinese cities, as well as the importance of accounting for the joint determination of wages and property prices. An important share of benefits of improved air quality is reflected in wages, and in our preferred specification elasticity estimates for wages and house prices with respect to PM_{10} concentration are 0.53 and -0.71 respectively. In a set of calculations to illustrate the magnitude of our findings, we show that, at the individual level, a reduction of PM_{10} concentration by $1\,\mu g/m^3$ is associated with an average value of CNY 261.28 ($\simeq$USD 40.50).[5] At the city level, our results suggests that a marginal change in PM_{10} concentration amounts to an aggregate change in wages of around CNY 122.98 million per year on average ($\simeq$USD 19.06 million), and an increase in the value of housing stock by CNY 766.37 million ($\simeq$USD 118.79 million). While these are large numbers, they are dwarfed by recent estimates attributing around 1.28 million premature deaths to ambient air pollution each year in China (OECD 2014).[6]

The remaining of this paper proceeds as follows. In Sect. 2 we briefly review the dual-market hedonic model. In Sect. 3 we provide descriptive evidence about wages, house prices, and air pollution across Chinese cities, and discuss evidence about our regression discontinuity identification strategy. Section 4 reports our main estimation results and illustrative calculations. Section 5 concludes.

2 Theory: Compensating Differentials and Local Amenities

This section presents the basic theoretical framework underlying our estimation. It builds on Rosen's (1979) idea that individuals' decisions to locate in a given city involves both employment and housing. Intuitively, locations with higher levels of local amenities will attract relatively more workers, which induces an increase in the supply of labor and in the demand for housing. This, in turn, will drive wages down and property prices up. Thus as compared to the traditional hedonic property value model (Rosen 1974), a dual-sorting equilibrium implies that the economic value of local amenities will be reflected in both wages and house prices, and spatially compensating price differentials on both markets can be identified by jointly estimating a hedonic wage function and a hedonic property value function.

4 In the present context, another benefit of using a regression discontinuity design is that it mitigates concerns about the quality of Chinese air pollution data. While we discuss this issue further below, it is important to note that our identification strategy essentially compares equilibrium market interactions near to the policy boundary, so that our results would be affected by data quality only insofar as cities included or not under the River Huai policy differ in how they report the data (Almond et al. 2009).

5 Throughout the paper we use an average exchange rate for 2011 of CNY 1 $\simeq$USD 0.155.

6 More specifically, OECD (2014) calculates that, in 2010, deaths attributed to ambient air pollution translate into 24.58 million years of life lost. Based on this, they estimate that the economic cost of outdoor air pollution and associated health impacts is about USD 1.4 trillion.

Equilibrium interactions between wages, house prices, and the provision of local amenities is formalized in the model by Roback (1982). In this framework, implicit prices of local amenities is an outcome of individuals and firms' location decisions considering (respectively) the attributes and production costs associated with different locations. Specifically, a representative individual maximizes a utility function $U(X, H; \ Q)$ by making choices over a numeraire good X (with price normalized to one) and a non-traded good H (i.e. housing), as well as a location-specific amenity, here a measure of air quality Q, subject to a budget constraint:[7]

$$\max_{X,H,Q} \quad U(X, H; \ Q) \quad s.t. \quad w + I = X + Hr \tag{1}$$

where w is the wage rate, I is non-labor income (independent of location), and r is the price of housing.

Market equilibrium implies that wages and house prices adjust to make individuals indifferent between locations. Thus in equilibrium individuals achieve the same utility level $\overline{V}$ in different locations (otherwise they would move), so that indirect utility is constant across locations: $V(w, r; \ Q) = \overline{V}$. Here non-labor income I and the price of good X are assumed constant and omitted for simplicity. Denoting partial derivatives by $\partial V / \partial w = V_w$, we have $V_w > 0$ and $V_r < 0$, and, since air quality can a priori be assumed to have a positive impact on household's welfare, $V_Q > 0$.

Firms' location decisions follows a similar logic. Consider a representative cost-minimizing firm which admits a constant return to scale production technology. Profit maximization requires that unit cost $C(w, r; \ Q)$ of producing X is equal to the price of X (here normalized to one), and in equilibrium production costs have to be the same in all locations, so that: $C(w, r; \ Q) = 1$. While we have that $C_w > 0$ and $C_r > 0$, the impact of air pollution on production costs depends on technology. Specifically, if pollution is a by-product of the production process, then pollution abatement is likely to be costly to the firm, so that $C_Q > 0$. In other words, improved air quality requires firms to undertake some mitigating actions, which would increase their costs. It is also possible, however, that air pollution negatively affects firms production possibilities, for example if it accelerates depreciation of the firm's stock of capital. Thus improving air quality would reduce the cost of production, $C_Q < 0$.

Market interactions between workers and firms imply that the impact of air pollution on wages and housing costs depends on both preferences and technology. This can be seen by totally differentiating equilibrium conditions for individuals and firms and collecting terms:

$$\frac{dw}{dQ} = \frac{1}{\Phi}\left(-V_Q C_r + V_r C_Q\right) \tag{2}$$

$$\frac{dr}{dQ} = \frac{1}{\Phi}\left(-V_w C_Q + V_Q C_w\right) \tag{3}$$

where $\Phi = V_w C_r - V_r C_w > 0$. When $V_Q \geq 0$ (e.g. through health impacts), increasing air quality Q while maintaining utility at level $\overline{V}$ would be associated with either higher house prices r or lower wages w. If in addition $C_Q > 0$ (e.g. through mitigating actions), increasing Q while keeping production costs constant would require lower expenditures on wages or housing costs. Taken together, this implies that locations with better air quality command lower equilibrium wages (i.e. Eq. (2) is unambiguously negative). However, the equilibrium impact of pollution on housing price (Eq. 3) is indeterminate, as it reflects conflicting interests of households and firms. Symmetrically, when $C_Q < 0$ (firms also benefit from improved air quality) the sign of (2) is indeterminate, while Eq. (3) is positive.

[7] As in Roback (1982), the use of a representative agent implicitly imposes that all individuals chose their location simultaneously, and that they are identical in tastes and skills.

These equations can be used to derive an expression for the implicit price for local amenities P_Q^*, which measures the change in income required to compensate individuals for marginal changes in Q. In particular, solving for the ratio V_Q/V_w we have that:

$$P_Q^* = \frac{V_Q}{V_w} = -\frac{dw}{dQ} - \frac{V_r}{V_w}\frac{dr}{dQ}, \tag{4}$$

From Roy's identify $-\frac{V_Q}{V_w}$ can be interpreted as the inverse demand curve or marginal willingness to pay (MWTP) for air quality, and similarly the demand for housing is $-\frac{V_r}{V_w} = H^*$. Hence we have:

$$MWTP_Q = -\frac{dw}{dQ} + H^* \cdot \frac{dr}{dQ}. \tag{5}$$

MWTP for air quality (i.e. the change in income that would leave individuals indifferent to marginal air pollution reduction) can be estimated though a hedonic wages equation and a hedonic property value model, respectively identifying dw/dQ and dr/dQ.[8]

One fundamental issue with the identification of implicit prices using spatially compensating variations is the endogeneity of local amenities. If individuals have heterogeneous tastes for amenities (here air quality), then Tiebout's (1956) sorting mechanism implies self-selection of individuals with strong preferences for air quality in locations with better air quality (e.g. Chay and Greenstone 2005; Kuminoff et al. 2013). Similarly, firms with inefficient technologies will be attracted by locations with lax regulation, and since air quality problems in China are mainly driven by the use of energy (coal), this may affect labor productivity and wages through firms' technology. This endogeneity problem is also related to recurring concerns about omitted variables in hedonic regressions (Cropper et al. 1988; Kuminoff et al. 2010). Using exogenous sources of variation in air quality is thus crucial to identify (local) MWTP estimates.

A second noteworthy issue with the Roback (1982) framework is the absence of migration costs. In particular, if location decisions of individuals and firms are constrained, then adjustments in wages and house prices will not fully reflect the value of amenities. Intuitively, this implies that ignoring migration costs biases MWTP estimates downwards (see Bayer et al. 2009; Kennan and Walker 2011). China has notoriously implemented mobility restrictions through the *Hukou* policy to regulate migration of rural workers, and although this policy has been phased out since 1990 and completely abolished in some provinces (see Zheng et al. 2014), it should be kept in mind that our assumption of free labor mobility is a simplification.[9] One implication is that our estimates represent a lower bound to implicit prices that would prevail in the absence of migration costs and constraints to mobility.

3 Data and Empirical Strategy

In this section we discuss empirical identification of the implicit price of air quality. We first present descriptive evidence about variation in inter-city wages and house prices as well as

[8] As suggested in the initial Roback (1982) paper, this approach can be used to construct an index-ranking of cities capturing variations in the quality of life. See for example Gyourko et al. (1999). In this paper we rather focus on estimating the implicit price of air pollution as we were not able to locate plausibly exogenous variations for the set of amenities that would make a city-ranking exercise meaningful.

[9] Starting in 1958, the Hukou policy classifies people into local and non-local residents as well as agricultural and non-agricultural status. This classification was used mainly to grant access to local public services (such as children' access to public schools), and has thus restricted labor mobility for decades. Importantly however, in the year 2011 we consider the Hukou system did not impose significant restrictions for housing market transactions (see also Zheng et al. 2010).

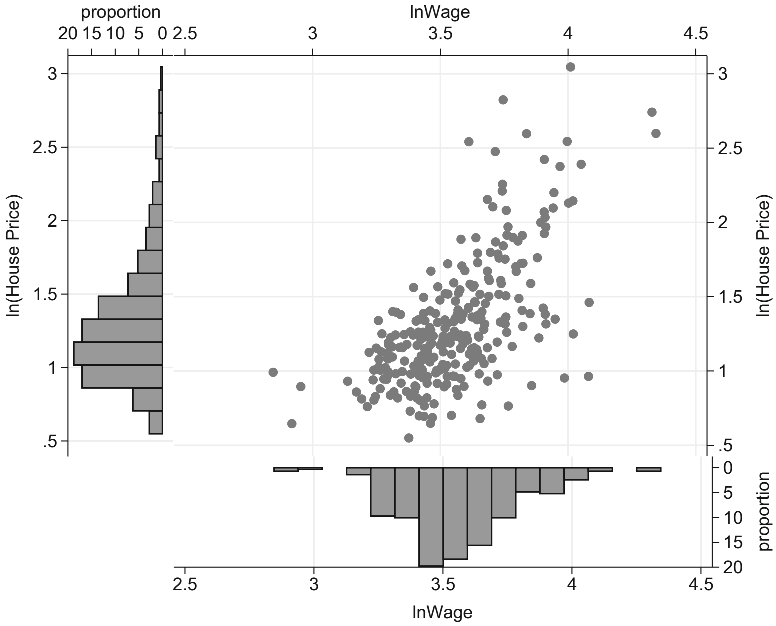

Fig. 1 Wages and house prices in 288 Chinese cities, 2011. *Source*: NBSC (2012a)

PM_{10} concentrations. We then present our identification strategy and provide evidence about discontinuity associated with the River Huai policy.

3.1 Descriptive Evidence: Wages, House Prices and Air Quality in China

The baseline year for our analysis is 2011, the year for which we could obtain access to data on air pollution for *all* 288 prefecture-level cities (MEP 2012). Data on regional wages and house prices are taken from NBSC (2012a) and also refer to 2011. Moreover, referring to 2011 is convenient because detailed data on regional labor and property markets is available from the 2010 census (NBSC 2010). Data sources and summary statistics for all the variables used in the analysis are provided in Appendix A.

Observed variation in wages and housing prices across Chinese cities are substantial, as illustrated by Fig. 1. Yearly wages are on average CNY 35,957 ($\simeq$ USD 5566) and house prices, which measures annual average transaction price for residential dwellings (in CNY/m^2), are on average CNY 4117 ($\simeq$ USD 637). Across cities, we observe a positive correlation between (log-)wages and (log-)housing prices ($\rho = 0.64$, p-val. < 0.01).

Our main measure of air quality is yearly average PM_{10} concentration in $\mu g/m^3$. This data is mapped in Fig. 2 (administrative areas that with no color are not classified as cities given the criteria defined previously). We also report the distribution of cities across air quality thresholds defined by WHO (2006).[10] The reported concentrations of PM_{10} is consistent

[10] According to the air quality guidelines from WHO (2006), the lowest level of annual average PM_{10} concentrations at which total, cardiopulmonary and lung cancer mortality have been shown to increase is $20\,\mu g/m^3$. There are also three intermediate targets of PM_{10}. At $30\,\mu g/m^3$ the long-term risk of premature

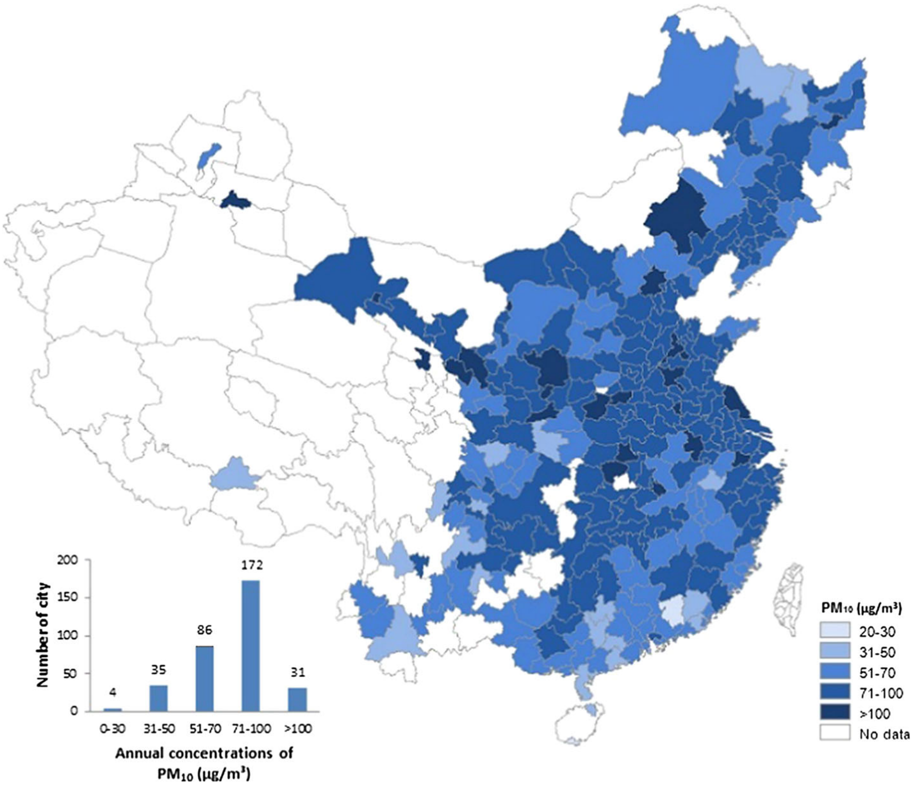

Fig. 2 Air quality in 288 Chinese cities, 2011. *Source*: MEP (2012)

with the widespread concerns about air pollution in Chinese cities. In 2011, among all the 288 prefectural cities, none of them achieved the lowest threshold level ($20\,\mu g/m^3$), and almost 70% of them do not meet the laxest standard ($70\,\mu g/m^3$).

An alternative widely used measure of air pollution in China is the API. As we detail in Appendix B, the API is computed by each city (NBSC 2012a) and combines data on the concentration of PM_{10}, SO_2 and nitrogen dioxide (NO_2). For our empirical results, we also consider the number of days during which air pollution in a given city area is "slightly polluted" or worse (i.e. daily API is above 100). The value of 100 is selected because it is the first threshold at which health issues are known to appear. While this provides another policy-relevant measure of air pollution, some researchers have raised questions regarding the manipulation of API data reported by cities. Recently, China's central government has used air quality as one of the criteria to evaluate the performance of local governments, and the "National environmental protection model city" award requires more than 85% days per year with daily API lower than 100. Therefore, the local governments have an incentive to manipulate reported API, likely inducing reported pollution levels below real values. For example, Andrews (2008) suggests the potential for a systematic under-reporting of API readings around the threshold of 100 in Beijing, which generates inconsistent metrics between

Footnote 10 continued
mortality increases by around three percent, at $50\,\mu g/m^3$ the risk increases by around 10 percent, and at $70\,\mu g/m^3$ the risk is around 15 percent higher.

API and PM_{10} concentrations. Similarly, Ghanem and Zhang (2014) provide evidence about discontinuities at different thresholds, which may be interpreted as data manipulation.

However, API data has also been shown to provide useful information about variation of air pollution among different regions. Chen et al. (2012) compare API data with visibility and aerosol optical depth measurement to examine potential data manipulation, showing that both measures are essentially consistent with each other. Moreover, correlations between API and aerosol optical depth does not change significantly when the API is closely below or above 100. Nevertheless, we will focus on PM_{10} concentrations as our primary measure of air quality, which is likely to be more difficult to manipulate. And since PM_{10} concentration is related to visibility, it is also expected to be more directly related to individual behavior and thus reflected in market outcomes.

3.2 Estimation and Identification Strategy

In the framework laid out by Rosen (1979) and Roback (1982), the implicit price of air pollution can be identified from inter-city wages and house prices differentials. Formally, indexing cities by i, we write the hedonic wages equation as:

$$Wages_i = \alpha_0 + \alpha_1 Air\ pollution_i + \alpha_2 House\ prices_i + \alpha_3 X_i^{wages} + \varepsilon_i^{wages} \tag{6}$$

where the α's are parameters to be estimated from the data, X^{wages} is a vector of covariates, and ε is an error term. Similarly the hedonic house prices equation is given by:

$$House\ prices_i = \beta_0 + \beta_1 Air\ pollution_i + \beta_2 Wages_i + \beta_3 X_i^{house\ prices} + \varepsilon_i^{house\ prices} \tag{7}$$

where notation follows the same logic as above.

Simultaneity in the determination of wages and housing prices calls for an instrumental variable (IV) approach. In particular, in the wage Eq. (6), we instrument housing prices with the set of determinants included in $X^{house\ prices}$ that can plausibly be excluded from X^{wages} ("house prices shifters"). These variables are: the share of houses with piped water, fitted toilets, and fitted shower, the amount of land traded, population density, a dummy for coastal cities, and the availability of universities. These variables all measure characteristics of and outcomes on local housing markets, and can plausibly be assumed to affect wages paid to workers only through their impact on house prices. Vice versa, in the house prices Eq. (7) we instrument wages with variables in X^{wages} that can plausibly be excluded from $X^{house\ prices}$ ("wages shifters"). These variables are: the population share of male, university graduates, and migrants, and the rate of unemployment. These variables are direct determinants of local labor market outcomes, and are assumed to affect house prices only through their effect on wages. We also stress that individual coefficients for variables included in the set of shifters are not of direct interest, as these are likely biased by confounding factors.

The main coefficients of interest are α_1 and β_1, which are the constituting elements of the MWTP for air quality (see Eq. 5) and capture how air quality interacts with the joint determination of wages and house prices. As discussed above, air pollution is itself likely endogenous, and we use a regression discontinuity estimation strategy based on the River Huai policy, as initially suggested by Almond et al. (2009). The River Huai policy subsidizes winter heating in northern Chinese cities, and this policy was set up because winter temperatures are on average colder in the north. The north/south boundary that is relevant for the policy is defined by the River Huai and Mountains Qinling along the 33° latitude. However, the climate and geography of cities located along the policy boundary are obviously very similar, and the boundary determining which city gets subsidized reflects an administrative decision and financial constraints.

Because deployed heating systems are coal-based and typically quite inefficient, the policy has been shown to be associated with a substantial amount of particulate matter emissions (Almond et al. 2009). In turn, based on the boundary of the policy, Chen et al. (2013) have used a regression discontinuity design to evaluate a causal impact of suspended particulate matter concentration on health and mortality. In our setting, we exploit the discrete change in the scope of coal-based heating systems and associated variation in air pollution to identify how air quality changes equilibrium interactions between wages and house prices prevailing across Chinese cities. Therefore, our research design involves two components. The first identifies a spatial equilibrium relationship driven by workers' location decision in the system of connected Chinese cities (Zheng et al. 2010). This necessitates the use of an extended geographical area, and thus a large number of cities. Second, we then use the discontinuity of the River Huai policy to identify how air quality affects this equilibrium relationship. By construction, this provides empirical evidence about the *local* effect of air quality differences on the system-wise equilibrium relationship.

Formally, we follow Chen et al. (2013) and model variation in PM_{10} concentration as:

$$\begin{aligned} Air\ pollution_i = \gamma_0 + \gamma_1 I_i^{Huai\ policy} + \sum_n \gamma_n \left(Latitude_i\right)^n \\ + \delta_1 X_i^{wages} + \delta_2 X_i^{house\ prices} + \varepsilon_i^{Huai\ policy} \end{aligned} \tag{8}$$

where the γ's and δ's are parameters to be estimated, $I_i^{Huai\ Policy}$ is an indicator variable which equals one if city i is located north of the 33° latitude, the variable *Latitude* measures the distance (in degrees) between the city and latitude 33° (computed from NGCC 2012), and ε is an error term. In Eq. (8), γ_1 captures a discrete change in air pollution among northern and southern cities associated by the River Huai policy (after adjusting for a flexible polynomial function in latitude). We use the $I_i^{Huai\ Policy}$ indicator variable to instrument air pollution in Eqs. (6) and (7).

First stage evidence about our instruments for air quality is presented in Table 1. In columns 1–3, we report results for Eq. (8) with the logarithm form of average PM_{10} concentration as the dependent variable and linear, quadratic and cubic specifications of latitude in each respective column. Columns 4–6 report results for Eq. (8) with the logarithm form of number of days in which API is greater than 100 as the dependent variable. All specifications include the full set of controls used in the second stage estimation discussed below.[11]

Results show that the discontinuity indicator is positive and highly statistically significant, and relatively similar across specifications/measures of air pollution. This confirms evidence from Almond et al. (2009) and Chen et al. (2013) that the River Huai policy generates significant variation in air quality nearby the policy boundary. Furthermore, a comparison of adjusted R^2 and AIC values suggest that cubic specifications perform better in fitting the

[11] Because suspended particles move with wind, we have checked for any systematic wind patterns in cities located within 2 degrees' latitude around the Huai River (the data source is lishi.tianqi.com). Among this subset of 55 cities, data indicate that 27 have no prevailing wind direction, 10 have east as their prevailing wind direction, 13 have southeast, 3 have south, 1 has west and 1 has northeast. This very heterogeneous pattern, with little evidence of systematic north/south dispersion, is in line with discontinuity in PM10 concentration reported in Almond et al. (2009) and Chen et al. (2013).

Table 1 Estimation results for alternative specifications of the pollution equation

	$\ln(PM_{10})$ (1)	$\ln(PM_{10})$ (2)	$\ln(PM_{10})$ (3)	ln(polluted days) (4)	ln(polluted days) (5)	ln(polluted days) (6)
Huai policy	0.21***	0.17***	0.26***	0.99***	0.76***	1.08***
	(0.05)	(0.05)	(0.06)	(0.23)	(0.21)	(0.26)
Latitude	0.002	− 0.02*	− 0.03***	0.01	− 0.04	− 0.09*
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)
Latitude^2	–	− 0.003***	− 0.003***	–	− 0.01***	− 0.01***
		(0.003)	(0.0003)		(0.001)	(0.002)
Latitude^3	–	–	0.0001***	–	–	0.0004**
			(0.00004)			(0.0002)
Constant term	2.95***	2.96***	2.91***	0.72	0.73	0.53
	(0.31)	(0.27)	(0.26)	(1.35)	(1.26)	(1.25)
Adjusted R^2	0.311	0.495	0.509	0.270	0.371	0.382
AIC	− 26.41	− 114.7	− 122.1	683.3	646.5	643.2

288 observations for regressions 1-3, 252 for regressions 4-6. OLS estimates reported with heteroskedasticity-robust standard errors in parentheses. In columns 1–3 the dependent variable is the logarithm of average PM_{10} concentration in 2011 (in $\mu g/m^3$). In columns 4–6 the dependent variable is the logarithm of number of days with API $\geq$ 100 in 2011. Coefficient estimates for control variables are omitted here; full first-stage regression results are reported in Appendix C, Tables 5 and 7

*, ** and ***respectively denote statistical significance at 10, 5 and 1% levels

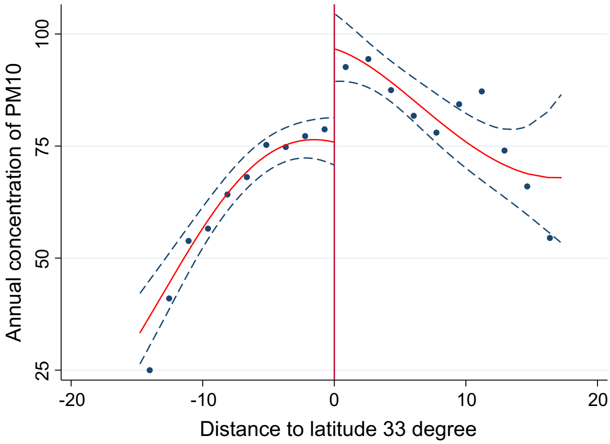

Fig. 3 Summary measure of average PM_{10} concentration around the policy boundary. *Notes*: Yearly average PM_{10} concentration (in $\mu g/m^3$) as a function of distance to the Huai River policy threshold (in latitude). Points represent average value across cities, with cities grouped in ten bins according to the distance to policy threshold (N = 288)

data, and in the remaining of the analysis we thus focus on cubic polynomial functions for Eq. (8). The resulting pattern and discontinuity for our preferred measure of air pollution, namely PM_{10} concentrations, is illustrated graphically in Fig. 3.

4 Estimation Results

This section first reports regression results for the hedonic wages and house prices equations. We then illustrate the magnitude of the results by computing average individual-level MWTP as well as aggregate value of marginal air quality improvements across Chinese cities.

4.1 Regression Results

Table 2 presents the results for the wage equation across several specifications. In columns 1–5, we regress average yearly log-wages (in 1000 CNY/Year) on average log-house prices (in 1000 CNY/m^2), log-PM_{10} concentrations (in $\mu g/m^3$), and a number of controls that characterize the labor market across cities. In order to assess the importance of endogeneity for house prices and air quality, we start by reporting OLS estimates that treat house prices and air pollution as exogenous (column 1). Columns 2 and 3 then separately consider endogeneity of house prices and air pollution respectively. Specifically, in column 2 we instrument house prices with characteristics of regional housing markets, and in column 3 we instrument PM_{10} concentrations with the $I_i^{Huai\ policy}$ indicator variable. We report results for the first stage regressions in Appendix C.[12] Column 4 provides our main results, jointly instrumenting house prices and pollution. Column 6 reports results based on our alternative measure of air pollution, namely the number of days in which the API is no less than 100. Recall that this measure captures average daily API values, and combines information on the concentration of PM_{10}, SO_2 and NO_2 (see Appendix B). The final specification for the wages equation, reported in column 7, is based on level-coded wages, house prices and PM_{10} concentrations.

While the positive and statistically significant impact of house prices on wages differs only modestly when house prices are instrumented, the impact of air quality on wages is only of economic and statistical significant once we instrument for both house prices and PM_{10} concentration. This is important because it suggests that accounting for house prices variation in cities around the policy boundary reveals a capitalization of air quality in wages that is policy-relevant. In particular, specification 4 suggests the elasticity of wages with respect to PM_{10} concentration is positive and highly statistically significant, with a point estimate of 0.53. At the mean of the sample, this implies that a unit increase in PM_{10} concentration is associated with an increase of average yearly wages by CNY 244.68 ($\simeq$ USD 37.92).

Other determinants of the labor market outcomes generally have the expected effect on average wages. It should be emphasized, however, that these estimates are not meant to represent causal relationships, but mainly capture features of the labor market that co-vary with wages. For example, the positive effect associated with the share of immigrant workers reflects a supply–demand interaction and this specific estimate is obviously biased by reverse causality. But given the simultaneous equation framework we consider, these variables are mainly used as price shifters for the identification how wages impact house prices (see Table 3 below). Moreover, the inclusion of spatial control variables, which are used in the pollution equation, also complicate the interpretation of other control variables.

Turning to our alternative measure of air pollution (column 5), we find that the number of polluted days is also a statistically significant driver of wages. We find an elasticity of around 0.1, so that a marginal increase in the number of polluted days is associated with an increase of wages by CNY 175.92 ($\simeq$ USD 27.27) at the mean of the sample. The final specification

[12] All IV regressions are estimated with limited information maximum likelihood (LIML), as this approach is generally more reliable than two stage least square (TSLS). We report critical values of the Cragg–Donald statistics in the notes of the result tables. Note that TSLS estimates are, however, very similar to LIML estimates reported here.

Table 2 Estimation results for the hedonic wages equation

	OLS ln(wages) (1)	IV1 ln(wages) (2)	IV2 ln(wages) (3)	IV3 ln(wages) (4)	IV4 ln(wages) (5)	IV5 Wages (6)
$\ln(PM_{10})$	− 0.01	− 0.002	0.002	0.53**	–	–
	(0.04)	(0.04)	(0.15)	(0.22)		
ln(polluted days)	–	–	–	–	0.11**	–
					(0.05)	
PM_{10}	–	–	–	–	–	0.34**
						(0.15)
ln(house prices)	0.21***	0.31***	0.21***	0.30***	0.28***	–
	(0.03)	(0.09)	(0.03)	(0.09)	(0.08)	
House prices	–	–	–	–	–	1.68***
						(0.62)
Male	− 0.001	0.0001	− 0.001	0.001	0.002	− 0.01
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.09)
College	0.01***	0.01**	0.01***	0.004	0.01**	0.20
	(0.003)	(0.004)	(0.003)	(0.01)	(0.004)	(0.24)
Unemployment	− 0.02*	− 0.02	− 0.02*	− 0.03	− 0.05**	− 1.38**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.70)
Migrants	0.001**	0.001	0.001**	0.0005	0.001	0.01
	(0.0004)	(0.0005)	(0.0004)	(0.001)	(0.001)	(0.03)
Temp mean summer	− 0.01*	− 0.01**	− 0.01	− 0.03***	− 0.02**	− 1.12***
	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)	(0.43)
Temp mean winter	− 0.01**	− 0.02***	− 0.01**	− 0.01	− 0.01	− 0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.33)
Latitude	− 0.01**	− 0.01**	− 0.01**	− 0.01*	− 0.02**	− 0.52*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.31)
$Latitude^2$	− 0.001***	− 0.001***	− 0.001*	0.001	0.0003	0.03
	(0.0002)	(0.0002)	(0.0005)	(0.001)	(0.001)	(0.03)
$Latitude^3$	− 0.00004*	− 0.00005*	− 0.00004*	− 0.00005*	− 0.0001*	− 0.0003
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00003)	(0.001)
Constant term	3.59***	3.47***	3.57***	1.67**	3.34***	33.83***
	(0.21)	(0.24)	(0.55)	(0.81)	(0.24)	(8.54)
IV: house price	N	Y	N	Y	Y	Y
IV: pollution	N	N	Y	Y	Y	Y
R^2	0.582	–	–	–	–	–
Cragg–Donald F statistic	–	9.354	21.43	4.074	3.222	4.154
1st part. F-stat: house prices	–	9.354	–	9.650	10.49	11.59
1st Shea part. R^2: house prices	–	0.195	–	0.217	0.263	0.253

Table 2 continued

	OLS ln(wages) (1)	IV1 ln(wages) (2)	IV2 ln(wages) (3)	IV3 ln(wages) (4)	IV4 ln(wages) (5)	IV5 Wages (6)
1st part. F-stat: PM_{10}	–	–	21.43	4.272	3.240	4.207
1st Shea part. R^2: PM_{10}	–	–	0.0720	0.109	0.0995	0.110

288 observations for each regression, except column 5 with 252 observations. The dependent variable is the logarithm of average yearly wage (in 1000 CNY/year), except for column (6) where it is in levels. Heteroskedasticity-robust standard errors are reported in parentheses. In the IV panel, 'Y' indicates that the variable is instrumented, 'N' that it is not. LIML estimates reported. Critical values for the Cragg–Donald statistics (Stock and Yogo 2005) for a maximal LIML size (10% significance level) are: 4.18 for Wages IV1, 16.38 for Wages IV2, 3.78 for Wages IV3–IV5. Estimation results of the first stage for IV estimation are reported in Appendix C Tables 5 and 6

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

for the wages equation, reported in column 6, is based on level-coded wages, house prices and PM_{10} concentrations. We find that the results are broadly consistent with the corresponding log–log specification in terms of signs and statistical significance. The implied elasticity of wages with respect to PM_{10} concentration is around 0.72 at the mean of the sample, which is higher than the 0.53 elasticity reported in column 4. This reflects the propensity of linear specification to be affected by observations that are relatively far away from the mean.

Table 3 shows results for the house prices equation. Columns 1–4 again report logarithm specifications, and provide evidence about the importance of endogeneity on implicit price estimates. Column 1 reports OLS estimates, in column 2 we instrument wages with shifters for the labor market, in column 3 PM_{10} concentration is instrumented with the indicator variable $I_i^{Huai\ policy}$, and in column 4 both wages and PM_{10} concentration are instrumented. Results for the first stage regressions associated with IV specifications are reported in Appendix C.[13] In the last two columns of Table 3, we first use the number of days with API greater or equal to 100 as an alternative measure of air quality (column 5), while column 6 reports results from a linear specification.

As above, results suggest that endogeneity biases marginal effects of both wages and PM_{10} concentration towards zero. In our preferred specification, in which both wages and PM_{10} concentration are instrumented (column 4), the elasticity of house prices with respect to PM_{10} is negative and highly statistically significant (point estimate: -0.71). At the mean of the sample, this implies that a marginal increase in average PM_{10} concentration is associated with reduction of house prices by around CNY 37.93/m^2 ($\simeq$ USD 5.88). Given an average per capita living space of 30.63 m^2 (NBSC 2010), this corresponds to CNY 1161.67 ($\simeq$ USD 180.06). We note that other determinants of house prices have the expected sign, but we again warn against interpreting these as they are mainly used as shifters to identify the wage equation.

Results for our alternative measure of air quality (column 5) suggest qualitatively similar findings, with an elasticity estimate of -0.11; at the average of the sample, an increase in the number of days with API $\geq$ 100 is associated with a reduction of house prices by CNY 32.26/m^2 ($\simeq$ USD 5.00). Finally, the linear specification in column 6 again suggests

13 Table 3 again reports LIML estimates (with critical values for the Cragg–Donald test statistics reported in the notes), although as for the wage equations the TSLS estimates are very similar to LIML.

Table 3 Estimation results for the hedonic property market equation

	OLS ln(house prices) (1)	IV1 ln(house prices) (2)	IV2 ln(house prices) (3)	IV3 ln(house prices) (4)	IV4 ln(house prices) (5)	IV5 House prices (6)
$\ln(PM_{10})$	0.003	−0.02	−1.09***	−0.71**	–	–
	(0.07)	(0.08)	(0.42)	(0.30)		
ln(Polluted days)	–	–	–	–	−0.11*	–
					(0.06)	
PM_{10}	–	–	–	–	–	−0.06**
						(0.02)
ln(wages)	0.80***	1.37***	0.86***	1.67***	1.40***	
	(0.09)	(0.18)	(0.12)	(0.25)	(0.22)	
Wages	–	–	–	–	–	0.28***
						(0.04)
Piped water	0.004***	0.003**	0.01***	0.004**	0.004***	0.02**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.01)
Fitted toilets	0.002**	0.002*	0.002	0.002	0.001	0.01
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.01)
Fitted shower	−0.0004	−0.002	−0.001	−0.003*	−0.003*	−0.04***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.01)
Density	0.11***	0.07*	0.17***	0.08*	0.10**	0.73***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.28)
Land supply	−0.06*	−0.07*	−0.07	−0.08*	0.33*	−0.80***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.19)	(0.27)
Coastal	0.30***	0.28***	0.25***	0.24***	0.20***	1.53***
	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)	(0.48)
Universities	9.33***	7.04**	12.19***	7.82**	6.16*	26.96
	(2.56)	(2.75)	(3.56)	(3.34)	(3.18)	(20.35)
Temp mean Summer	0.02*	0.03***	0.06***	0.06***	0.04***	0.38***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.10)
Temp mean Winter	0.02*	0.03**	−0.01	0.02	0.02*	0.08
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.08)
Latitude	0.001	0.01	0.001	0.01	0.01	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)
Latitude^2	0.0001	0.0001	−0.003**	−0.001	−0.001	−0.004
	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.005)
Latitude^3	0.0001***	0.0001***	0.0001**	0.0002***	0.0002***	0.001**
	(0.00004)	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Constant term	−2.67***	−4.69***	0.79	−3.42***	−4.73***	−12.08***
	(0.46)	(0.72)	(1.43)	(1.01)	(0.87)	(2.26)
IV: Wages	N	Y	N	Y	Y	Y
IV: Pollution	N	N	Y	Y	Y	Y
R^2	0.683	–	–	–	–	–

Table 3 continued

	OLS ln(house prices) (1)	IV1 ln(house prices) (2)	IV2 ln(house prices) (3)	IV3 ln(house prices) (4)	IV4 ln(house prices) (5)	IV5 House prices (6)
Cragg–Donald F statistic	–	24.42	14.59	5.148	5.977	5.777
1st part. F-stat: wages	–	24.42	–	19.56	13.79	26.38
1st Shea part. R^2: wages	–	0.266	–	0.205	0.222	0.241
1st part. F-stat: PM_{10}	–	–	14.59	7.810	6.336	9.401
1st Shea part. R^2: PM_{10}	–	–	0.0507	0.0973	0.116	0.109

288 observations for each regression, except column 5 with 252 observations. The dependent variable is the logarithm of average house prices (in 1000 CNY/m^2), except for column (6) where it is in levels. Heteroskedasticity-robust standard errors are reported in parentheses. In the IV panel, 'Y' indicates that the variable is instrumented, 'N' that it is not. LIML estimates reported. Critical values for the Cragg–Donald statistics (Stock and Yogo 2005) for a maximal LIML size (10% significance level) are: 5.44 for Housing IV1, 16.38 for Housing IV2, 8.96 for Housing IV2, 4.32 for Housing IV3–IV5. Estimation results of the first stage for IV estimation are reported in Appendix C Tables 7 and 8

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

an implied elasticity of house prices with respect to PM_{10} concentration that is slightly larger than a log–log specification, with an estimate of -1.41 (evaluated at the mean of the sample).

4.2 Marginal Willingness to Pay Estimates

We now combine evidence derived from inter-city wages and house prices differentials to illustrate the magnitude of our estimates. First, using Eq. 5, we compute MWTP estimates for a change in air quality at the individual level, evaluated at the mean of our sample. Second, at the aggregate city level, we evaluate how a marginal change in air quality would affect both aggregate wages for the working population and the value of the stock of dwellings of each city. We stress that the numbers we produce here represent 'back-of-the-envelope' calculations with the objective of quantifying the relative importance of each component across cities, rather than produce city-level estimates of the marginal value of air quality.

Starting with individual MWTP for air quality improvements, we use results reported in Table 3, column 4, to obtain an estimate for the average of our sample. This involves using the coefficient α_1 (Eq. 6), which captures the partial MWTP associated with the change in individual yearly wages, and β_1 (Eq. 7), which measures the impact on housing prices. The latter needs to be multiplied by a measure of the per capita living space and then spread over the tenure length of the property. For the purpose of illustration, we use an average per capita living area of of 30.63 m^2 (NBSC 2010) and a tenure length of 70 years, which is in line with the fact that property law in China effectively grants residential land-use rights only for 70 years.[14] Given our elasticity estimates, we find that average MWTP for a unit reduction of PM_{10} concentration is CNY 261.28 (p-val. $<$ 0.01; 95% confidence interval: 61.03–461.52) or USD 40.50 (p-val. $<$ 0.01; 95% confidence interval: 9.46–71.54).

[14] According to the 1982 Constitution of China, land is publicly owned and private ownership is legitimately prohibited.

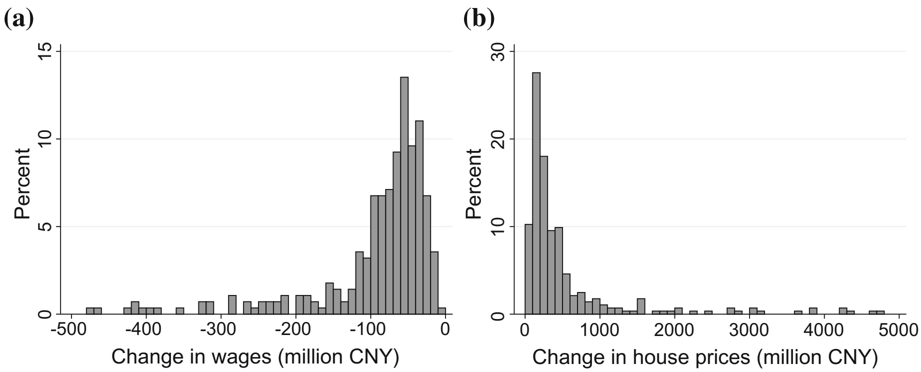

Fig. 4 Aggregate marginal impact ($\mu g/m^3$) across Chinese cities (CNY 1 $\simeq$ USD 0.155, 2011). **a** Aggregate change in wages across cities. **b** Aggregate change in house prices across cities

Next, we evaluate aggregate MWTP for cities in our sample to illustrate how compensating differentials of air pollution vary across cities.[15] Results are displayed in Fig. 4. Panel (a) shows the distribution of changes in wages across cities for a unit reduction of PM_{10} concentration, multiplying our elasticity estimate reported in Table 2 (column 4) by the ratio of pollution to wages in each city and the number of workers. The mean of the distribution is CNY 122.98 million ($\simeq$ USD 19.06 million), while the median is CNY 67.77 million ($\simeq$ USD 10.50 million). Panel (b) shows the distribution for the aggregate change in house prices, multiplying the elasticity estimate reported in Table 3 (column 4) by the ratio of pollution to housing prices in each city and total living area. The mean of the resulting distribution is CNY 766.37 million ($\simeq$ USD 118.79 million) and the median is CNY 264.88 million ($\simeq$ USD 41.06 million). Note that variation of aggregate MWTP across cities mainly reflects the size of the city (in terms of workers and total living space), so that larger cities are mechanically associated with larger aggregate benefits. Also, as discussed in Roback (1982), aggregate change in wages involves a transfer from firms to workers, so that it should not be counted as part of aggregate benefits of air quality improvements.

5 Summary and Conclusion

This paper has studied compensating price differentials across China, focusing on how variation in air quality is capitalized in wages and house prices. In an attempt to measure the effect of *exogenous* variation in air quality on the joint determination of wages and house prices, we have exploited a regression discontinuity design afforded by the River Huai policy. Empirical evidence we report suggests that the policy subsidizing winter heating in northern cities has a significant impact on air pollution in China, which is consistent with results reported in Almond et al. (2009) and Chen et al. (2013). In turn, we have shown that the observed discontinuity in air quality locally affects a country-level equilibrium relationship between house prices and wages. From our data, we estimate that the elasticity of wages with respect to PM_{10} concentration in the vicinity of the policy boundary is around 0.53, while that of house prices is -0.71.

[15] As mentioned above, our regression discontinuity strategy generates a local estimate. It is therefore important to emphasize that we are extrapolating it assuming that the elasticity is constant across all cities in China.

Combining evidence from labor and property markets to illustrate the magnitude of our results, we estimate average individual MWTP to be around CNY 261.28 for 1 $\mu g/m^3$ reduction in PM_{10} concentration, or about USD 40.50. A key contribution of our work is to show that interrelationships between the labor market, the housing market, and air quality are quantitatively important in measuring the welfare effect of marginal air quality improvements. First, our results suggest that accounting for the joint determination of wages and housing prices in the estimation of marginal value of air quality improvements has quantitative implications for the elasticity estimates. Second, at the individual level, wage impacts represent an important component of the welfare change associated with air quality improvements.

We close by highlighting the need for further research on the relationship between market and environmental outcomes in China. First, one drawback of our IV estimation strategy is that it provides a local estimates of how air quality affects country-level determination of wages and house prices. Therefore, further evidence should seek alternative identification approaches to establish a broader understanding about the value of air quality in China. Second, much work remains to be done to account for the dynamics of labor and property markets in China. On the one hand, real-estate prices have been growing rapidly, with some commentators describing this phenomenon as a price "bubble." On the other hand, per capita income in China has also increased dramatically over the past ten years. This continued growth has, of course, implications for the demand for environmental quality. Moreover, general awareness about environmental degradation problems has been on the rise, too. Therefore, understanding how the capitalization of air quality evolves over time is of both policy and academic interest. Finally, we have essentially ignored costs and constraints associated with migration. An implication is that our MWTP estimates represent a lower bound to the welfare effect of air quality improvements (Bayer et al. 2009). Future research should address the broader issue of relocation costs that firms and households face in China, in relation to local amenities and public policies.

Appendix A: Data Sources and Summary Statistics

Variable	Definition	Mean	SD	p10	p25	p50	p75	p90	Source
Wages	Average yearly wages (1000 CNY/Year)	35.96	8.24	27.02	30.48	34.62	39.81	47.05	NBSC (2012a)
Male	Share of population: male (%)	52.77	8.80	42.48	50.20	52.43	57.93	62.51	NBSC (2012b)
College	Share of population: college graduates (%)	8.10	4.85	3.93	5.02	6.73	8.98	15.07	NBSC (2010)
Unemployment	Unemployment rate (%)	3.30	0.74	2.20	2.80	3.50	3.90	4.20	NBSC (2012a)
Migrants	Share of population: immigration (%)	21.64	32.78	6.40	8.62	13.24	22.39	42.46	NBSC (2010)
House prices	Average house prices (1000 CNY/m^2)	4.12	2.47	2.40	2.73	3.38	4.37	6.68	NBSC (2012a)

Variable	Definition	Mean	SD	p10	p25	p50	p75	p90	Source
Piped water	Share of houses with piped water (%)	63.25	21.46	35.00	45.00	61.50	83.00	93.00	NBSC (2010)
Fitted toilets	Share of houses with toilet (%)	70.68	16.50	49.00	58.00	73.00	84.00	90.00	NBSC (2010)
Fitted shower	Share of houses with shower (%)	51.19	22.79	18.00	32.50	52.00	67.50	81.00	NBSC (2010)
Density	Population density (1000 persons /km^2)	0.47	0.54	0.08	0.18	0.34	0.62	0.87	NBSC (2012a)
Land supply	Traded land area (100 km^2)	0.13	0.42	0.02	0.04	0.07	0.12	0.22	CLRA (2012)
Coastal	Indicator equal to 1 if city is on the coast	0.09	0.28	0.00	0.00	0.00	0.00	0.00	NGCC (2012)
Universities	Number of universities per 10,000 residents	0.01	0.01	0.00	0.01	0.01	0.01	0.02	NBSC (2012a)
PM_{10}	Average PM_{10} concentration ($\mu g/m^3$)	77.44	19.11	53.00	64.00	78.00	91.00	100.00	MEP (2012)
Polluted days[a]	Number of days with API $\geq$ 100	21.94	21.59	0.00	4.50	17.00	34.00	48.00	NBSC (2012a)
Huai policy	Indicator equal to 1 if city is included in the River Huai policy	0.43	0.50	0.00	0.00	0.00	1.00	1.00	NGCC (2012)
Latitude	Distance to latitude 33° (degree °)	− 0.06	6.67	− 9.27	− 5.17	− 0.56	4.71	8.80	NGCC (2012)
Temp mean summer	Mean temperature in summer (°C)	26.10	2.87	22.24	23.66	26.85	28.32	29.37	CMA (2012)
Temp mean winter	Mean temperature in winter (°C)	1.91	8.34	− 9.62	− 3.04	3.27	6.83	13.16	CMA (2012)

288 observations

[a]Definition of API is in Appendix B. Exchange rate for 2011: CNY 1 $\simeq$ USD 0.155

Appendix B: Definition of the Air Pollution Index (API)

The conversion method from pollutant concentrations to API values is available from the website of China's Ministry of Environmental Protection. First, average concentration of air pollutants are reported from the monitoring stations in each city (cities with a population of over 3 million people are required to use at least eight monitoring stations to measure urban air quality). Specifically, concentrations of PM_{10}, SO_2 and NO_2 are measured with daily averages.

The API is then constructed from piecewise linear indexes computed for each pollutant. Conversion of concentrations into pollutant-specific indexes is as follows:

$$I_k = \frac{I_{high} - I_{low}}{C_{high} - C_{low}} (C_k - C_{low}) + I_{low} \tag{B1}$$

Table 4 Air pollution index (API). *Source*: China's Ministry of Environmental Protection (MEP)

API level	API score	Description	Thresholds[1]		
			PM_{10}	SO_2	NO_2
I	0–50	Excellent	0.05	0.05	0.08
II	51–100	Good	0.15	0.15	0.12
III-1	101–150	Slight	0.35	0.8	0.28
III-2	151–200	Light			
IV-1	201–250	Moderate	0.42	1.6	0.565
IV-2	251–300	Heavy			
V	301–400	Severe	0.52	2.1	0.75
	401–500		0.6	2.62	0.94

[1] PM_{10}, SO_2 and NO_2 concentration are measured as average mg/m^3 per day

where I_k is the pollution index of pollutant k, C_k is pollutant k's concentration, C_{low} is the concentration threshold below C_k (defined in Table 4), C_{high} is the concentration threshold above C_k, I_{low} is the index threshold corresponding to C_{low}, and I_{high} is the index threshold corresponding to C_{high}. The API then represents the highest value of those indexes:

$$\text{API} = \max\left(I_{PM_{10}}, I_{SO_2}, I_{NO_2}\right) \tag{B2}$$

Note that the scale for each pollutant is non-linear, as is the final API value. An implication is that an API of 100 is not equivalent to a doubling of air pollution associated with an API of 50.

As shown in Table 4, an API of 100 is regarded as the threshold of air pollution that can lead to non-negligible health consequences. Thus days with an API under 100 are defined as a "Blue Sky" days (i.e. days in which air pollution poses little or no risk to human health). When the API is between 101 and 200, air pollution may generate slight irritations to breathing and lead to heart diseases. When API is between 201 and 300, air pollution will aggravate the symptoms of patients with cardiac and lung diseases, even healthy people will be noticeably affected. When API is above 300 air is severely polluted and may cause irritations and other symptoms. People are advised to avoid outdoor activities.

Appendix C: First Stage Regression Results

Table 5 First stage results for pollution in the wages equation (Table 2)

	IV2 ln(PM_{10}) (1)	IV3 ln(PM_{10}) (2)	IV4 ln(polluted days) (3)	IV5 PM_{10} (4)
Huai policy	0.25***	0.26***	1.08***	19.21***
	(0.05)	(0.06)	(0.26)	(3.99)
Latitude	− 0.03***	− 0.03***	− 0.09*	− 1.87**
	(0.01)	(0.01)	(0.05)	(0.77)
Latitude^2	− 0.003***	− 0.003***	− 0.01***	− 0.19***
	(0.0003)	(0.0003)	(0.002)	(0.02)
Latitude^3	0.0001***	0.0001***	0.0004**	0.01**
	(0.00004)	(0.00004)	(0.0002)	(0.003)
Male	− 0.001	0.001	− 0.01	0.08
	(0.002)	(0.002)	(0.01)	(0.17)
College	0.01***	0.02***	0.04**	1.58***
	(0.003)	(0.004)	(0.02)	(0.31)
Unemployment	0.03*	0.04**	0.32***	3.14**
	(0.02)	(0.02)	(0.09)	(1.35)
Migrants	0.0002	0.0001	− 0.002	0.003
	(0.001)	(0.001)	(0.003)	(0.05)
Temp mean summer	0.04***	0.04***	0.05	2.67***
	(0.01)	(0.01)	(0.04)	(0.54)
Temp mean winter	− 0.03***	− 0.02***	− 0.07*	− 1.28**
	(0.01)	(0.01)	(0.04)	(0.56)
ln(house prices)	0.02	–	–	–
	(0.04)			
Piped water	–	0.002***	0.01*	0.15**
		(0.001)	(0.004)	(0.06)
Fitted toilets	–	− 0.0002	− 0.004	0.02
		(0.001)	(0.004)	(0.07)
Fitted shower	–	− 0.001	0.002	− 0.08
		(0.001)	(0.01)	(0.09)
Density	–	0.01	0.16	0.34
		(0.04)	(0.17)	(2.53)
Land supply	–	− 0.001	0.36	− 0.01
		(0.03)	(0.61)	(2.02)
Coastal	–	− 0.04	− 0.26	− 3.69
		(0.05)	(0.24)	(3.48)
Universities	–	− 5.50**	− 20.40	− 431.19**
		(2.71)	(13.15)	(194.70)
Constant term	3.09***	2.91***	0.53	− 20.42
	(0.23)	(0.26)	(1.25)	(18.86)
R^2	0.46	0.49	0.47	0.48

288 observations for each regression, except column 3 with 252 observations. OLS estimates reported with heteroskedasticity-robust standard errors in parentheses. In columns 1 and 2 the dependent variable is the logarithm of average PM_{10} concentration in 2011 (in $\mu g/m^3$). In column 3 the dependent variable is the logarithm of number of days with API $\geq$ 100 in 2011. In columns 4 the dependent variable is 2011 average PM_{10} concentration ($\mu g/m^3$) in levels

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

Table 6 First stage results for house prices in the wages equation (Table 2)

	IV1 ln(house prices) (1)	IV3 ln(house prices) (2)	IV4 ln(house prices) (3)	IV5 house prices (4)
Piped water	0.005***	0.005***	0.005***	0.02***
	(0.001)	(0.001)	(0.001)	(0.01)
Fitted toilets	0.003**	0.003**	0.003**	0.01*
	(0.001)	(0.001)	(0.001)	(0.01)
Fitted shower	− 0.001	− 0.002	− 0.002	− 0.03***
	(0.002)	(0.002)	(0.002)	(0.01)
Density	0.03	0.06	0.06	0.59**
	(0.05)	(0.05)	(0.05)	(0.26)
Land supply	− 0.04	− 0.04	− 0.04	− 0.57***
	(0.04)	(0.04)	(0.04)	(0.20)
Coastal	0.33***	0.32***	0.32***	2.21***
	(0.06)	(0.06)	(0.06)	(0.35)
Universities	− 4.18	− 2.69	− 2.69	− 50.70**
	(3.54)	(3.49)	(3.49)	(19.65)
Temp mean summer	0.02*	0.01	0.01	0.13**
	(0.01)	(0.01)	(0.01)	(0.05)
Temp mean winter	0.01	0.02	0.02	0.09
	(0.01)	(0.01)	(0.01)	(0.06)
Latitude	− 0.01	0.02	0.02	0.07
	(0.01)	(0.01)	(0.01)	(0.08)
Latitude^2	− 0.001**	− 0.001	− 0.001	− 0.003
	(0.0004)	(0.0004)	(0.0004)	(0.002)
Latitude^3	0.0001**	0.00001	0.00001	0.0002
	(0.00004)	(0.00005)	(0.00005)	(0.0003)
ln(PM_{10})	− 0.06	–	–	–
	(0.08)			
Huai policy	–	− 0.23***	− 0.23***	− 1.25***
		(0.07)	(0.07)	(0.40)
Male	0.0001	− 0.001	− 0.001	− 0.02
	(0.003)	(0.003)	(0.003)	(0.02)
College	0.03***	0.03***	0.03***	0.21***
	(0.01)	(0.01)	(0.01)	(0.03)
Unemployment	− 0.03	− 0.05*	− 0.05*	− 0.23*
	(0.02)	(0.02)	(0.02)	(0.14)
Migrants	0.003***	0.002**	0.002**	0.02***
	(0.001)	(0.001)	(0.001)	(0.005)
Constant term	0.45	0.53	0.53	0.21
	(0.41)	(0.34)	(0.34)	(1.90)
R^2	0.69	0.71	0.70	0.71

288 observations for each regression, except column 3 with 252 observations. OLS estimates reported with heteroskedasticity-robust standard errors in parentheses. The dependent variable is the logarithm of average house prices (in 1000 CNY/m^2), except for column 4 where it is in levels

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

Table 7 First stage results for pollution in the house prices equation (Table 3)

	IV2 ln(PM_{10}) (1)	IV3 ln(PM_{10}) (2)	IV4 ln(polluted days) (3)	IV5 PM_{10} (4)
Huai policy	0.21***	0.26***	1.08***	19.21***
	(0.06)	(0.06)	(0.26)	(3.99)
Latitude	− 0.02**	− 0.03***	− 0.09*	− 1.87**
	(0.01)	(0.01)	(0.05)	(0.77)
Latitude^2	− 0.003***	− 0.003***	− 0.01***	− 0.19***
	(0.0003)	(0.0003)	(0.002)	(0.02)
Latitude^3	0.0001***	0.0001***	0.0004**	0.01**
	(0.00004)	(0.00004)	(0.0002)	(0.003)
Piped water	0.002**	0.002***	0.01*	0.15**
	(0.001)	(0.001)	(0.004)	(0.06)
Fitted toilets	− 0.001	− 0.0002	− 0.004	0.02
	(0.001)	(0.001)	(0.004)	(0.07)
Fitted shower	− 0.0001	− 0.001	0.002	− 0.08
	(0.001)	(0.001)	(0.01)	(0.09)
Density	0.04	0.01	0.16	0.34
	(0.03)	(0.04)	(0.17)	(2.53)
Land supply	− 0.01	− 0.001	0.36	− 0.01
	(0.03)	(0.03)	(0.61)	(2.02)
Coastal	− 0.04	− 0.04	− 0.26	− 3.69
	(0.05)	(0.05)	(0.24)	(3.48)
Universities	2.37	− 5.50**	− 20.40	− 431.19**
	(2.09)	(2.71)	(13.15)	(194.70)
Temp mean summer	0.04***	0.04***	0.05	2.67***
	(0.01)	(0.01)	(0.04)	(0.54)
Temp mean Winter	− 0.02***	− 0.02***	− 0.07*	− 1.28**
	(0.01)	(0.01)	(0.04)	(0.56)
ln(wages)	0.08	–	–	–
	(0.07)			
Male	–	0.001	− 0.01	0.08
		(0.002)	(0.01)	(0.17)
College	–	0.02***	0.04**	1.58***
		(0.004)	(0.02)	(0.31)
Unemployment	–	0.04**	0.32***	3.14**
		(0.02)	(0.09)	(1.35)
Migrants	–	0.0001	− 0.002	0.003
		(0.001)	(0.003)	(0.05)
Constant term	2.94***	2.91***	0.53	− 20.42
	(0.33)	(0.26)	(1.25)	(18.86)
R^2	0.45	0.49	0.47	0.44

288 observations for each regression, except column 3 with 252 observations. OLS estimates reported with heteroskedasticity-robust standard errors in parentheses. In columns 1 and 2 the dependent variable is the logarithm of average PM_{10} concentration in 2011 (in $\mu g/m^3$). In columns 3 the dependent variable is the logarithm of number of days with API $\geq$ 100 in 2011. In columns 4 the dependent variable is 2011 average PM_{10} concentration ($\mu g/m^3$) in levels

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

Table 8 First stage results for wages in the house prices equation (Table 3)

	IV1 ln(wages) (1)	IV3 ln(wages) (2)	IV4 ln(wages) (3)	IV5 wages (4)
Male	0.001	0.001	0.001	− 0.01
	(0.002)	(0.002)	(0.002)	(0.07)
College	0.03***	0.03***	0.03***	1.14***
	(0.00)	(0.00)	(0.00)	(0.12)
Unemployment	− 0.02	− 0.02	− 0.02	− 0.93*
	(0.01)	(0.01)	(0.01)	(0.52)
Migrants	0.002***	0.002***	0.002***	0.05***
	(0.0005)	(0.0005)	(0.0005)	(0.02)
Temp mean summer	− 0.01	− 0.01*	− 0.01*	− 0.35*
	(0.01)	(0.01)	(0.01)	(0.21)
Temp mean winter	− 0.01*	− 0.01*	− 0.01*	− 0.25
	(0.01)	(0.01)	(0.01)	(0.22)
Latitude	− 0.01*	− 0.01	− 0.01	− 0.25
	(0.01)	(0.01)	(0.01)	(0.29)
Latitude^2	− 0.001***	− 0.001***	− 0.001***	− 0.03***
	(0.0002)	(0.0002)	(0.0002)	(0.01)
Latitude^3	− 0.00003	− 0.00003	− 0.00003	− 0.0005
	(0.00002)	(0.00003)	(0.00003)	(0.001)
ln(PM_{10})	− 0.03	–	–	–
	(0.04)			
Huai policy	–	− 0.01	− 0.01	− 1.13
		(0.04)	(0.04)	(1.53)
Piped water	0.001**	0.001**	0.001**	0.05**
	(0.001)	(0.001)	(0.001)	(0.02)
Fitted toilets	0.0001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.03)
Fitted shower	0.0004	0.0005	0.0005	0.002
	(0.001)	(0.001)	(0.001)	(0.03)
Density	− 0.01	− 0.02	− 0.02	0.39
	(0.03)	(0.03)	(0.03)	(0.97)
Land supply	0.03	0.03	0.03	0.95
	(0.02)	(0.02)	(0.02)	(0.78)
Coastal	0.03	0.04	0.04	1.31
	(0.04)	(0.04)	(0.04)	(1.34)
Universities	− 8.52***	− 8.35***	− 8.35***	− 370.05***
	(2.04)	(2.05)	(2.05)	(74.71)
Constant term	3.72***	3.62***	3.62***	40.66***
	(0.24)	(0.20)	(0.20)	(7.24)
R^2	0.57	0.60	0.60	0.64

288 observations for each regression, except column 3 with 252 observations. OLS estimates reported with heteroskedasticity-robust standard errors in parentheses. The dependent variable is the logarithm of average yearly wage (in 1000 CNY/Year), except for column 4 where it is in levels

*, ** and *** respectively denote statistical significance at 10, 5 and 1% levels

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