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ABSTRACT

Over the last thirty years, China's major cities have experienced significant income and population growth. Much of this growth has been fueled by urban production spurred by world demand. Using a unique cross-city panel data set, we test several hypotheses concerning the relationship between home prices, wages, foreign direct investment and ambient air pollution across major Chinese cities. Home prices are lower in cities with higher ambient pollution levels. Cities featuring higher per-capita FDI flows have lower pollution levels.

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Introduction

Chinese cities have experienced dramatic income and population growth over the last thirty years, spurred by the inflow of foreign direct investment (FDI) and privatization of state-owned enterprises. The annual real income of an average urban resident in 2006 was four times higher than in 1990. The liberalization of the land market and the housing market has encouraged urban growth. The share of the population living in cities in China has increased from 28% in 1990 to 44% in 2006. In 2007, there were 36 cities with a population of two million or greater.

Rural to urban migration is responsible for roughly 70% of China's urban population growth (Zhang and Song 2003). Increasing labor mobility in urban China is pushing Chinese cities towards a system of open cities.[1] They are differentiated with respect to their industrial specialization and their spatially tied amenities (Henderson 1988). China's economic growth is fueled by urban production spurred by world demand. For example, Shenzhen is a leading exporter of toys. In 2008, it produced 28% of the world's toys.[2] At the same time, Chinese cities are also ranked among the most polluted places in the world.[3] China is the largest emitter of sulfur dioxide in the world today. The World Bank estimates that the total health cost of air pollution in China equals 3.8% of GDP (World Bank, 2007). In 2006, ambient air pollution (as measured by small particulate matter, PM10) was roughly four times higher thanit was in Los

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[1] The binding force of the "*Hukou*" (household residential registration) system on labor mobility has weakened over time. Migrants without *Hukou* are allowed to work in cities (with the exception of some occupation restrictions in the largest cities). 1998 marked the end of the state-provided housing welfare system and the beginning of a private housing market boom. There is no *Hukou* restriction on buying housing units in the housing market. (However, migrants without formal jobs have difficulty receiving home loans from banks, and therefore face credit constraints. The *Hukou* system remains an impediment to efficient urban agglomeration (Au and Henderson, 2006). Migrants without *Hukou* are credit constrained and lack the access to urban social security benefits such as education, public housing and health services in their current residence city.

[2] http://www.chinairn.com/doc/4080/267398.html

[3]See http://www.nap.edu/catalog.php?record_id=11192 and http://www.chinadaily.com.cn/china/2007-11/19/content_6264621.htm.

Angeles. This suggests that Chinese cities are intentionally or unintentionally positioning themselves as "producer cities" rather than as high amenity "consumer cities" (Glaeser, Kolko, Saiz 2000, Glaeser and Saiz 2003).

In an open system of cities, the labor market and the land market clear simultaneously. People will "vote with their feet" and migrate to cities offering higher real wages (productivity advantages) and/or higher quality of life. In equilibrium, cross-city prices of real estate and wages will adjust to reflect spatially-tied attributes. The growth and integration of China's major cities raises a set of basic urban and regional research questions. Using a unique panel data set covering the years 1997 to 2006 for 35 "superstar" cities in China (Figure 1 shows the location of these cities) that includes information on home prices, amenities, city-specific labor demand shifts, and FDI, we revisit classic urban economics questions based on the recent Chinese experience.[4]

We investigate three main empirical questions. First, based on pooled cross-sectional regression analysis, we measure the size of home price compensating differentials for urban productivity inputs and urban environmental and climate amenities. Second, by exploiting within major city variation over time, we test for how home prices respond to local labor demand shifts and influxes of FDI. We also test for whether real estate prices are more responsive to local demand shifts in cities with a more inelastic housing supply. Finally, this paper presents novel results in explaining cross Chinese city variation in ambient pollution levels. We test whether FDI inflow into a city improves or degrades a city's local air quality.

[4] The 35 major Chinese cities represent all municipalities directly under the central government, provincial capital cities, and quasi provincial capital cities in China.

Our first empirical contribution is to present a new set of compensating differential estimates for local public goods that vary across Chinese cities. Our findings build on the U.S cross-city studies such as Blomquist et. al. 1988 and Gyourko and Tracy 1991. One robust finding is that cities with higher particulate levels, all else equal, have lower home prices. We report evidence that this capitalization effect has grown over time. In contrast to the U.S compensating differential literature on climate (Costa and Kahn 2003) and human capital (Rauch1993), we find little evidence of climate or human capital capitalization effects.

Our within-city dynamics results reveal that home prices in Chinese cities do rise in response to local labor demand increases and FDI in-flows. We classify our 35 cities by their housing supply elasticity using the earlier work by Fu et. al. (2008). These price responses in the face of rising local demand are even larger for cities featuring an inelastic housing supply. Our findings are consistent with results from the United States literature (Glaeser, Gyourko and Saks 2006).

FDI is the main source of production technology transfer driving the phenomenal growth of China's manufacturing exports over the last 30 years. By 2005 Chinese inward FDI flows had reached \$72bn, up from an average of \$30bn between 1990 and 2000. The stock of FDI has increased similarly, rising from \$20bn in 1990 to \$317bn in 2005 (Cole, et. al., 2008). In the final section of the paper, we explore the cross-city relationship between ambient urban air pollution and FDI flows. China's cities provide a unique opportunity here because the pollution levels and the FDI flows are both so large. Ex-ante, there are two different possible outcomes associated with urban FDI flows. One possibility is that cities experiencing increased FDI inflows become dirtier as the scale of industrial production increases and the composition of industries tilts towards dirtier heavy manufacturing. In a system of cities where foreign investors can choose between many cities within a nation such as China, they may seek out the low regulation cities. This is a pollution haven effect (Wheeler 2001). Conversely, it is possible that FDI improves air quality in city because such new capital helps to modernize the capital stock and the resulting technology effect outweigh scale effect.[5] Using an OLS and an IV strategy, we document that FDI does lower ambient air pollution in China's major cities. We offer possible explanations for this optimistic finding that foreign investment does not appear to facilitate the growth of "pollution havens".

Data for Major Chinese Cities

Our panel data set covers 35 major Chinese cities over the time period from 1997 to 2006. This 10-year period coincides with China's peak phase of urbanization and the private housing market boom. The 35 major cities account for one quarter of the total urban population in more than 600 Chinese cities. These cities represent all municipalities directly under the federal government, provincial capital cities, and quasi provincial capital cities in China. For this subset of cities, we have access to a high quality transaction based hedonic home price index by city and year.

The city variables we collect can be grouped into 4 categories. Table 1 provides the variable names, the definitions and descriptive statistics for all the variables used in this study.

** Insert Table 1 about here **

(1) City Home Price Indices and Housing Supply

[5] This optimistic claim has been argued in the macro/time series literature (Dasgupta et. al. 2002).

The lack of reliable home price data is an obstacle for conducting cross-city urban and real estate research based on Chinese cities. We have quality-controlled housing price indices (*HP*) for these 35 major cities.[6]

The construction of this city housing price index is based on the real transaction prices of all newly-constructed housing units in a city. The municipal housing authority keeps all the transaction contracts of these units in a database. The contract contains the information on the transaction price (RMB/square meter), the dwelling's physical attributes (unit size, floor number, building structure type, decoration status, etc.) and its detailed address, from which locational attributes (distance to the city center, distance to the closest subway stop, etc.) can be derived. A standard hedonic model is used to compute the quarterly price index, using all the transaction observations:

$$\ln(HP_i) = a_0 + a_1 \cdot X_{i1} + a_2 \cdot X_{i2} + b \cdot T + \varepsilon_i \qquad (1)$$

Where, HP_i is the transaction price per square meter of unit i; X_{i1} is a vector of physical attributes of unit i; X_{i2} is a vector of locational attributes of unit i; T is a vector of quarter dummies, indicating the quarter when the unit was sold; ε_i is the error term; a_0, a_1 and a_2 are vectors of coefficients to be estimated.

A standard housing unit $X = (X_1^0, X_2^0)$ is defined. After Equation (1) is estimated, the standard unit's quarterly prices are computed and reported as the hedonic housing price index. The annual price index is aggregated from the quarterly index.Every municipal housing authority

[6] In Zheng et. al. (2008), they also attempt to estimate the compensating differentials for several urban amenities. However, they do not have a reliable home price measure.

then reports the updated index to the State Central Office. This set of hedonic housing price indices is proprietary data and has not been published publicly.[7] From our perspective, the important point is that we have access to the annual quality-adjusted price index for each of the 35 cities covering 10 years.

A second key variable used in this analysis is a cross-city measure of housing supply elasticity. We borrow this measure from Fu et. al. (2008). Using data from 85 Chinese cities, they find that housing supply elasticity depends on the availability of infrastructure, the cost of redevelopment, income inequality in the city, and whether the city is a provincial capital. Such capitals have more political power. They estimate an empirical equation from which supply elasticity can be derived as a linear function of several city attributes, including road space per capita (infrastructure), the age of the housing stock (redevelopment cost), income inequality index (the ratio of 75th percentile to 25th percentile household income), and a provincial capital dummy, using data from 1998.The detailed equation and coefficients can be found in Table 3 in their paper. We use their equation to compute the housing supply elasticity index for the 35 major cities in our study.

(2) City Productivity

We have three variables measuring city productivity and its determinants. There is no accurate measure of a city's average wage. Thus, city average annual income per capita (*INC*) is used as a rough measure of city productivity. However, since non-wage income (end-of-year bonuses, non-taxed income) is important in China, city income may not be a very good proxy for a worker's wage in a city.

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[7] Researchers with questions on this data set can contact Dr. Siqi Zheng.

Foreign direct investment (FDI), which is a leading indicator of city productivity, is measured in terms of both annual FDI flow per capita (*FDIPC*) and cumulative FDI flow per capita (*CFDIPC*).[8] City FDI data is drawn from the Urban Statistic Yearbooks published by China's State Bureau of Statistics[9], which publish annual FDI data for 200+ prefecture-level cities. This data set has been widely used by Chinese urban economics and geography scholars (for instance, He, 2002, 2006).

To measure the labor market demand for a given city i in a given year t, we follow Bartik (1991) and Blanchard and Katz (1991) and create a labor demand index where we weight national industry growth by the city's base year share of employment in that industry:

$$Demand_{it} = \sum_{j=1}^{J} EMP_{ij,base} \cdot GROWTH_{jt} \tag{2}$$

Where, $Demand_{it}$ is the labor demand index for city i in year t; $EMP_{ij,base}$ is the employment share of industry j in city i in the base year (year 1997); $GROWTH_{jt}$ is the national employment growth rate of industry j in year t.

China's State Bureau of Statistics identifies 19 industries. The demand index exploits the fact that if some industries in the nation are booming relative to others, cities with larger shares

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[8] In calculating this cumulative FDI variable, it is important to note that 1997 is the first year in our data set. In the regressions we report below, calendar year fixed effects will be included in the specifications.

[9] National Bureau of Statistics of China (NBSC) defines FDI as: "Foreign Direct Investment refers to the investments inside China by foreign enterprises and economic organizations or individuals (including overseas Chinese, compatriots from Hong Kong, Macao and Taiwan, and Chinese enterprises registered abroad), following the relevant policies and laws of China, for the establishment of ventures exclusively with foreign own investment, Sino-foreign joint ventures and cooperative enterprises or for co-operative exploration of resources with enterprises or economic organizations in China. It includes the re- investment of the foreign entrepreneurs with the profits gained from the investment and the funds that enterprises borrow from abroad in the total investment of projects which are approved by the relevant department of the government." (http://www.stats.gov.cn/tjsj/ndsj/2007/indexeh.htm)

of these industries will experience greater labor demand. From the city's perspective, the labor demand index can be regarded as an exogenous demand shock.

(3) City Geography

In accord with the cross-national economic geography literature (Demurger et. al. 2002, Gallup et. al. 1998), we believe that a city's geography plays an important role with respect to its economic performance. This is especially true in the case of China where the economy's take off has largely relied on export demand and FDI. Cities close to the east coast enjoy better access to the world export market. Starting with the Economic Reform, the Chinese government has sought to build up the nation's export capacity. To achieve this goal, the federal government has pursued a spatial "favoritism" strategy. This has meant that cities in the eastern region ("open coastal cities" and the cities in "special economic zones") have received favorable fiscal and administration policies to help them grow first. The policy package includes tax reductions (business tax, company income tax and other taxes) for foreign-invested companies and joint ventures, simplified examination and approval processes, and more infrastructure investments (for details of this spatial "favoritism" strategy, see Chen, Jin and Lu, 2008; Chen and Lu, 2008). We create an *EAST* dummy to represent the "open coastal cities" and the cities in "special economic zones" that have received favorable development policies from the federal government since the 1980s.

To further measure each city's access to world market opportunities, we calculate its distance to the closest major port (Hong Kong port, Shanghai port and Tianjin port) (*DIS_PORT*) and whether the city had an airport in the base year (*AIRPORT*). Together with *EAST*, these three variables will be used to explain the spatial distribution of *FDI* across cities. We also construct a set of human capital indicators based on the educational attainment of the city's adults.

(4) Quality of Life

Similar to the U.S cross-city compensating differentials literature (see Blomquist, Berger and Hoen 1988, Gyourko and Tracy 1991), we focus on a subset of key spatially tied attributes, namely, air quality, climate, green space per capita, beach view. Given the worldwide media coverage of China's environmental challenges, we devote special attention to urban air pollution. In 2003, the Statistic Yearbooks started to report yearly average particulate (PM_{10}, *PM*) and sulfur dioxide (SO_2, *SO2*) concentrations (in microgram per cubic meter) in 30 major cities (a subsample of our 35 cities). Thus, we have access to a short four year panel dataset for two key ambient pollutants. Figure 2 shows the particulate and sulfur dioxide concentrations in year 2003 and 2006 across the 30 cities. Across our sample, the average pollution level slightly declined over this time span. This is impressive given ongoing population and per-capita income growth during this time period. We will estimate pollution production functions. Two factors that we posit are relevant for ambient pollution levels are city population (*POP*) and rainfall (*RAIN*).

** Insert Figure 2 about here **

U.S researchers have documented the large capitalization effects of cross-city climate differentials and how these have grown over time (Costa and Kahn 2003). Building on the work by Zheng et. al. (2008), we measure each city's climate amenity by its city temperature discomfort index (*TEMP_INDEX*). This is defined as:

$$TEMP\_INDEX_k = \sqrt{\begin{matrix}[Winter\_temperature_k - \max(Winter\_temperature)]^2 \\ + [Summer\_temperature_k - \max(Summer\_temperature)]^2\end{matrix}} \quad (3)$$

It represents the distance of the city's winter and summer temperatures from the most mild of the winter and summer temperatures across the 35 cities (this measure is based on 2006 data, no time variation). A higher *TEMP_INDEX* means harsher winter or a hotter summer, which makes the city less a pleasant place to live. Although other climate conditions, especially the humidity level, would also affect comfort, in China local humidity tends to be highly correlated with local temperature.

Green space per capita (*GREEN*, in square meter) varies across cities and over time. Beach cities (*BEACH*) are the cities in "China's Most Beautiful Beach City List".[10] There are three beach cities, Dalian, Qingdao and Xiamen, in our set of 35 cities.[11]

Empirical Framework

Chinese cities are experiencing dramatic economic and environmental changes. In such a dynamic setting it is interesting to ask whether lessons learned based on the more "stationary" system of U.S cities apply to Chinese cities. To answer this question, we take a series of empirical predictions from the U.S. urban economics, regional science and environmental economics literatures and use our Chinese panel data set to test them.

(1) Determinants of Home Price Variation

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[10] http://city.cctv.com/html/chengshilvyou/d069bda44d9d1c6df2451ab9ca709ab5.html, released on 7/25/2008.

[11] The U.S. literature has documented that crime is an important disamenity. Big cities in the United States have more crime per-capita (Glaeser 1998). Unfortunately, no official data on crime exists in China.

Similar to the U.S cross-city compensating differentials literature, we will begin by estimating a series of pooled cross-sectional home price regressions. Equation (4) presents the first regression of interest.

$$Home\ Price_{jt} = \alpha + \beta_1 {*} Amenity_{jt} + \beta_2 {*} CFDIPC_{jt} + \beta_3 {*} log(Pop_{jt}) + \varepsilon_{jt} \qquad (4)$$

This regression allows us to test for the size and statistical significance of amenity effects, the productivity effect and the city scale effect.

Our second empirical set of regressions will focus on within-city home price dynamics. Note that in equation (5) we include city fixed effects.

$$HP_{jt} = \alpha_j + f(CFDIPC_{jt}, POP_{jt}, DEMAND_{jt}, Housing\ Supply\ Elasticity(ELA)_j) + U_{lt} \qquad (5)$$

We use estimates of this equation to test whether local demand shifts, as measured by FDI dynamics and local industry demand shifts, are associated with changing home prices. In addition, we test whether this equilibrium response to local demand shifts is steeper in cities with inelastic housing supply. We also employ similar specifications to examine the determinants of cross-sectional wage variation and within-city wage dynamics (using city income as a proxy for city wage).

(2) Air pollution Production Functions

We seek to explain cross-city differences in ambient air pollution. Given the extremely high levels of ambient air pollution in China and the worldwide media attention this key quality of life issue has attracted, we believe that it is important to investigate the determinants of air pollution. We estimate simple cross-city ambient pollution production equations (see Kahn 1997, 2006 for U.S examples) of the form:

$$Air\ Pollution(PM, SO2)_{jt} = \alpha + \beta_1 * log(POP_{jt}) + \beta_2 * INC_{jt} + \beta_3 * INC_{jt}^2 + \beta_4 * CFDIPC_{jt} + \beta_5 * DEMAND_{jt} + \varepsilon_{jt} \quad (6)$$

This simple equation embeds the effects of the scale of urban activity (*Pop*). We will provide a new estimate of the scale effects of urban population size β_1 . This provides direct evidence on the question of quantifying the cost of city "bigness" (Tolley 1974, Glaeser 1998). The level and quadratic terms of per capita income (*Inc, Inc*^{2}) are included to estimate an air pollution Environmental Kuznets Curve (Dasgupta et. al. 2002). Auffhammer and Carson (2008) use Chinese province/year data and reject the hypothesis that greenhouse gas emissions follow an Environmental Kuznets Curve (inverted U) pattern. Since ambient air pollution's health effects are felt immediately, the EKC is likely to be a better model for local pollutants than for global pollutants such as greenhouse gases.

Holding all other explanatory variables constant, the most novel piece in this regression is to examine the impact of FDI on air pollution. Economic theory is ambiguous concerning whether β_4 will be positive or negative, because it embodies two separate effects. The first is the raw scale of investment in capital equipment such as factories. This should lead to a positive effect of FDI on air pollution. Conversely, FDI may help a city upgrade the quality of its capital stock and such technology effects may translate into lower air pollution. This optimistic case would be more likely if new capital is significantly cleaner than older durable capital.

When examining FDI's effect on air pollution, we recognize that there is a valid concern about possible reverse causality. In a nutshell, FDI may flow to those cities with light regulation and these cities may have either higher or lower ambient air pollution levels. Suppose that FDI flows to Chinese cities with more lax environmental regulation. In the U.S, researchers have documented that manufacturing growth is taking place in less regulated counties (Kahn 1997, Becker and Henderson 2000, Greenstone 2002). If dirtier cities in China impose more regulation, then FDI will be pushed to cleaner cities and OLS estimates of equation (6) are biased toward finding that FDI lowers air pollution. Conversely, if clean cities in China are clean because they impose more regulation, then OLS estimates are biased against finding that FDI lowers air pollution (Keller and Levinson 2002). Dean, Lovely and Wang (2005) find that investors from Hong Kong, Macao and Taiwan are attracted by weak environment regulations while those from OECD nations are not. They explain this behavior diversity by technological differences. In either case, this would mean that the error term in equation (6) is correlated with the FDI variable. Therefore, an instrumental variable strategy may be necessary here. The regional favoritism exhibited by China's government offers us a plausible set of instrumental variables. Cities on the east coast receive favorable development policies from the federal government and this encourages greater FDI to flow to these cities. To document this geographical effect, we estimate equation (7);

$$CFDIPC_{jt} = \alpha + \beta_3 * log(POP_{jt}) + \beta_2 * Geography_{jt}\ (EAST,\ DIS\_PORT,\ AIRPORT) + \varepsilon_{jt} \qquad (7)$$

In the next section, we will use equation (7) to instrument for city cumulative FDI per capita. We will also contrast OLS and instrumental variables estimates of equation (6).

Hedonic Regression Results

Table 2 reports eight OLS estimates of home price equation (equation (1)) and one income hedonic regression. In these regressions, the unit of analysis is a city/year and the standard errors are clustered by city. Year fixed effects are included in each regression. The first fact we learn from the home price regressions is that bigger cities have higher home prices. This elasticity equals .15 in the 10-year period. Perhaps surprisingly, we only find very weak and insignificant capitalization effect of city climate in home prices. While Rauch (1993) documents that U.S. cities with high levels of human capital feature higher real estate prices, we find no statistically significant evidence for this hypothesis in Chinese cities.

Turning to ambient air pollution, across the specifications we find consistent evidence that ambient particulate matter (*PM*) is negatively correlated with home prices. Note that we only have air pollution data for 30 cities from year 2003, so the regressions reported in Table 2's columns (1-4) only have 120 observations (30 cities x 4 years). A one standard deviation increase in PM10, lowers home prices by roughly 9%. As shown in columns (2) (year 2003 to 2004) and (3) (year 2005 to 2006), this capitalization effect is growing over time. While this is a short time series, this result is consistent with work by Costa and Kahn (2004) that the disamenity capitalization grows as per-capita income grows. While China's cities have been known for being production centers, our findings of a positive and statistically significant effect of green space and beach access (see column 6) are consistent with the claim that Chinese urbanites value "green amenities". Comparing column (6) to column (7), we see that these amenity effects shrink in size when we control for the "east coast" city fixed effect. All else equal, east coast cities have 36% higher home prices. We recognize that this represents a mixture of productivity effects and amenity effects.

This cross-sectional regression framework also allows us to measure the capitalization effects due to productivity inputs such as FDI. We recognize that questions can be asked about FDI's exogeneity in estimating versions of equation (4). A valid concern is that an omitted city specific factor (such as favorable national government policies) both attracts FDI and raises local home prices. In this case, OLS cross-sectional estimates will over-state the role of FDI in raising home prices. We do see strong evidence that cities enjoying favorable development policies (*EAST*=1) have much higher home prices than others (Column (4) and (5)). When we do not control for whether a city is in the eastern region, cumulative FDI inflow has a positive and statistically significant elasticity of .14 (Column (6)). When we include the *EAST* dummy (see column (7)), this knocks out the FDI coefficient. We will document below in Table 5 that FDI inflows are concentrated in eastern cities. Column (9) presents the estimation results for a hedonic income regression for 30 cities, over the years 2003 to 2006. Bigger cities with agglomeration advantages have higher incomes. The population elasticity equals .19. Among the amenities and the human capital variable, only the green space variable (*GREEN*) is significant, but with a counter-intuitive sign, which may be due to that city income is not a good proxy for city wage rate.

In Table 3, we use the hedonic home price results (Column (4) in Table 2) to estimate a "Quality of Life" (QOL) ranking of cities, as well as a "Best Cities" ranking, as of year 2006, in a similar spirit as those created by Blomquist et. al. (1988) and Gyourko and Tracy 1991. Intuitively, we use the OLS coefficients as index weights and then use each city's attributes to create the indices that we sort from best to worst. In creating these indices, we do not use a city's population level to create the QOL index while we do use this information to create the "Best Cities" ranking. Guangzhou ranks at the top of the QOL ranking, attributed to its mild climate and ample green space. Shanghai ranks No. 6 and Beijing ranks No. 7. Several heavily industrial cities with extremely high air pollution rank at the end of the list, such as Lanzhou, Wulumuqi and Chongqing. In the "Best Cities" ranking list, the three largest cities, Shanghai, Beijing and Guangzhou, rank at the top.

We now turn to our within-city hedonic estimates based on equation (5). These results are reported in Table 4. As shown in column (1), real home prices rise in cities featuring population growth and local labor demand growth. Column (2) shows that holding these factors constant, inflows of FDI have a small but significant effect on increasing home prices. The FDI elasticity equals .05. In columns (3) through (5), we augment the specification to include interaction terms. Our key hypothesis of interest is to test whether cities with more inelastic housing supply feature greater home price appreciation in response to local demand shifts. We find consistent evidence supporting this claim. As shown in column (3), in cities featuring an elastic housing supply, population growth translates into a much smaller home price increase than in cities with inelastic housing supply. The interaction terms on cumulative FDI and labor demand are negative (the expected sign) but statistically insignificant. In contrast to these house price regressions, the cross-city income regressions reported in Table 4's columns (6) and (7) yield few interesting results.

Results on FDI and Air Pollution

We now turn to testing for FDI's role as a factor in determining city ambient air pollution. As we discussed above, FDI embodies two separate effects: scale effect and technology effect. The concern about reverse causality require us construct an instrumental variable. We first examine the spatial distribution of FDI across China's major 35 cities. Table 5 reports the OLS results of equation (7). It reveals that cities in the East that enjoy favorable policies do receive much more per-capita FDI than cities outside the eastern region. Cities with airports and those that are closer to ports receive more FDI. From an econometric standpoint, the results reported in

Table 5 offer us a set of geography instrumental variables that we will use below to instrument for FDI in a regression where city ambient air pollution is the dependent variable.

Table 6 reports the ambient air pollution regression results. Ambient pollution is measured using particulate matter (PM10, *PM*) and ambient sulfur dioxide (*SO2*). Column (1) and (2) just show the time trend of air pollution in the 35 major cities from 2003 to 2006. Most cities enjoyed a decrease in particulate concentrations, but they did not see significant drop in SO_2 concentration. The average city, holding population constant, in our sample experienced a 10% decline particulate matter between 2003 and 2006. The results in columns (3) and (5) reveal several new facts. First, the city size/ambient pollution elasticity equals .24 for particulates and .39 for sulfur dioxide. Perhaps surprisingly, these elasticities are pretty close in range to the U.S estimates (see Kahn 2006). Our second finding is the negative coefficients on cumulative per-capita FDI. Based on the OLS estimates (columns (3) and (5)), the particulate/FDI elasticity is -.09 (marginally significant) and the sulfur dioxide/FDI elasticity equals -.40. Concerned that FDI may be an endogenous variable, as we discussed above, we instrument for city FDI using as a first stage the results we presented in Table 5. Intuitively, we instrument for a city's FDI using geographical variables such as whether it is an east coast city and its distance to the nearest port. Our justification for this strategy is that these measures are correlated with FDI flows (see Table 5) but are unlikely to be correlated with the error term in equation (6). We contrast the OLS and IV results for particulates in columns (3) and (4) and for sulfur dioxide concentrations in columns (5) and (6). We see clear evidence that the IV estimates are much larger in absolute value, negative and statistically significant. These results are consistent with the claim that the beneficial technology effect outweighs the scale effect. The net effect is that FDI improves ambient air pollution in China's major cities[12]. One explanation for this finding is offered by Cole, Elliot and Zhang (2009). Using Chinese province level data, they conclude that FDI flows to provinces with relatively low levels of corruption. If this is true, then our FDI flow measures may represent a bundle of "good governance" and a "greening" of the capital stock. Both effects would tend to be correlated with low levels of air pollution.

Our estimates of the cross-city air pollution relationship also speak directly to the Environmental Kuznets Curve literature (see Dasgupta et. al. 2002, Harbaugh, Levinson and Wilson 2002). In the IV regressions (see columns 4 and 6), both the level and quadratic terms of per capita income are significant and have the expected signs. The income turning point in the PM10 curve is 15.95 thousand RMB per year per capita; in the SO2 curve it is 16.58 thousand RMB. If we set 16 thousand RMB (2003 constant RMB) as the approximate turning point, 8 cities have per-capita incomes that exceed this level by the year 2006. This is encouraging evidence that ongoing growth in Chinese cities may help to improve urban air pollution levels. The potential causes of this empirical finding merit further research.

Conclusion

Over the last thirty years, China's cities have boomed. Hundreds of millions of people have moved to these major cities. This radical adjustment has changed the landscape of China as

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[12] In interpreting these results, we recognize that cumulative FDI is likely to proxy for several correlated variables. If cities that attract FDI also attract more domestic capital, then the FDI effect is proxying for a new capital stock and we are likely over-stating the role of "foreign" capital because it is highly correlated with total new capital investment.

major capital investments have been made to allow these new urbanites to be housed, to commute to work and to work in new factories and office buildings.

Newly available data on home prices within and across China's major cities offers the opportunity to use hedonic techniques to measure compensating differentials for non-market local public goods in this important developing country. In recent work (Zheng and Kahn 2008), we have used detailed micro data within one major city (Beijing) to examine how the housing market is evolving. In that paper, we documented the power of the classical urban monocentric model in explaining the within city real estate pricing gradient and documented the capitalization effects of different local public goods including local air pollution, proximity to subway stations and access to university amenities and green space.

This paper extends our research program by providing new empirical insights on the determinants of cross-city differences in real housing prices, FDI flows and ambient air pollution levels. By working with a unique 35 city panel data set covering the years 1997 to 2006, we were able to test several hypotheses about major Chinese cities. We have found that "green amenities" are capitalized into cross-city housing prices and that this marginal valuation is rising over time. Cities experiencing inflows of FDI have lower air pollution levels than observationally identical cities.

Our results suggest a promising line of research related to rising environmental amenity demand in China's cities. As shown in Table 2, we documented some suggestive evidence that the implicit hedonic price of clean air is rising over time. We also find air quality Kuznets Curves in Table 6. Future research should examine whether rising Chinese per-capita income increases the demand for environmental goods and environmental regulation. As documented by U.S researchers, major U.S cities have made the transition from "producer cities" to “consumer cities” (see Glaeser, Kolko and Saiz 2001). China cities may now be starting to make a similar transition. Beijing’s 2008 push to close dirty factories to create “Blue skies” for the Summer Olympics may foreshadow a long run trend.

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Table 1 Variable definitions and summary statistics

Variable	Definition	Period	Obs.	Mean	Std.dev.	Min	Max
HP	Average sale price of new homes in each year (RMB/sq.mt.)	1997-2006	350	3178.5	1293.1	1636.8	8297.5
INC	City mean annual income per worker (RMB)	1997-2006	350	15451.4	7060.7	5380	41314.4
POP	Total population size in each year (million)	1997-2006	350	2.433	2.011	0.423	1.151
FDIPC	Foreign direct investment per capita in each year (RMB)	1997-2006	342	412.5	504.4	3.3	2960.2
CFDIPC	cumulative FDI per capita in each year, from 1996 (RMB)	1997-2006	350	1751.5	2419.2	19.9	13456.1
DEMAND	index as an indicator of labor market shock	1997-2006	350	0.106	0.033	0.042	0.193
MANU	Share of manufacturing employment	1997-2006	350	0.332	0.103	0.084	0.653
PM	PM_{10} concentration in the air in each year (mg/m3)	2003-2006	120	0.113	0.029	0.03	0.192
SO2	SO_2 concentration in the air in each year (mg/m3)	2003-2006	120	0.056	0.025	0.007	0.152
GREEN	Green space per capita in each year (sq.mt.)	1997-2006	350	31.8	58.4	0.6	590.9
RAIN	total rain fall in 2006 (mm)		30	833.5	514.3	195.8	2175.7
EAST	Binary, 1=cities in China's east region that receive favorable development policies (*special economic zones* and *open cities*), 0=otherwise		35	0.371	0.49	0	1
BEACH	Binary, 1=beach cities with nice sea view, 0=otherwise.		35	0.086	0.284	0	1
TEMP_INDEX	Temperature discomfort index in year 2006, defined as Equation (3)		30	27.733	3.532	19.326	33.978
DIS_PORT	Distance to the closest port (km)		35	654.1	539.4	0	2507
AIRPORT	Binary: 1= the city has airport in the base year, 0=otherwise		35	0.914	0.284	0	1
HUMANCAP	% of people with college degree or above, in 2003		35	0.093	0.032	0.03	0.175
ELA	Housing supply elasticity index (adapted from Fu et. al., 2008)		35	0.998	0.123	0.838	1.316

Table 2 Cross-city House Price Index and Income Regression Results

	Log(*HP*)								Log(*INC*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log (*POP*)	0.373	0.352	0.395	0.285	0.146	0.152	0.135	0.305	0.186
	[5.55]***	[4.98]***	[5.70]***	[4.88]***	[2.77]***	[2.39]**	[2.56]**	[3.47]***	[4.40]***
TEMP_INDEX	-0.006	-0.004	-0.008	-0.02					0.011
	[-0.44]	[-.035]	[-0.52]	[-1.44]					[1.22]
PM	-3.088	-2.848	-3.439	-1.613				-1.479	-0.842
	[-2.17]**	[-2.02]**	[-2.00]**	[-1.33]				[-0.95]	[-0.93]
Log (*GREEN*)	0.094	0.091	0.097	0.041	0.067	0.09	0.058	0.09	0.107
	[2.19]**	[2.19]**	[2.03]**	[1.00]	[1.25]	[2.07]**	[1.20]	[1.98]*	[3.57]***
BEACH					0.155	0.201	0.129		
					[1.07]	[1.74]*	[0.97]		
Log(*HUMANCAP*)	0.102	0.089	0.118	0.024	-0.015				0.053
	[0.95]	[0.88]	[0.99]	[0.29]	[-0.15]				[0.94]
EAST				0.350	0.447		0.357		
				[3.43]***	[5.47]***		[3.49]***		
Log(*CFDIPC*)						0.139	0.048	0.06	
						[4.62]***	[1.35]	[1.45]	
constant	6.435	6.415	6.436	6.906	6.834	6.023	6.668	5.816	7.842
	[12.67]***	[12.99]***	[11.07]***	[16.47]***	[14.29]***	[18.19]***	[23.04]***	[17.51]***	[23.73]***
Observations	120	60	60	120	350	350	350	120	120
R-squared	0.649	0.631	0.642	0.769	0.732	0.661	0.743	0.657	0.698
F test of QOL variables	5.47***	5.16***	14.16***	6.60***	14.00***				8.50***
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data coverage	30 cities, 2003-2006	30 cities, 2003-2004	30 cities, 2005-2006	30 cities, 2003-2006	35 cities, 1997-2006	35 cities, 1997-2006	35 cities, 1997-2006	30 cities, 2003-2006	30 cities, 2003-2006

Notes: See Table 1 for variable definitions. T-statistics are reported in parentheses. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level. In each regression, the standard errors are adjusted for within city correlation over time.

Table 3 City Rankings (30 cities, Year 2006)

	QOL Ranking		"Best Cities" Ranking	
Ranking	City ID	City Name	City ID	City Name
1	23	Guangzhou	10	Shanghai
2	11	Nanjing	1	Beijing
3	15	Fuzhou	23	Guangzhou
4	2	Tianjin	2	Tianjin
5	26	Haikou	11	Nanjing
6	10	Shanghai	12	Hangzhou
7	1	Beijing	15	Fuzhou
8	12	Hangzhou	6	Shenyang
9	29	Guiyang	27	Chongqing
10	30	Kunming	28	Chengdu
11	25	Nanning	21	Wuhan
12	34	Yinchuan	9	Haerbin
13	5	Huhehaote	26	Haikou
14	33	Xining	18	Jinan
15	20	Zhengzhou	31	Xian
16	8	Changchun	8	Changchun
17	18	Jinan	30	Kunming
18	6	Shenyang	4	Taiyuan
19	4	Taiyuan	29	Guiyang
20	14	Hefei	3	Shijiazhuang
21	17	Nanchang	20	Zhengzhou
22	28	Chengdu	25	Nanning
23	3	Shijiazhuang	17	Nanchang
24	9	Haerbin	14	Hefei
25	22	Changsha	22	Changsha
26	31	Xian	32	Lanzhou
27	32	Lanzhou	35	Wulumuqi
28	21	Wuhan	33	Xining
29	35	Wulumuqi	5	Huhehaote
30	27	Chongqing	34	Yinchuan

Table 4 Within-city Regression Results

	Log(*HP*)					Log(*INC*)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (*POP*)	0.155	0.203	0.786	0.875	0.234	-0.088	0.234
	[3.53]***	[4.55]***	[3.73]***	[3.60]***	[4.90]***	[-1.91]*	[0.81]
Log (*POP*) ×*ELA*			-0.519	-0.588			-0.294
			[-2.82]***	[-2.64]***			[-1.05]
DEMAND	2.211	2.144	1.779		2.507	-0.238	-0.44
	[3.45]***	[3.42]***	[2.81]***		[2.02]**	[-0.37]	[-0.28]
DEMAND ×*ELA*					-0.511		0.014
					[-0.47]		[0.01]
Log(*CFDIPC*)		0.047	0.039	0.052	0.106	0.103	0.11
		[3.80]***	[3.05]**	[1.03]	[2.31]**	[7.72]***	[2.08]**
Log(*CFDIPC*)×*ELA*				-0.014	-0.065		-0.013
				[-0.29]	[-1.45]		[-0.26]
constant	6.864	6.385	6.127	6.221	6.282	1.788	1.635
	[30.02]***	[24.86]***	[22.70]***	[22.94]***	[23.94]***	[6.69]***	[5.76]***
Observations	350	350	350	350	350	345	345
R-squared	0.971	0.973	0.973	0.973	0.973	0.974	0.974
F test of interaction terms				5.91***	1.73		0.03
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 1 for variable definitions. T-statistics are reported in parentheses. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level.

Table 5 The Determinants of a City's Cumulative Foreign Direct Investment

	Log(*CFDIPC*)	
	(1)	(2)
EAST	1.977	1.982
	[6.86]***	[6.76]***
Log(*DIS_PORT*)	-0.079	-0.073
	[-0.93]	[-0.82]
AIRPORT	0.054	0.037
	[0.09]	[0.06]
Log(*POP*)		0.027
		[0.13]
Constant	6.238	6.075
	[7.06]***	[3.83]***
Observations	350	350
R-squared	0.717	0.717
Year Fixed Effects	Yes	Yes

Notes: See Table 1 for variable definitions. T-statistics are reported in parentheses. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level. In each regression, the standard errors are adjusted for within city correlation over time.

Table 6 Air Pollution and FDI

	Trend regressions		Log(*PM*)		Log(*SO2*)	
	Log(*PM*)	Log(*SO2*)				
	(1)	(2)	(3)	(4)	(5)	(6)
Log (*POP*)	0.148	0.258	0.18	0.199	0.406	0.423
	[1.54]	[1.75]*	[3.89]***	[2.29]**	[3.00]***	[2.98]***
INC			0.125	0.372	0.399	0.607
			[1.41]	[3.21]***	[2.16]**	[2.25]**
INC^2			-0.004	-0.012	-0.013	-0.019
			[-1.48]	[-3.01]***	[-2.09]**	[-2.22]**
Manuf			0.945	1.779	-0.061	0.64
			[1.37]	[2.82]***	[-0.04]	[0.49]
Log(*CFDIPC*)			-0.113	-0.414	-0.394	-0.647
			[-1.77]*	[-4.00]***	[-3.39]***	[-2.14]**
Log(*RAIN*)			-0.227	-0.041	-0.072	0.084
			[-3.98]***	[-0.37]	[-0.54]	[0.32]
YEAR2004	-0.052	0.008				
	[-2.54]**	[0.18]				
YEAR2005	-0.122	0.032				
	[-6.49]***	[0.49]				
YEAR2006	-0.099	0.006				
	[-4.02]***	[0.08]				
Constant	-2.966	-4.444	-1.95	-3.143	-4.697	-5.702
	[-5.34]***	[-5.12]	[-4.00]***	[-4.05]***	[-3.86]***	[-3.14]***
Observations	120	120	120	120	120	120
R-squared	0.13	0.09	0.596	0.162	0.424	0.344
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	IV	OLS	IV

Notes: See Table 1 for variable definitions. T-statistics are reported in parentheses. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level. In each regression, the standard errors are adjusted for within city correlation over time. Income is measured in 1,000s of RMB.

Figure 1: 35 Major Cities in China

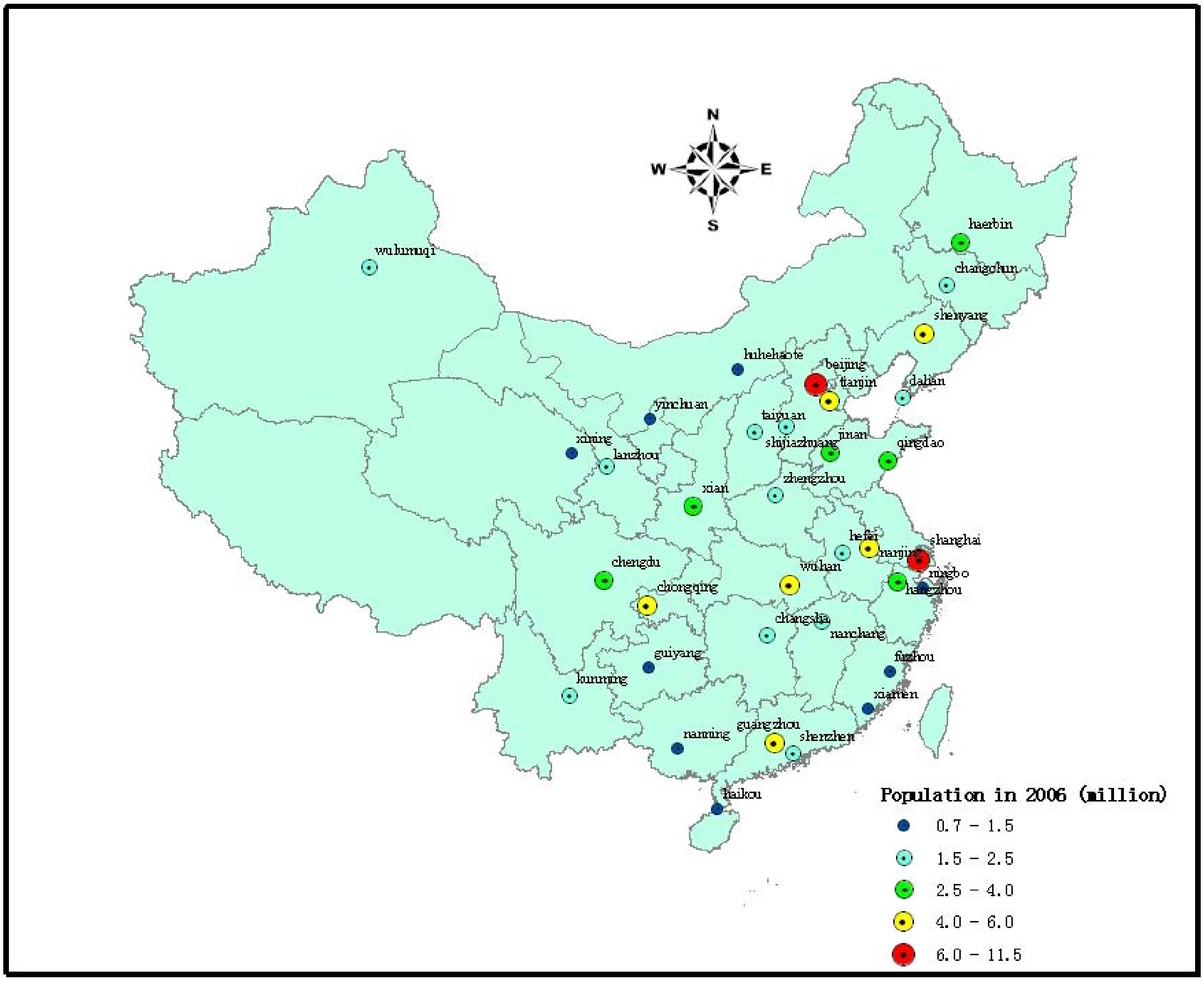

Figure 2: particulate and sulfur dioxide concentrations across the 30 cities in 2003 and 2006