Urban structure, subway system and housing price: evidence from Beijing and Hangzhou, China

This paper studies the relationship between subway station and the housing price. While this topic is well researched, this paper provides several twists. First, the paper employs Getis-Ord local statistics to locate some “hot spots,” and formalize the idea of “spatial clustering.” Second, the paper constructs a metro index to reflect the commute efficiency for each metro station. The index mainly compares the commute time between the station and some particular location with and without using the metro. Third, the paper embeds some clustering techniques in an otherwise standard hedonic pricing equation (HPE).

Overall, I think the results are interesting, especially the sharp contrast between Beijing and Hangzhou (for instance, see Table A3). And the authors also demonstrate their deep knowledge about the Hangzhou city (for instance, see section 4.3).

On the other hand, there are several areas that can be further improved, before the paper can be considered published in a journal like Sustainability.

First, the authors need to hire a professional English editor. Here are a few examples.

(a) Spatial heterogeneity is co-exists with local homogeneity because a submarket is usually a geographic boundary of different submarkets. Obviously, both of spatial heterogeneity and

(b)

Second, the authors may have missed some relevant references.

For instance, it writes

people relocate away from rail transit to avoid its adverse environmental impacts. [9] find that in Hong Kong there seems no subway effect, because the care for surrounding environment seems to outweigh the accessibility brought by rail transport.
More recent research, such as Huang et al. (2018), Leung et al. (2014), all found the subway station to be important for housing prices. Besides, it is virtually impossible to distinguish the effect of subway station from railway station because in some areas, they are geographically close. The revised edition should correct that station and relate to these papers.

Also, the paper writes,

hidden variables, such as the urban structure. Second, many previous studies focus exclusively on accessibility to metro stations, which is measured by distance to metro stations and/or the dummy variables derived from distance, such as whether there is a metro station within the range of one mile [11–15]. These studies ignore the heterogeneity among different metro stations and might over estimate the positive effect of subway system on housing prices.

In fact, Tse and Chan (2003) measures the commute time instead of the commute distance and how it would affect the property price gradient. And the latter is clearly related to the urban structure, especially in the context of mono-centric city. The revised edition of the paper should relate to that paper.

Third, there are some data issues.

dynamics very well. For the purpose of this study, the authors only collected a cross-sectional dataset recording all the information of on-sale second-hand apartments listed on fang.com during Oct., 2017.

In addition, it is also needed the accurate geographic location of every listed apartment, while fang.com only provide a description of their addresses. So Baidu Geocoding API is used to extract the

It is not clear whether those are (a) listing prices only, (b) transaction prices only, or (c) a combination of listing and transaction prices. In the literature, it is well known that the listing price can be a strategy used by the sellers, while the transaction price is the part of the equilibrium. For instance, Leung et al. (2002) study the ratio of the listing and transaction price and relate it to the time-on-the-market (TOM), i.e. the time between the property is listed and the time the property is actually transacted and find that there is a clear statistical relationship. The revised edition should clarify this point and relate to the literature.

Another issue is about the identification of the “hot spot.” The paper writes

high or low values can be found. To be considered as a statistically significant hot spot, a feature has to have a high value and simultaneously be surrounded by other features with high values. A higher z-score corresponds to more intense clustering of high values (a hot spot). Conversely, a lower z-score corresponds to more intense clustering of low values (a cold spot). The Getis-Ord local statistic is given

The paper should clarify more. For instance, are those data also collected only in Oct., 2017? Or in a different time period? And it is not clear what it means for “more intense clustering.” For instance, some
spots in Beijing and Hangzhou may have a lot of tourists in some seasons, but not other seasons. Some districts may have a lot of people working there, but may be almost empty during, say, Lunar New Year.

Some districts may have a lot of high apartment buildings for residents, but not much commercial activities, except for grocery shops. And some major transit point such as the airport or major train station would have a lot of people come and go all day long, but not much economic activities there, except for meals and selling gifts. How should we compare these different types of places? The paper should clarify more.

The paper also writes

interpreted as the major destinations of the entire city. In the current paper, the authors set $K = 18$ because based on preliminary experiment, 18 is the largest number that can guarantee all destinations not too close to each other in both Beijing and Hangzhou. The spatial distribution of 18 major destinations are plotted in Fig. A2, section 4.1.

I understand that the authors may want a fair comparison and hence choose 18 major destinations in both cities. On the other hand, the two cities are very different.

<table>
<thead>
<tr>
<th>Table A1. Beijing vs. Hangzhou</th>
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<tbody>
<tr>
<td>City</td>
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<tr>
<td>------</td>
</tr>
<tr>
<td>Beijing</td>
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<tr>
<td>Hangzhou</td>
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</table>

It is clear from Table A1 that even restricted to “core area,” Beijing is almost three times as Hangzhou. Hence, is it a sensible to choose the same amount of major destinations for the two cities.

Also clear from Table A1 is that in Beijing there are 18 subway lines and Hangzhou only has 2. While the population of Beijing is bigger and has more population (about twice) than Hangzhou, the density of subway stations of Beijing should be much higher than Hangzhou.

Also, the location of that lines is not random. The government might have certain considerations before they build the subway lines. It may be especially important for Hangzhou, where the whole city has only 2 lines. (In comparison, Guangzhou has slightly more population and probably has 10 subway lines).

These are data issues. If the authors cannot do much about it, they should at least recognize these issues and qualify their results in the paper.

Fourth, it is about the results. The paper writes
In contrast to Beijing, Hangzhou shows a completely opposite situation, the coefficient for metro 1 and metro 2 are all negative significantly, which conflicts to both the positive effect hypothesis and the “bell”-shape effect [11] hypothesis on the relation between accessibility to subway and housing prices. If look at the metro index as well, it becomes more controversial. The coefficient of metro

It is an interesting result. It is also in line with other Chinese housing market studies. For instance, Leung et al. (2011) compare four major cities of China and find that their house price dynamics are very different. Huang et al. (2015) compare 35 first-tier cities in China and find that the difference in amenities and bank loans provided locally are important in explaining the cross-city housing price differences. Furthermore, they find indirect evidence of sorting, meaning that due to the differences in amenities, the people drawn to different cities are different and Huang et al. (2015) take a multi-stage approach to analyze this problem. The revised edition of this paper should relate to these cross-city comparisons.

The paper also writes

One explanation of the weird relation between accessibility to subway, metro index and housing prices is the existence of spatial heterogeneity. More precisely, there might exist multiple housing submarkets in Hangzhou. The pricing mechanisms within different sub-markets are different, putting data from different sub-markets into one single HPM pollutes the correct relation between housing prices and its determinants.

... must be positive significantly within every cluster. Such a criterion can be written formally as a set of mathematical constraints as below:

\[
\begin{aligned}
\hat{\beta}_{S,m} &> 0 \\
P_{\hat{\beta}_{S,m}} &< \alpha \\
\text{det} \left( x^T_{-1,S} x_{-1,S} \right) &\neq 0 \\
S &\in S_K \\
K &\geq 1
\end{aligned}
\]  

(8)

where \(\hat{\beta}_{S,m}\) represents the estimated coefficients of metro index for a cluster \(S\), \(P_{\hat{\beta}_{S,m}}\) is the \(P\)-value associated with that coefficient and \(\alpha\) denotes the significant level which will be taken as 0.1. **we do not select a finer significant level because all needed is just to exclude the negative premium induced by metro index**, and it is totally admissible that there is no significant connection between subway system and housing prices given that a housing unit is far away from subways. To this purpose, it is not necessary to impose a high significant level on the positivity.

The paper is correct to point out the submarket issue and proposes a procedure to study it. It should be noted that the relationship among different sub-markets can vary over the housing market cycles (i.e.
when the market goes up and down). Leung et al. (2013) provide a case-study of Hong Kong, which is based on more than 200,000 transactions. The paper should qualify their results and explain how sensitive their procedure could be affected by the housing cycle and relate to the literature.

Also, due to its geographical or residential composition, some sub-markets may be more frequent to have fire-sale (Leung and Zhang, 2011) or speculation (Leung and Tse, 2017). In that case, the price effect may be over or under-estimated. Taking data of one month only is dangerous. The authors should either expand their dataset, or recognize these limitations and qualify their results in the paper.

Overall, the manuscript seems interesting and promising. The revised edition should address the issues highlight in this report.

Reference


