Intercity Information Diffusion and Price Discovery in Housing Markets: Evidence from Google Searches

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Abstract

In this paper we provide an innovative measurement of information flow in Chinese housing markets based on the Google search records, which depicts a substantial flow of house price information from national level "superstar" cities like Beijing and Shanghai and regional level "star" cities like Tianjin and Chongqing to other "normal" cities. The empirical results also suggest that such information diffusion is at least one of the major factors in determining intercity house price discovery in the short run. The "superstars" and "stars" are found to be lead most other cities in house price changes.

Key Words: information diffusion; price discovery; house price

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I. Introduction

The phenomenon of information diffusion and price discovery in the housing market has been documented in numerous researches. As a result of market inefficiency, typically the available information cannot be immediately and simultaneously reflected in house prices in all markets. Instead, market price formation may firstly occur in certain market, and then such information (price signal) is transmitted from the leading market to other markets and significantly affects the house price formation in those lagged markets (Grossman and Stiglitz, 1976; Hong and Stein, 2007).

While existing literatures have provided extensive empirical evidences on the interdependence of house price dynamics across different markets, so far the pattern of information spillover and its effect can only be examined via some indirect tests due to the lack of an accurate measurement on information flow. In this paper we seek to fill this gap by providing a direct measurement on the direction and density of intercity information flow in the housing markets following the recent trend on the analysis of web search query records (Da, Engelberg and Gao, 2011; Bank, Larch and Peter, 2011). More precisely, based on the search query data provided by "Google Trends", we build the indicator of "Information Flow Index", which quantitatively measures Google users' propensity to focus on certain city when they are searching for house price related information on web, including the spatial and temporal variations of such propensity. This provides a unique view on the process and pattern of information dissemination in the housing markets.

Using the data from mainland China between 2004 and 2011 as the example, the information flow index suggests that, while the house price information in most "normal" cities cannot spread beyond their native provinces, a few major cities have substantial influence in the national or regional level. Especially, there exist three national level "superstar" cities including Beijing, Shanghai and Shenzhen, from which we can observe significant house price information flows to almost all other provinces; or in other words, the house price information from these three cities can spread around the whole country. There are also several regional level "star" cities like Tianjin, Chongqing and Wuhan, which mainly attract attentions from market participants in nearby provinces.

The empirical analysis based on the newly-built house price series in 35 major cities also suggests that, such information spillover pattern does significantly correlate with the spatial pattern of intercity house price discovery. First, the Granger causality in short-run house price changes is more likely to exist if the information is transmitted from the leading city to the lagged city. As a consequence house price changes in "superstar" cities like Beijing is found to Granger cause that in most other cities. Second, we follow the idea by Ferreira and Gyourko (2011) and identify the key time points during the recent housing booming during 2009-2010 in each city. On average the whole process of the booming in the "superstar" cities is about 3-4 months before the "star" cities, and 6-8 months before the "normal" cities. Finally, we decompose the temporal process of information diffusion and house price discovery using the information flow from Beijing as an example. As revealed in the panel data model, a sharp house price change in Beijing (either increase or decrease) will lead to a dense information flow to other provinces (i.e., more Google searches on Beijing's house price information from other provinces) during the following half year, which in turn significantly and immediately affects the house price changes in the corresponding provinces, controlling for other factors.

The key contribution of this paper is to provide a novel and intuitive measurement of information flow in the housing market, which not only enables a detailed description for the spatial pattern and temporal process of house price information dissemination for the first time, but demonstrates the role of information factor in intercity house price discovery. Moreover, this research also contributes to the growing literatures on house price discovery, and it is among one of the first empirical researches on the intercity house price discovery pattern in mainland China.

The paper proceeds as follows. Section II provides a brief review on researches on information diffusion and price discovery in the housing market. Section III introduces how we build our Information Flow Index, and describes the key features of information diffusion pattern in Chinese housing markets based on the index. Section IV provides two empirical evidences on intercity price discovery in China, and Section V investigates the linkage between information diffusion and price discovery, using information from Beijing as an example. Section VI concludes.

II. Literature Review

Diffusion of house price dynamics across different markets (or different segments within one market) has long been of interest in the housing literatures. Hitherto researchers especially focus on two aspects. The first is the relationship between securitized (public) and unsecuritized (private) real estate markets. In general most researches point out that the price/return dynamics in the securitized sector leads that in the unsecuritized sector (Giliberto, 1990; Gyourko and Keim, 1992; Barkham and Geltner, 1995; Yunus, Hansz and Kennedy, 2010), albeit to a few counterexamples Tuluca, Myer and Webb (2000). The second topic attracting most concerns exist in the spatial dimension. The results suggest that house price changes can diffuse between contiguous areas (Clapp, Dolde and Tirtiroglu, 1995; Pollakowski and Ray, 1997; Holly, Pesaran and Yamagata, 2011), or from certain "core" country/city/neighborhood to others (Meen, 1999; Oikarinen, 2004; Bandt, Barhoumi and Bruneau, 2010). Recently researchers also expand the scope to several other aspects, and the diffusion of price changes is proved to exist between land and housing markets (Ooi and Lee, 2009; Chau et al, 2010), public and private housing sectors (Ong and Sing, 2002), various quality tiers (Ho, Ma and Haurin, 2008), and spot and presale housing markets (Wong, Chau and Yiu, 2007).

The literatures also provide several possible explanations for such cross-market interdependence of house price, among which the information factor is expected to play an important role, especially in the short-run perspective. The logic can date back to the idea originally introduced by Grossman and Stiglitz (1976), which is later developed as the theory of "gradual information flow" (Hong and Stein, 1999, 2007). As for the housing market, due to the market heterogeneity in efficiency, certain markets/segments can react faster to the newly available information and hence adjust the house price more quickly because the participants are more experienced, the transactions are of higher frequency, or the information cost is lower (Gyourko and Keim, 1992; Clapp, Dolde and Tirtiroglu, 1995; Oikarinen, 2004; Chau et al, 2010). In contrast, some markets are comparably slower to the new information, but the participants in those markets can try to learn from the leading markets via the price signals. By this means the information will spread from the leading markets to the lagged markets, and facilitate the price adjustment in these lagged markets.

However, due to the lack of a direct and reliable measurement on information flow, so far the pattern and effect of information diffusion in the housing market can only be indirectly investigated in the empirical analyses. One approach is to learn from the financial literatures and perceive the unexpected component in return/price or volatility in the leading markets as the signal of "news". As a recent example, Chau et al (2010) use the unexpected outcome of land auctions in Hong Kong as the proxy of "new information" from the land market, which is proved to have significant effects on house prices. Some other researches choose to design the proxy from the aspect of information cost. For instance, Clapp, Doldo and Tirtiroglu (1995) adopt the population density as the information cost proxy, and conclude that cities with higher density tend to lead cities with lower density in house price changes. Nevertheless, these indirect analyses still could not provide a detailed picture about the information diffusion, nor the direct evidence on its effect on the price discovery.

The financial literatures have provided more ideas on how to measure information flow. Besides the analyses based on traditional medias like articles on *Wall Street Journal* or *Dow Jones Newswire* (Tetlock, 2007, 2010; Tetlock, Saar-Tsechansky and Macskassy, 2008; Fang and Peress, 2009), recent researches also start to borrow instruments from emerging information channels like web search engines. Da, Engelberg and Gao (2011) are the first to propose the idea of applying Google search volume as the information indicator in the financial market, and their empirical researches suggest that this indicator can predict the stock price in the short run. Then Bank, Larch and Peter (2011), Mondria and Wu (2011), Dzielinski (2011) and some other researchers also adopt similar proxy on various topics on financial market. In this paper we will follow this strategy in order to to fill the gap in existing housing literatures by providing a direct measurement of information flow in the housing markets, using mainland China as the example. We particularly focus on the spatial pattern of the intercity information spillover, which is seldom analyzed even in the financial literatures, although will also provide some preliminary temporal analysis at the end of the story.

III. Intercity Information Diffusion Pattern in Chinese Housing Markets

a. Web Search Engine as An Emerging Information Channel in China

Similar with most other major economics, the internet is playing a increasingly important role in China's economic and social developments. After a continuous and rapid growth, currently China owns the largest group of internet users around the world. As reported by the China Internet Network Information Center (CNNIC),[1] at the end of 2011 the volume of internet users reached 513.1 million in China, making up 38.07% of the total population,[2] and each user spends 18.7 hours on internet per week on average. The internet is especially popular in the cohorts of educated and young people, which are

[1] CNNIC is an non-profit organization with the supports from both Ministry of Information Industry of China and Chinese Academy of Sciences. Since 1997 CNNIC has been publishing the "Statistical Report on Internet Development in China" semi-annually. The latest version of the report was published in Jan 2012 and available in the official website of CNNIC (www.cnnic.cn).

[2] Some other institutes like National Bureau of Statistics of China and World Bank also provide their independent estimates on the volume of internet users in China, and the figures are very close to CNNIC's report.

also the major potential home buyers. The CNNIC's report points out that in 2011 over 95% of the graduates and some 60% of those aged 20-39 use internet.

Among all the potential usages, web search engine is one of the most important tools for Chinese internet users. According to the sample survey by CNNIC, in 2011 79.4% of the respondents list "searching for information via web search engines" as one of their major activities on web[3], which is only second to "instant message" (80.9%) in all the 18 options. This implies currently over 400 (513.1 * 79.4% = 407.4) million Chinese people are searching information on web. Thus although it is far too early to say whether (or to what extent) web search engines can eventually replace the traditional medias, it is undoubted that they have already become one most important information dissemination channel in China. In addition, considering house price is currently one of the most highly concerned topics in China, it is reasonable to expect the web search engines should also play an important role in the spillover of house price information.

Compared with the traditional medias like newspapers or TVs, the web search engines are especially helpful for understanding the information diffusion in the housing markets for at least two reasons. First, in the traditional channels typically it is almost impossible (or at least very costly) to accurately identify how many people have acquired certain information from newspapers or TVs, where these people locate, and when they get such information, all of which have been proved to be essential in understand the effect of information diffusion (Engelberg and Parsons, 2011). In contrast, technically all the queries including their originating IP addresses are automatically recorded on the web search engine servers, which can be used to quantitatively measure the spatial and

[3] This figure keeps quite stable and varies between 70%-80% in CNNIC's annual sample survey during the recent 5 years.

temporal distribution of users' queries for certain information, and thus provides a detailed picture on the information flow. Second, the information diffused on web via search engines is target oriented: anybody may happen to read some information from newspaper articles/TV programs, even if he/she is not interested at all, but in most cases one will search for certain information only if he/she needs it. For instance, most queries for "house price" should come from (potential) sellers and buyers of housing units, developers, brokers, market analysts, or policy makers, all of which are the major participants in the housing markets, and hence the information diffused via this way is more likely to affect the following dynamics in the housing markets.

Fortunately several major internet search companies have been collecting and providing statistics on web search records. In this paper we choose to rely on the data provided by "Google Trends" (www.google.com/trends/) to build our measurement on information flow in Chinese housing markets.[4] "Google Trends" is a free service provided by Google since May 2006, and (currently) covers the query records from January 2004 to present. For any given term, "Google Trends" can report its "Search Volume Index", which quantitatively measures how often this term is searched via Google in stated region and period.[5] This provides the raw inputs for our information flow measurement.

b. The National Level Information Flow Index

[4] Another major web search engine in China, Baidu, also provides similar service named "Baidu Index" (index.baidu.com). But in most provinces this index only date back to 2008. Besides its calculation formula is opaque. Therefore in this research we still choose to rely on "Google Trends".

[5] More technical details on the "Search Volume Index" are available in the website of "About Google Trends" (www.google.com/intl/en/trends/about.html); or see discussions in Da, Engelberg and Gao (2011).

We start with the aggregated level analysis by measuring the influence of each city's house price information in the national level. This indicator can allow us to: (1) identify the most influential cities in Chinese housing markets, which will be the emphasis in the following analysis; and (2) testify the reliability of this index by comparing it with information measurements based on other information diffusion channels (Da, Engelberg and Gao, 2011).

Here one city's national level Information Flow Index (*NIFI*) is defined as the propensity of all Google users in mainland China to focus their scope on this city when they are searching for house price related information. More specifically, for city i its index ($NIFI_i$) is calculated as the volume of searches on the combination of this city's name and the keyword of "House Price" (*fang jia* in Mandarin) [6] from mainland China during the sample period, normalized by the total volume of searches on "House Price" only during the same interval. Thus this index reflects the degree of relative importance of each city's house price information in the country level, while cities with higher scores in this index can be perceived as more influential.

We calculate the index for all the 287 cities in China during the sample period of 2004-2011,[7] with results depicted on the map in Figure 1. The average and standard deviation of the index are 0.18% and 0.69%, respectively, but these statistics alone mask a large heterogeneity in cities' influence. On the one end, the house price information in Shanghai and Beijing attracts high concerns. The NIFI in these two cities reach 7.5% and

[6] In this paper we adopt the keyword of "House Price" (*fang jia*). The evidences from "Google Trends" suggest that this term is much more frequently used by Chinese users than other options: the searches on "Price of House" (*zhu fang jia ge*), "Real Estate Price" (*fang di chan jia ge*) and "Building Price" (*fang wu jia ge*) are only 1.5%, 2.0% and 3.5% as the volume of searches on "House Price" (*fang jia*), respectively.

[7] In early 2010 Google closed its business in mainland China, but after that the users in mainland China could still access the Google server in Hong Kong.

6.5%, respectively, which means that on average one of every 13 searches on house price information from Chinese Google users explicitly restrict his/her scope to Shanghai, while one of every 15 searches just focus on Beijing. On the other end, the index is lower than 1.0% in 267 cities, which implies that the influence of their house price information is almost neglectable in the national level. Particularly, in 244 of these 267 cities the index is reported to be very close to 0.0%. Between these two extremes are there 18 cities with their NIFIs between 1.0% and 2.5%, and thus could be expected to have a limited influence in the national level. Several important cities like Shenzhen, Tianjin, Chongqing, Chengdu and Wuhan are included in this group.

*** Insert Figure 1 about here ***

To verify whether this index can effectively capture the information flow, we calculate another indicator based on a traditional information diffusion channel, the newspapers. So far we still cannot find an equivalent of *Wall Street Journal* in China which can dominate the business medias in the national level, and hence we choose to combine multiple sources as Engelberg and Parsons (2011). Based on the Genius Database (www.genius.com.cn), we count the number of articles with both each city's name and the keyword of "House Price" from over 30 kinds of nationwide Chinese newspapers during 2004-2011, and then normalize it by the number of articles with the keyword of "House Price" only. The correlation coefficient between this "newspaper index" and the NIFI reaches as high as 0.935. Therefore at least in the aggregated level the index based on "Google Trends" is consistent with the pattern revealed in channels.

c. The Provincial Level Index and the Spatial Pattern of Information Diffusion

The national level index has suggested about 20 cities with substantial influence in the national housing market. But an even more important question is the spatial pattern. Even with exactly the same NIFI, the searches may only come from users within the city, or concentrate in nearby areas, or distribute all around the country, which will result in totally different effects on house price. Therefore we further decompose the national level index to the provincial level, especially focusing on each city's influence beyond its own province.[8]

The basic logic of the provincial level Information Flow Index (PIFI) is consistent with the national level indicator. In particular, the index capturing the information flow from city i to province j ($PIFI_{i,j}$) is defined as the volume of Google searches on the combination of city i's name and "House Price" from province j, normalized by the total volume of searches on "House Price" from province j during the same interval. Hence for each of the 287 cities we can get 30 provincial level indexes, including the one for its native province.[9] Obviously a higher value of $PIFI_{i,j}$ indicates a denser flow of house price information from city i to province j.

Again the results suggest a large divergence between the cities.[10] For 258 of the 287 cities the provincial level index reaches 1.0% at most in its own province, which suggests that for most "normal" cities the house price information could hardly diffuse beyond the province scope. This left only 19 cities with considerable influence beyond the local province, which are our major interests.

[8] Ideally a city level index can reflect the spatial pattern of information diffusion more detailedly than the provincial level indicator, especially in describing the information flows within the same province. But currently in a large portion of cities the total volume of Google searches for "House Price" is not large enough to report, and so we can only leave the calculation of city level index for future researches.

[9] There are 31 provinces (including 4 municipalities and 5 autonomous region) in mainland China. The Xizang (Tibet) Autonomous Region is not included in the following analysis because its volume of Google searches for "House Price" is too small to report.

[10] The detailed results are available on request.

The summary statistics of the provincial level indexes for these 19 cities are listed in Table 1. As expected all these cities get highest indexes in their native provinces. Then the rest 29 provinces are further divided into two groups in order to investigate the spatial pattern more detailedly: the provinces with any part of their jurisdictions within 500 kilometers of the target city are defined as nearby provinces within the same region, and all the other provinces are defined to be outside the region.

*** Insert Table 1 about here ***

According to the results, in general these 19 cities can be grouped as two tiers. The first tier, or the national level "superstars", includes Beijing, Shanghai and Shenzhen, whose house price information has nationwide influences. As the extreme case, the PIFIs of Beijing are not only quite large in all the 8 nearby provinces within 500 kilometers, but also reach at least 1.0% in 20 of the 21 provinces beyond that scope (Figure 2-A), and as a whole the average PIFI in all the 29 provinces reaches 3.59%. This indicates that housing market participants in almost all provinces are watching the house price dynamics in Beijing, and as a result there exist dense information flows from Beijing to all other areas in China. The situation is similar for Shanghai (Figure 2-B), with the average PIFIs in all 29 provinces as 2.45%. Comparably the influence of Shenzhen is smaller (Figure 2-C). Its influence mainly exist in the east and middle regions (especially the southern part), while the density of the information flows (i.e., the magnitude of PIFIs) is also lower than Beijing and Shanghai.

The second tier includes the other 16 cities, which can be perceived as the "regional stars". In general these cities can be very influential in the regional level, but such influence quickly decays with the increase of distance, and thus could hardly reach provinces outside the region. A typical example is Tianjin (Figure 2-D), whose house price information is disseminated in most provinces in northern China, with PIFIs reaching 1.0% in 7 of the 8 provinces within 500 kilometers, but only has limited impacts in other regions. Similar cases include Chongqing (Figure 2-E) and Chengdu in the southwestern region, Wuhan in the central region, Xian in the northwestern region, Guangzhou in the southern region (Figure 2-F), Nanjing and Hangzhou in the eastern region, and Dalian and Shenyang in the northeastern region. The influence of other cities like Hefei, Suzhou, Xiamen and Fuzhou are even smaller and concentrates in few adjacent provinces.

*** Insert Figure 2 about here ***

These results naturally lead to two questions. The first is why such pattern exists. In particular, the existence of the three nationwide "superstars" is especially striking in a huge country like China – why people in provinces like Yunnan (southwest) or Xinjiang (northwest) keep an eye on the house price in Beijing, which is over 2000 kilometers away? Moreover, a preliminary international comparison suggests this may be a unique phenomenon in China. We apply the similar calculation method to U.S. and calculate both the national and state level information flow indexes for major cities like New York and Los Angeles, but do not find any evidences for the existence of "superstars" whose house price information can spillover in most states.[11] For example, besides the state of New York, the home price information in New York city only attracts limited attentions from nearby states like New Jersey, Pennsylvania and Massachusetts, and only peoples in California are searching for information on Los Angeles's home price on web.

[11] We adopt the key word of "home price" in the analysis in U.S. The results based on other key words like "house price" are consistent.

One explanation is, as suggested by Wu, Gyourko and Deng (2012), one major characteristics in Chinese housing market is the existence of strong common trend – prices tend to move in the same way across most markets in a given period, reflecting strong influence of the national effect due to shifts in the macro environment, market sentiment, or central government's intervention policies. The city specific effects, by contrast, are found to be far less important in determining local house price change. This implies that understanding such national-level common trend is a most important task for housing market participants to predict local house price changes, and a most feasible way is to learn such information from the "superstar" and "star" cities.

The second question is the determinant of specific city's influence – why cities like Beijing, instead of some other cities, can seize the top positions in the hierarchy. A detailed investigation on this issue is beyond the scope of this research, but the statistics listed in Table 2 can provide some preliminary evidences. According to the statistics in 2009,[12] the "superstar" cities are with the most developed real estate industry (i.e., highest share of employment in the real estate industry), most active housing market, highest population density, followed by the regional "stars", which are all consistent with the attributes of a more efficient market suggested in existing literatures. Therefore the newly available information can be expected to be captured by house price changes in these markets first, and so will attract attentions from market participants in other cities.[13]

*** Insert Table 2 about here ***

[12] The data will be updated to 2010 in later version when such statistics are available. But this will not affect the key results of the table since the pattern is general stable during recent years.

[13] Another possible explanation is that more peoples from other provinces plan to purchase housing units in these "superstar" or "star", and thus are search for related information in advance. The last column in Table 2 calculates the average percentage of home buyers from other provinces, whose pattern is consistent with this explanation. But the differences between various tiers are only marginally significant.

IV. Empirical Results on Intercity House Price Discovery

After the analysis on intercity house price information diffusion pattern, in this section we will turn to the other side of the story and investigate the pattern of intercity price discovery in Chinese housing markets.

a. Data

The following empirical analysis adopts the constant quality price indexes of newly-built housing units in 35 major Chinese cities[14] from January 2006 to December 2011 provided by Tsinghua University. This index is calculated based on full sample micro-level data of newly-built housing transactions, while the conventional hedonic model is applied to control for the potential quality changes, and hence this index can be expected to reflect the short-run house price changes more accurately than the non-constant quality indexes reported by the Nation Bureau of Statistics of China[15].

One major limitation of the data is the sample period only covers six years, which is shorter than most existing empirical literatures on intercity price correlations. But it is the only interval during which the reliable house price indicator is available in China. Besides, the following two factors can at least partly offset this limitation. First, the Chinese housing market has witnessed a pendulum of price change during these six years. Figure 3 depicts the annual growth rate calculated based on the aggregated index of these 35 cities. The price substantially increased in 2007 until the market was hit by the financial crisis in 2008. Then the huge government stimulus package fueled another

[14] The 35 major cities include all the 3 "superstar" cities defined above, 15 of the 16 "star" cities with Suzhou as the only exemption, and 17 of the 268 "normal" cities. So far the constant quality house price indicator is not available in other cities.
[15] More details about this index and its comparison with the official house price indicators are reported in Wu, Deng and Liu (2011).

round of even more crazy booming in 2009 and early 2010, but the policy quickly swung to the opposite side in mid-2010, followed by the sharp drop of price growth rate. Therefore the sample period can already provide large variance of short-run house price changes, which is the focus of the analyses. Second, the huge volume of the underlying sample makes it feasible to apply a high frequent series of monthly data in the analysis.[16] In addition, we choose to adopt two different approaches in the test in order to achieve in a robust result of the intercity price discovery pattern.

*** Insert Figure 3 about here ***

b. Granger Causality Test

The first method is the standard Granger causality test (Granger, 1969) which is widely applied in most existing literatures on inter-market house price relationship. For city *i* and *j*, the model is estimated as:

$$\mathrm{dlog}(PRICE_{i,t}) = \sum_{m=1}^{l} \alpha_m \cdot \mathrm{dlog}(PRICE_{i,t-m}) + \sum_{m=1}^{l} \beta_m \cdot \mathrm{dlog}(PRICE_{j,t-m}) + \varepsilon_t \quad (1)$$

where the variable of dlog($PRICE_{i,t}$) is the log difference of city *i*'s house price index in period *t*, which is stationary in all the 35 cities during the sample period according to the conventional Augmented Dickey Fuller (ADF) test. The lag structure (l) is determined by the Akaike information criteria (AIC), with the maximum lag allowed of 6 months. Then if the null hypothesis that β_1=… β_l=0 is rejected by the conventional F test, the price change in city *j* is excepted to Granger cause the price change in city *i* in the short run.[17]

[16] The total volume of newly-built housing units transacted in these 35 cities in the sample period reaches 8.39 million, or 3,330 units per city per month on average.

[17] The standard Granger causality test augmented with error correction terms, or the VEC approach, is suggested in some literatures if the price levels (in log term) in the two cities are cointegrated. However in

The above procedures are applied to each of the 1190 (35*34) pairs between the 35 major cities, of which the Granger causality is found to be significant at the 95% or higher level in 466 pairs[18]. Table 3 lists the distribution of these 466 pairs by the leading cities, which provide some evidences for the strong relationship between the price discovery pattern revealed by the Granger causality test and the information diffusion pattern discussed before. In general both the national level "superstars" and regional level "stars" can affect more cities, especially for the former group. The house price change in Beijing can Granger cause that in 28 of the 34 cities in the short run, with the number for Shanghai also reaching 24; in other words, the house price changes in these two cities can affect almost all the other major cities around the country. The influence of Shenzhen is comparably weaker and only leads 15 cities. As for the "stars", on average the house price changes in each of them can Granger cause house prices changes in about 14.8 other cities, which is significantly smaller than the "superstars" (22.3 cities on average), but still significant higher than the 17 "normal" cities (10.4 cities on average).

*** Insert Table 3 about here ***

As a more direct evidence of the correlation between information diffusion and house price discovery, in all the 110 pairs with significant information flow (i.e., the PIFI from the leading city to the province of the lagged city reaches at least 1.0%), the causality is also found in 72 pairs, making up a proportion of 65.45%. In contrast, only 36.48% of the rest 1080 pairs (i.e., 394 pairs) exist causality, which is significant lower

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this analysis the sample period is too short to conclude in a reliable result in testing the cointegration relationship, while the focus of the analysis is just the short-run house price dynamics. Accordingly the standard Granger causality test without error correction term is adopted.

[18] The detailed results are available on request.

than the proportion in the other group. This all explain why the house price changes in the "superstars" and "stars" can affect much more cities than the "normal" cities.

c. Detection of Key Time Points in the Recent Housing Booming

The second method aims to reveal the price discovery pattern more intuitively. Following the recent work by Ferreira and Gyourko (2011), we seek to identify the key time points in the recent housing booming during 2009 and 2010, which allow us to compare the whole process of this booming in different.

More specifically, for each city we define three key time points in the booming period. First is the point when the market witnessed the first signal of recovery from the "recession" period during the financial crisis, $T_{i,recover}$, which is technically defined as the month with the lowest annual house price growth rate during the period of 2008-2010. Similarly, the second point is the end of the booming period, $T_{i,end}$, which is defined as the month with the highest annual house price growth rate after $T_{i,recover}$.

The third point is the start of the housing booming, $T_{i,booming}$, which is more difficult to identify. Here we adopt the method by Ferreira and Gyourko (2011) to detect the structure breakpoint during the period between $T_{i,recover}$ and $T_{i,end}$. We estimate the following question for all potential structural breakpoints ($T^*_{i,booming}$) for each city i and month t:

$$PG_{i,t} = a + d_i 1[T_{i,t} \geq T^*_{i,booming}] + \varepsilon_{i,t}, \text{ for } T_{i,recover} < T^*_{i,booming} < T_{i,end} \qquad (2)$$

where $PG_{i,t}$ is the annual house price growth rate, d_i estimates the importance of the potential break, $T_{i,t}$ is a quarter, and $T^*_{i,booming}$ is the location of the potential structural break. The breakpoint point, $T_{i,booming}$, is defined as the month which maximize the R^2 of this equation.

Figure 4 depicts the results in Beijing as an example. First, as shown in Figure 4-b, according to the definition it is obvious that housing market started to recover in December 2008 ($T_{Beijing,recover}$), and the booming period ends in April 2010 ($T_{Beijing,end}$). During this period, the equation (2) reaches its maximum value in R^2 in October 2009 as shown in Figure 4-c, while the coefficient d_i depicted in Figure 4-d is also significantly larger than 0 is that month, and thus is identified as the starting point of the booming period.

*** Insert Figure 4 about here ***

Following these procedures, Table 4 lists the three key time points for all the 35 cities. In cities of Haerbin, Yinchuan and Xining, the coefficient d_i is not significantly larger than 0 at the 90% confidence level when the R^2 reaches its maximum value, which suggests that there is no booming in this city by definition.

*** Insert Table 4 about here ***

Again the results show a clear lead-lag relationship between the three tiers of cities defined in Section III. In general three "superstars" started to resumed house price growth at the end of 2008, which was almost the same time when the Chinese government unfolded its huge stimulus package, and then the housing booming started around October 2009. Finally the house price growth rate reached its peak and then started to decline in May 2010, immediately after the central government issued the intervention policies in the housing market. Comparably, the process in the "star" cities is about 3 to 4 months lagged on average. According to the result a representative "star" city resumed house price growth in the first quarter of 2009, began booming around the end of 2009 and the beginning of 2010, and reached the peak in about mid-2010. The time points in the "normal" cities are even later and about 3 more months lagged after the regional "stars". This provides an intuitive picture on intercity housing price discovery during the recent housing booming.

V. Temporal Analysis on the Information Diffusion and Price Discovery Process

The two sections above provide some evidences on the relationship between intercity information diffusion and house price discovery patterns, but these analyses are not enough to support the causality relationship. Instead the question remains whether the price changes in the lagged cities are affected by the leading cities via the channel of information flow. In this section we seek to provide some preliminary results for this question based on analyses from the temporal perspective.

a. Model and Data

Theoretically the process of intercity price discovery resulted from information diffusion can be decomposed as two steps. First, the house price changes in the leading city will lead to information flow from the leading city to the lagged city, which can be reflected by more Google searches on leading city's house price information from the lagged city. Thus for leading city *i* and lagged city *j*, we can have:

$$IFI_{i,j,t} = f\,(\,PG_{i,t-n}, \text{control variables}) \tag{3}$$

where, $IFI_{i,j,t}$ is the volume of Google searches on city *i*'s house price information from city *j* in period t, $PG_{i,t-n}$ is the magnitude of house price change in city *i* during certain previous period. Controlling for other factors, the effect of $PG_{i,t-n}$ is expected to be positive and significant at least in some lagged periods.

As the second step, the information flow from the leading city will affect the market price formation in the lagged city, or:

$$PG_{j,t} = f\,(\,IFI_{i,j,t\text{-}m}, \text{control variables}) \qquad (4)$$

where $PG_{j,t}$ is the magnitude of house price change in city j, which is expected to be significantly and positively affected by $IFI_{i,j,t\text{-}m}$.

Ideally we could estimate both equation (3) and (4) in all the pair of cities. But in most pairs the time series of Google searches is not available due to the limited volume, and hence here we just adopt the “superstar” city of Beijing as the example. In 24 of the 29 provinces we can get continuous quarterly series of Google search volume on Beijing’s house price information (*BJIFI*) between 2006Q1 and 2011Q4. We also get the absolute value of quarterly house price growth rate in both Beijing (*APGBJ*) and 29 major cities located in these 24 provinces (*APG*). Table 5 provides the summary statistics for these variables.

*** Insert Table 5 about here ***

b. Empirical Results

First, Table 6 reports the results on equation (4), with the information flow proxy, *BJIFI*, as the dependent variable. Controlling for the city fixed effects, the coefficient of the variable of *APGBJ* is consistent with the expectation that large house price changes in Beijing (either increase or decrease) will lead to information flows from Beijing to other provinces. According to the results, the house price change in Beijing cannot immediately attract attentions from other provinces in the same quarter, but only starts to take effect in the next quarter. The density of such information flow reaches the maximum degree in two quarters later, and then shrinks with the lapse of time.

*** Insert Table 6 about here ***

Then we turn to the second step with the magnitudes of house price change in corresponding cities, *APG*, as the dependent variable. As listed in Table 7, controlling for the lagged term of local house price change magnitude and the city and time fixed effects, the variable of *BJIFI* is positive and statistically significant in the model. The result is robust if we adopt the two periods lagged value of *APGBJ* as the instrument variable of *BJIFI*, instead of directly introducing *BJIFI* to the model. The effect of one quarter lagged term of *BJIFI* is also positive in the model, but at most marginally significant.

*** Insert Table 7 about here ***

As a summary, a sharp house price change in Beijing will lead to house price information flows to other cities during the following one to three quarters, and such information will immediately affect the house price in the corresponding cities. These results supports the essential role of information flow in the intercity house price discovery, although more confirmative conclusions at this point still rely on evidences from more cities.

VI. Concluding Remarks

In this paper we suggest an innovative measurement indicator of information flow in Chinese housing markets based on the Google search records, which depicts a substantial flow of house price related information from national level “superstar” cities like Beijing and Shanghai and regional level “star” cities like Tianjin and Chongqing to other “normal” cities. The empirical results also suggest that such information diffusion is at least one of the major factors in determining intercity house price discovery in the short-run.

Obviously these results highlight the fact that cities like Beijing and Shanghai should be the major target for the investors, market analysts, researchers or policy makers if they want to better understand China's housing market. An even more important implication is, house price dynamics in "superstar" cities will have substantial externalities in the national level – a bubble in Beijing may mislead market participants in other cities and thus quickly spread around the country. Unfortunately, these cities have been proved to be vulnerable to exceptional house price surges (Gyourko, Mayer and Sinai, 2006), while some unique institutional factors in China further expand such vulnerability (Deng et al, 2011). Therefore the policy makers should be especially cautious with any potential mispricing in these core cities.

We believe this research can also serve for much broader and in-depth future works on information issues in the housing market. In this paper we do not separate the market participants' rational learning process with the (irrational) herding or positive feedback behaviors, which can be a major target in future researches. Similarly, the analysis on variance during the booming and recession periods is also interesting. Moreover, while this paper mainly focus on the spatial information flow, we can also build an index based on searches for house price information from local market participants. Possible topics related include how certain events (announcements of new intervention policies, land auctions, or listing of new complexes, etc) affect market participants' attentions, whether the Google search volume can predict house price change or transaction volume, and so on, which can be helpful in understanding the market participants' behaviors.

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Figure 1: National Level Information Flow Index

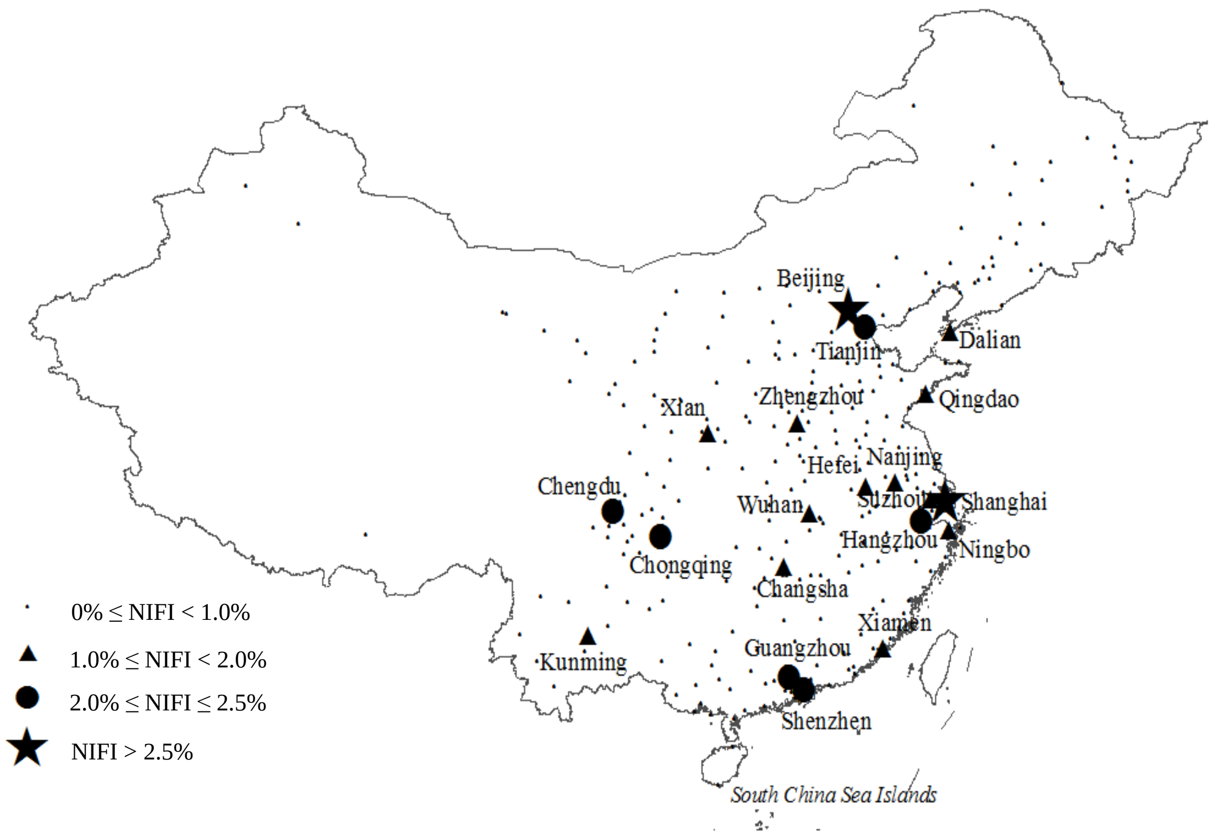


Figure 2: Provincial Level Information Flow Indexes of Select Cities

(A) Beijing

(B) Shanghai

(C) Shenzhen

(D) Tianjin

(E) Chongqing

(F) Guangzhou

(: native province; : $5 \leq$ PIFI < 10; :$3 \leq$ PIFI < 5; : $1 \leq$ PIFI < 3; : PIFI < 1)

Figure 3: Annual Growth Rate of Aggregated House Price Index in 35 Major Cities

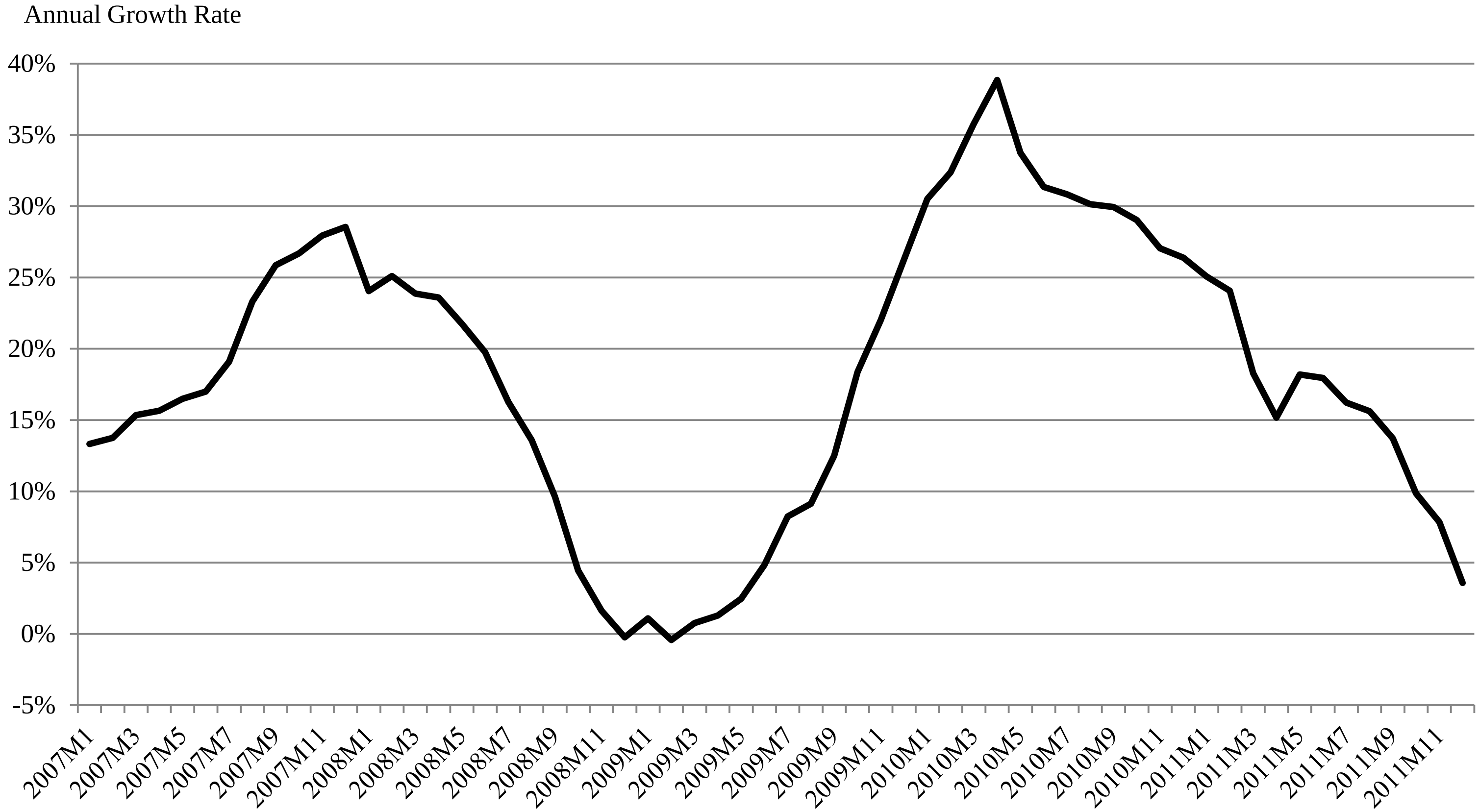
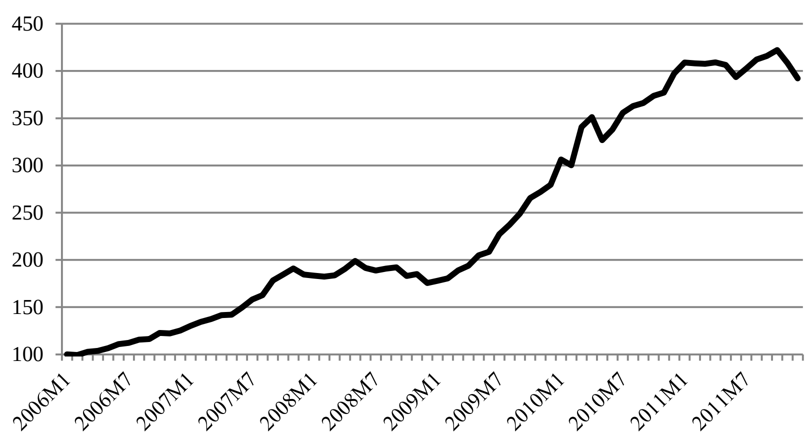
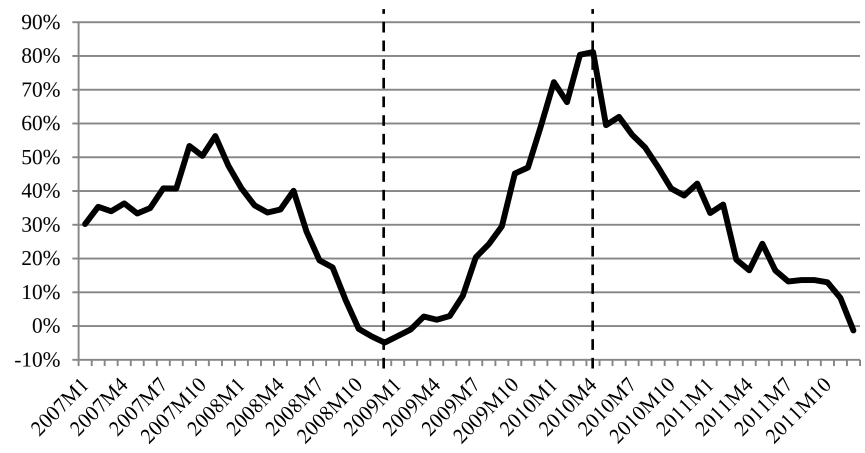


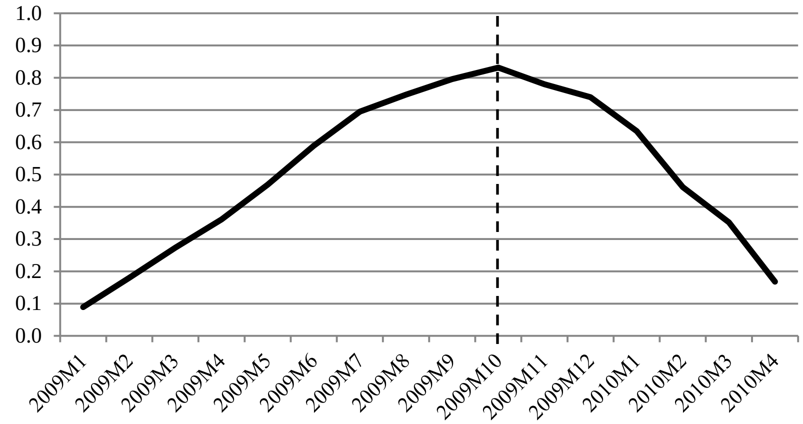
Figure 4: Detecting of Key Time Points during the Housing Booming in Beijing



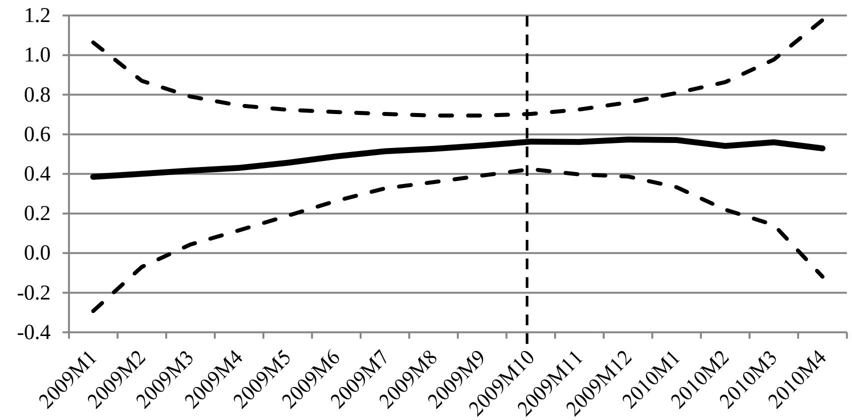
(A) House Price Index



(B) Annual Growth Rate



(C) R Square



(D) Coefficient of Breakpoint Dummy

Table 1: Summary Statistics of Provincial Level Information Flow Index (PIFI)

		All Other Provinces			Other Provinces Within 500 KM			Other Provinces Beyond 500 KM		
City	Local Province	Total Number of Provinces	Number of Provinces with PIFI above/in 1.0%	Average of PIFI	Total Number of Provinces	Number of Provinces with PIFI above/in 1.0%	Average of PIFI	Total Number of Provinces	Number of Provinces with PIFI above/in 1.0%	Average of PIFI
Beijing	22.00%	29	28	3.59%	8	8	5.75%	21	20	2.76%
Shanghai	34.00%	29	27	2.45%	6	6	3.92%	23	21	2.07%
Shenzhen	16.00%	29	19	0.86%	5	4	1.30%	24	15	0.77%
Chongqing	45.50%	29	11	0.74%	7	5	1.50%	22	6	0.50%
Chengdu	35.50%	29	10	0.72%	7	5	1.29%	22	5	0.55%
Tianjin	50.00%	29	10	0.60%	8	7	1.44%	21	3	0.29%
Wuhan	30.50%	29	6	0.41%	8	3	0.69%	21	3	0.31%
Xian	34.00%	29	5	0.50%	8	2	0.81%	21	3	0.38%
Guangzhou	13.00%	29	5	0.43%	5	3	0.90%	24	2	0.33%
Nanjing	16.00%	29	4	0.41%	8	3	0.81%	21	1	0.26%
Hangzhou	20.50%	29	3	0.34%	7	2	0.64%	22	1	0.25%
Dalian	20.00%	29	3	0.33%	6	2	0.75%	23	1	0.22%
Qingdao	14.00%	29	3	0.28%	7	1	0.50%	22	2	0.20%
Changsha	28.50%	29	2	0.24%	6	1	0.42%	23	1	0.20%
Hefei	25.00%	29	2	0.17%	9	2	0.39%	20	0	0.08%
Shenyang	15.50%	29	2	0.14%	4	2	0.63%	25	0	0.06%
Suzhou	11.50%	29	1	0.17%	6	1	0.50%	23	0	0.09%
Xiamen	19.50%	29	1	0.16%	4	1	0.50%	25	0	0.10%
Fuzhou	16.50%	29	1	0.07%	4	1	0.38%	25	0	0.02%

Table 2: Major Features of Cities in Three Tiers

	Percentage of Urban Employments in Real Estate Industry	Per Capita Annual Housing Transaction Volume (yuan)	Population Density (population / sq.km.)	Percentage of Home Buyers from Other Provinces
Average of “Superstar” Cities	4.433%	1.330	3221	22.283%
Average of “Star” Cities	2.175%	0.855	792	15.100%
Average of “Normal” Cities	0.099%	0.186	411	10.403%
T Test Stat. for the Difference between “Superstar” and “Star”	3.53***	2.48**	4.99***	1.53
T Test Stat. for the Difference between “Star” and “Normal”	5.97***	11.61***	3.78***	1.28

Source: Authors’ calculations based on statistics published by National Bureau of Statistics and Ministry of Housing and Urban-Rural Development of China.

Table 3: Number of Cities with Granger Causality

<table>
<tr><th></th><th>City</th><th>Number</th><th></th><th>City</th><th>Number</th></tr>
<tr><td rowspan="4">National Level “Superstars”</td><td>Beijing</td><td>28</td><td rowspan="17">“Normal” Cities</td><td>Ningbo</td><td>22</td></tr>
<tr><td>Shanghai</td><td>24</td><td>Guiyang</td><td>18</td></tr>
<tr><td>Shenzhen</td><td>15</td><td>Nanning</td><td>14</td></tr>
<tr><td>Average</td><td>22.3</td><td>Xining</td><td>14</td></tr>
<tr><td rowspan="16">Regional Level “Stars”</td><td>Chengdu</td><td>21</td><td>Haikou</td><td>12</td></tr>
<tr><td>Nanjing</td><td>21</td><td>Changchun</td><td>11</td></tr>
<tr><td>Chongqing</td><td>20</td><td>Haerbin</td><td>11</td></tr>
<tr><td>Hangzhou</td><td>19</td><td>Yinchuan</td><td>11</td></tr>
<tr><td>Xiamen</td><td>18</td><td>Nanchang</td><td>10</td></tr>
<tr><td>Fuzhou</td><td>17</td><td>Lanzhou</td><td>10</td></tr>
<tr><td>Tianjin</td><td>16</td><td>Wulumuqi</td><td>10</td></tr>
<tr><td>Xian</td><td>15</td><td>Kunming</td><td>9</td></tr>
<tr><td>Qingdao</td><td>15</td><td>Shijiazhuang</td><td>8</td></tr>
<tr><td>Dalian</td><td>13</td><td>Huhehaote</td><td>7</td></tr>
<tr><td>Wuhan</td><td>11</td><td>Zhengzhou</td><td>7</td></tr>
<tr><td>Changsha</td><td>11</td><td>Jinan</td><td>2</td></tr>
<tr><td>Shenyang</td><td>11</td><td>Taiyuan</td><td>1</td></tr>
<tr><td>Guangzhou</td><td>9</td><td>Average</td><td>10.4</td></tr>
<tr><td>Hefei</td><td>5</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>Average</td><td>14.8</td><td>-</td><td>-</td><td>-</td></tr>
</table>

Table 4: Key Time Points in the Recent Housing Booming

City	Recover	Boom	End	City	Recover	Boom	End
A. National Level "Superstars"				**C. Normal Cities**			
Shenzhen	2008M10	2009M10	2010M04	Ningbo	2009M1	2009M10	2010M1
Shanghai	2008M12	2009M09	2010M04	Nanchang	2009M1	2009M10	2011M6
Beijing	2008M12	2009M10	2010M04	Zhengzhou	2009M2	2010M9	2011M6
Average	2008M11	2009M10	2010M04	Haikou	2009M2	2009M12	2010M2
B. Regional Level "Stars"				Changchun	2009M3	2010M3	2010M4
Guangzhou	2008M11	2009M9	2010M2	Nanning	2009M3	2009M11	2010M4
Chengdu	2008M12	2009M10	2010M2	Shijiazhuang	2009M4	2010M10	2011M5
Tianjin	2008M12	2009M10	2010M6	Taiyuan	2009M5	2010M2	2010M5
Wuhan	2008M12	2009M11	2010M5	Guiyang	2009M5	2009M12	2010M5
Xiamen	2009M2	2009M10	2010M4	Kunming	2009M6	2011M7	2011M12
Fuzhou	2009M2	2010M1	2010M12	Lanzhou	2009M6	2011M4	2011M5
Hangzhou	2009M3	2009M10	2010M4	Haerbin	2009M8	-	2011M4
Changsha	2009M3	2010M3	2011M2	Jinan	2009M9	2010M1	2010M9
Chongqing	2009M4	2009M11	2010M4	Yinchuan	2009M9	-	2010M7
Nanjing	2009M4	2009M11	2010M6	Huhehaote	2010M1	2011M1	2011M3
Dalian	2009M4	2010M3	2010M4	Wulumuqi	2010M4	2010M7	2011M2
Qingdao	2009M5	2009M11	2010M10	Xining	2010M7	-	2011M7
Hefei	2009M5	2010M1	2010M5	*Average*	2009M7	2010M5	2010M11
Xian	2009M5	2010M2	2010M10				
Shenyang	2009M5	2010M4	2010M12				
Average	2009M3	2010M1	2010M7				

Table 5: Summary Statistics of Variables

Variable	Definition	Average	Std. Dev
APGBJ	Absolute value of quarterly house price change rate in Beijing.	7.342	4.949
APG	Absolute value of quarterly house price change rate in the corresponding city.	4.663	3.949
BJIFI	Volume of Google searches on Beijing's house price information from the province where the city locates.	25.815	30.749

Table 6: Effect of Beijing's House Price Changes on Google Searches

	(1) *BJIFI*	(2) *BJIFI*	(3) *BJIFI*	(4) *BJIFI*
APGBJ	0.7784			
	(1.0426)			
APGBJ(-1)		1.8529		
		(0.9675)*		
APGBJ(-2)			2.4784	
			(1.0172)**	
APGBJ(-3)				1.6484
				(0.9187)*
City Fixed Effect	YES	YES	YES	YES
Observations	598	572	546	520
R^2	0.205	0.281	0.356	0.287

Note: (1) The observations are clustered by quarter.
(2) Standard errors in parentheses
(3) * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 7: Effect of Google Searches on House Price Changes

	(1) *APG* (OLS)	(2) *APG* (IV)	(3) *APG* (OLS)	(3) *APG* (IV)
BJIFI	0.0249	0.0560		
	(0.0083)***	(0.0163)***		
BJIFI(-1)			0.0083	0.0352
			(0.0085)	(0.0174)**
APG(-1)	0.1414	0.1062	0.1549	0.1271
	(0.0435)***	(0.0492)**	(0.0438)***	(0.0498)**
City Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	YES	YES	YES	YES
Observations	568	543	568	518
R^2	0.245	0.217	0.234	0.217

Note: (1) Standard errors in parentheses
(2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.