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Abstract: By raising road transportation costs, an increase in gasoline prices should be expected to reduce housing demand in locations further from the central business district (CBD) relative to inner-city locations. This study uses a monthly real estate area-level dataset for 19 large cities in China over 2010–2018 to investigate the impact of gasoline prices on intra-city spatial differentials in housing prices. The findings suggest that higher gasoline prices on average lead to a relative decline in housing prices in outer suburbs, with a 1% increase in gasoline prices on average leading to a 0.004% relative reduction in home values for every additional kilometer from the CBD. The effect is larger in cities that have higher automobile ownership rates and that are less densely populated. The results are consistent with a conclusion that the rise of electric vehicles, autonomous vehicles, and working from home is likely to contribute to a lowering of geographical price differentials within Chinese cities over time.

Keywords: gasoline price; housing price; transportation cost

JEL codes: R31, Q41, Q43

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1. Introduction

The cost of transport is likely to be a key factor that households take into account when choosing where to live. According to Renmin University of China (2016), Chinese households who own private automobiles on average spent about 5,500 Chinese yuan (CNY) per household on driving for commuting purposes in 2015, equal to about 10% of their total expenditure. When gasoline prices increase, it should be expected that road transport costs of automobile drivers and motorcyclists in outer areas will increase relative to the transport costs of others due to the longer average travel distance that they face. If asset values represent the present value of all future net benefits flowing to the owner, higher gasoline prices should thus reduce the market's willingness to pay for housing in outer areas relative to inner areas. If asset prices are relatively quick to adjust to economic information, this effect should be detectable over a relatively short response window.

The objective of this study is to investigate the effect of gasoline prices on housing prices in locations with different distances to the central business district (CBD) in major cities in China. To our knowledge this is the first study to investigate the effect of transportation costs on geographical variation in housing prices for China, the world's most populous country. The study uses monthly housing price data for 641 real estate areas (REAs) (板块) in 19 large cities for the period January 2010–December 2018. The sample of cities includes the famous megacities of Shanghai, a global financial center and the most populous city in China; Beijing, China's capital city; and Shenzhen, a thriving technology hub and location of the headquarters of many businesses.

In addition to estimations using monthly data, the study also explores yearly estimations, an approach that facilitates the inclusion of additional control variables measured on a less frequent basis. The yearly dataset is also used to estimate a first-differenced specification and to explore for potentially asymmetric effects. Heterogeneity analysis is also carried out for cities with higher automobile ownership rates versus others; cities with higher population density versus others; and cities with higher electric vehicle (EV) market shares versus others. A distributed lag model and a specification using an interaction between the log world crude oil price and the distance to the CBD to instrument the interaction between the log city-level gasoline price and the distance to the CBD are also estimated. The robustness of the results is examined for various sub-samples. Finally, we also test for potential effects of gasoline prices on spatial differentials in housing transaction volumes and housing transaction areas.

The results indicate that higher gasoline prices tend to reduce outer-urban housing prices relative to inner-city housing prices in China. The effect is larger in cities with higher automobile ownership rates and cities that are less densely populated. Interestingly, the effect is similar to earlier estimates for the United States (US). The results are consistent with a conclusion that the emergence of EVs and autonomous vehicles will tend to reduce housing price differentials across city areas given the lower marginal costs of operating these vehicles. The same is also true for the trend toward working from home given that this involves a reduction in urban transport demand.

The remainder of this paper is structured as follows. Section 2 introduces the literature review and provides key details about China's urban real estate market. Section 3 introduces the estimation approach. Section 4 describes the data. Section 5 reports the empirical results. Section 6 discusses the size of the effects. Section 7 concludes.

2. Background

2.1 Literature review and theoretical mechanisms

A rich literature has documented various links between fuel prices and real estate markets. For example, Breitenfellner et al. (2015) examined 18 OECD countries and found that oil price inflation raises the probability of housing price corrections. Antonakakis et al. (2016) found that co-movements between housing and oil market returns in the US were consistently negative over 1859–2013. An increase in oil prices could either increase or reduce the overall average value of housing, depending on the strength of various channels:

1. Oil price increases are often seen as a trigger of economic slowdowns or recessions (Hamilton 2009; Kilian 2008). When oil prices increase, households are likely to spend less on housing as household purchasing power reduces. This is an income effect. On the other hand, a substitution effect induces consumers to shift to less oil-intensive goods, perhaps including housing (as opposed to cars, for example).

2. Fuel is used to construct and maintain buildings and provide building services such as heating and cooling. Halvorsen and Pollakowki (1981) examined the effect of prices for space-heating fuels on housing prices. They found that fuel price changes indeed have significant effects on housing prices, but with substantial lags.

The idea that an increase in urban transport costs would lead to a decline in outer-city relative to inner-city housing prices is a longstanding one. The theory of urban land values developed by Alonso (1964) posited that property prices will be lower in locations where transport costs are higher, all else equal, as consumers have less funds available to spend on housing. If this is not the case, people would wish to move to areas with lower transport costs, which in a monocentric urban context would be closer to the city center. This process would return the city to an equilibrium in which there is an appropriate price premium paid for properties with lower transport cost requirements. In this framework, an exogenous increase in transport costs would lead to a steeper land price gradient as a function of distance from the city center. The urban spatial model developed by Wheaton (1974) for a city of fixed population size also predicts that intra-urban land price differentials will increase if transport costs exogenously increase, as property sellers will need to reduce their price asks in more distant locations. The underlying hypothesis tested in this paper is thus one of the central ideas from urban economics theory (DiPasquale and Wheaton 1996).

There are several additional channels via which an increase in gasoline prices may cause a relative decline in outer-city housing prices. Higher gasoline prices are known to induce substitution to public transport (Austin, 2008; Fullerton and Walke, 2013; Zhang and Burke, 2020). For the switchers, this is likely to be a more time-intensive and/or inconvenient option than driving (given that they had previously opted to drive). This thus reduces the net benefits obtained from their outer-city residence. In addition, lower gasoline use as a result of a higher gasoline price would tend to reduce local air pollution. This might be particularly relevant in and near the inner city, where congestion tends to be highest. If so, this may also tend to lead to increases in housing prices in the inner-city relative to the outer-city.

The existing empirical literature also details how fuel prices influence the spatial pattern of housing values across urban areas, with a focus on developed countries. Various studies have found that fuel costs influence choices of home location and that higher transportation costs increase the benefit of living closer to workplaces and amenities (Tse and Chan 2003; Erath and Axhausen 2010; Tanguay and Gingras 2012; Molloy and Shan 2013; Agarwal et al. 2015). Studies on the effects of gasoline prices in the US have found that higher gasoline prices lead to a relative decline in the values of homes in outer suburbs relative to inner suburbs (Coulson and Engle 1987; Cortright 2008; Morris and Neill 2014; Blake 2016; Larson and Zhao 2017a; Wu et al. 2019; Morris et al. 2020).

Our study is the first on the effect of gasoline prices on spatial patterns in urban residential housing values in China. China's private vehicle dependence, especially private automobile dependence, is lower than that in the US. For example, the public transport share of commuting travel in Beijing was about 32% in 2018, while the share for private motor-vehicle travel (automobiles and motorcycles) was 23% (Beijing Transport Institute 2019b).[1] In contrast, only about 7% of commuting travel in the US is by public transport, with 84% being by private motor vehicle (U.S. Department of Transportation 2018). In 2018, China had about 170 automobiles per 1,000 people nationwide, while the US had about 800 (Economic Information Daily 2019). Factors contributing to China's lower private vehicle dependence include a lack of parking space in cities, good availability of public transport infrastructure, and restrictions on the use of motorcycles in many cities. Therefore, one might hypothesize that the effect of gasoline prices on spatial patterns in real estate prices is likely to be smaller in China. While take-up is still well behind the US, automobiles are nevertheless increasingly popular in Chinese cities, with Beijing having 275 automobiles per 1,000 people in 2019 (Beijing Bureau of Statistics 2020).

In addition to its China focus, this study also makes several additional contributions to the literature. First, we utilize driving time measures at both peak and off-peak times using data from Baidu Maps. Second, we use a measure of the average commute distance of workers in each district based on a survey by Jiguang (2019). This is a more suitable measure for the importance of transport costs in the context of polycentric cities. Third, heterogeneity analysis is presented that includes assessing whether adoption of EVs modulates the spatial effect observed in this study. Finally, we take a number of steps to address potential endogeneity issues, including controlling for the impact of public transport and also pursuing an instrumental variable (IV) estimation approach. The IV approach involves using the log world crude oil price*distance to the CBD as an instrumental variable. The world crude oil price is

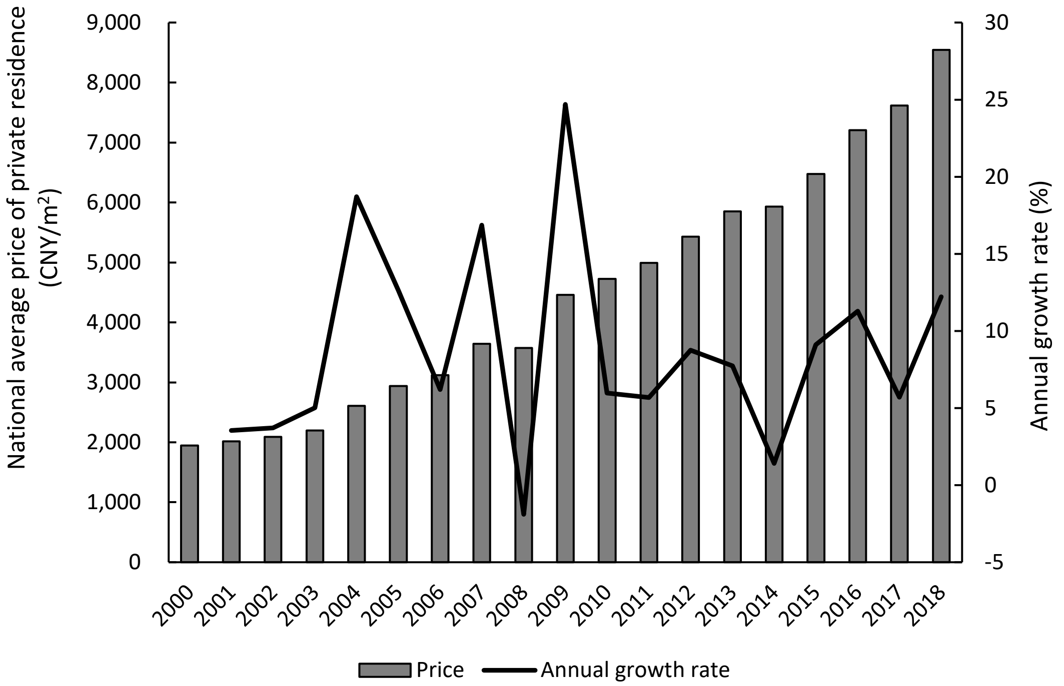
[1] Motorcycles include scooters. Other commuting modes including cycling, walking, and taxis.

likely to be more exogenous to individual Chinese urban localities than the city-level gasoline price, making for a useful instrument.

2.2 China's urban real estate market

High demand has led to rapid housing price increases in China. As shown in Figure 1, the national average unit transaction price for private residences in urban areas experienced a sharp increase in 2004. Although this price dropped during the global financial crisis in 2008, it started to increase again after a stimulus package of 4 trillion CNY (US$586 billion) was introduced by the government. Housing prices in China have now reached some of the highest levels in the world. According to the *Global Living Report 2019* (CBRE 2019), Shanghai ranked third among the most expensive residential property markets worldwide, having an average property price of US$872,555. Shenzhen ranked fifth (US$680,283) and Beijing ninth (US$629,276).

Figure 1 Average price and price growth rate for residential urban real estate in China



Sources: National Bureau of Statistics of China (2019a). *Notes:* The price is the national average unit transaction price for residential real estate in urban areas of China in nominal terms.

China's government has played an ongoing role in guiding the real estate market under the model of "socialism with Chinese characteristics". This has included the central and local governments taking a series of measures to cool surging housing prices and speculative purchases, with 2010–2011, 2013, and late 2016–2018 being restrictive periods (Koss and Shi 2018). Credit squeezes, limits on prices, purchase/resale restrictions, and tax increases have often been linked to households' status under the *hukou* system.[2] For example, one can only

[2] China's *hukou* system is a household registration program that is used to regulate both city-to-city and rural-urban migration.

purchase a residence in some big cities such as Beijing if in possession of local *hukou* or other evidence of long-term residency.

The interventions appear to have had some effect in controlling growth in housing prices, with the nominal growth rate in housing prices remaining at 12% per annum or lower in each year over 2010–2018 (See Figure 1). However, China's urban real estate markets remain heated. China's urban home ownership rate (the share of households who own their homes) was estimated to be about 90% in 2017 (Southwestern University of Economics and Finance 2018), which is high.

3. Method

3.1 Monthly specifications

The relationship between housing prices and gasoline prices will be estimated using the following model:

$$\ln HP_{i,t} = \alpha_0 + \alpha_1 \ln P_{i,t} + \alpha_2 K_i \ln P_{i,t} + M_t + S_i + \varepsilon_{i,t} \quad (1)$$

where $HP_{i,t}$ is the real housing price for REA i in month t, P is the real gasoline price measured at the city level, K is the driving distance from each REA's business center to the city's CBD, M is month fixed effects (i.e. month-by-year fixed effects), and S is REA fixed effects.[3] ε is an error term.

Eq. (1) regresses the log real housing price on the log real gasoline price and the interaction between the log real gasoline price and the driving distance to the CBD. The marginal effect of gasoline prices on housing prices is $\alpha_1 + \alpha_2 K_i$. Here α_1 is the estimated average effect of the gasoline price on housing prices in the CBD and $\alpha_2 K_i$ is the component of the effect of the gasoline price on housing prices that is a function of distance from the CBD. Our principal focus is α_2, with the expectation that this parameter is negative if higher transport costs cause people to place a relatively lower valuation on living in outer areas.

In theory, any effect of gasoline prices on housing prices is likely to be related to what consumers believe about *future* gasoline prices. However, oil and gasoline prices are difficult to forecast, including in China where market-oriented reforms have been pursued (as will be discussed). The most supportable assumption is that these prices are random walk variables, meaning that the current value is the best predictor of the future value (Anderson et al. 2013). Therefore, we follow previous researchers such as Molloy and Shan (2013) and Morris et al. (2020) in seeking to test the effect of the current gasoline price. As will be discussed below, we also explore the effects of recent monthly lags to consider potentially delayed effects.

The distance to the CBD is initially used for K because the CBD is the location of many jobs, shops, and services in Chinese cities. We define the CBD according to a city's official strategic

[3] Month fixed effects refer to a separate fixed effect for each actual month. They differ from month-of-year fixed effects, which means the inclusion of 11 month fixed effects to remove seasonal effects. Month-of-year fixed effects are redundant if month fixed effects are controlled for, so are not included. Wind direction is unlikely to be systematically correlated with distance from the CBD, so is not included as a control.

plan issued by the city administration. Each city's CBD is listed in the Appendix. The main specification uses the driving distance rather than the straight-line (as the crow flies) distance to the CBD, as the straight-line distance is likely to be less closely associated with gasoline consumption, especially in cities with hilly terrains and water bodies such as Chongqing. K is not logged because some REAs are in the CBD (and therefore have $K = 0$). Using an unlogged distance measure also allows us to obtain an effect size that is a linear function of kilometers from the CBD, aiding interpretability. The CBD is measured as an REA rather than as a single point.

REA fixed effects are included to control for cross-sectional variation that does not change over time during the sample period, including the distance of an REA to the CBD. The distance from the CBD thus does not need to be controlled for separately. The inclusion of month fixed effects is to control for factors that are common to all locations in each month, such as the state of China's economy, the central government's housing policies, and seasonal effects.

A number of additional specifications are then estimated. First, we control for a set of REA-specific time trends to account for the impact of gradual changes in each area, such as due to road improvements, the development of public transport, and population growth. A specification is also estimated that bins location into three driving distance rings: the inner-city (<5 km to the CBD); the mid-city (5–20 km from the CBD); and the outer-city (>20 km from the CBD). We then use the straight-line distance from each REA to the city's CBD as an alternative measure of K. Next, the driving time to the CBD at a peak time is used, as travel time is likely to be closely linked to transport costs. The driving time to the CBD at an off-peak time is then also used.

Our initial specifications follow the assumption in previous studies that cities are monocentric, i.e. there is a single center of each city. However some of China's metropolitan areas are polycentric, with a large number of people not commuting to the CBD. In Beijing, for example, trips to the CBD or areas near the CBD account for only about 59% of total trips during morning peak periods – and many residents work in the Shangdi and Yizhuang areas, more than 20 km from Beijing's CBD (Beijing Transport Institute 2019a, 2019b).[4] A specification using the average commute distance for a one-way trip to work for all workers in a district is thus also estimated. This measure is from a year-2017 survey conducted by Jiguang (2019).

3.2 Yearly specifications

The study also explores yearly estimations using the following model:

$$\ln HP_{i,y} = \beta_0 + \beta_1 K_i \ln P_{i,y} + \beta_2 Y_{i,y} + \beta_3 U_{i,y} + \beta_4 Sub_{i,y} + T_y + S_i + \varepsilon_{i,y} \tag{2}$$

where $HP_{i,y}$ is the average real housing price for REA i in year y, P is the real gasoline price measured at the city level, K is the driving distance from each REA's business center to the city's CBD, Y is city-level per capita disposable income, U is the city-level unemployment rate,

[4] Beijing's CBD occupies 3.99 km^2 of the Chaoyang District on the east side of the city.

Sub is the number of subway lines in the district, T is year fixed effects, and S represents REA fixed effects. ε is an error term.

The city-level per capita disposable income and unemployment rate are controlled for in this specification because there is likely to be higher demand for housing if income levels increase and/or a greater share of people are employed. The number of subway lines in each district is controlled for as this is likely to influence the importance of road transportation costs for the local real estate market. As some districts did not have any subways in some years, the number of subway lines is not logged. Year fixed effects are included to control for factors common to all areas in each year, including China's macroeconomic conditions. The un-interacted log gasoline term is not included separately in Eq. (2) because it is highly correlated with year fixed effects; the R^2 obtained when regressing the log gasoline price on year fixed effects is 0.98. Dropping the un-interacted log gasoline price does not substantially influence the estimated coefficient on the interaction term on which we are focused.

Two additional specifications are estimated using yearly data. First, an interaction between the log per capita disposable income of the city and the driving distance to the CBD and another between the unemployment rate and the driving distance to the CBD are controlled for. These are included because a stronger economy may lead to housing price differentials developing across REAs, and may also be correlated with the interacted gasoline price-distance term. Second, the year fixed effects are excluded and the national GDP growth rate is instead controlled for. The GDP growth rate variable helps to account for a likely broad link between economic conditions and home prices. The un-interacted log gasoline price is included in this specification.

Issues arising from unit roots seem not to be a major concern given that the sample has short panels and covers a large number of individual REAs (Entorf 1997). Nevertheless, a first-differenced estimator is also estimated for an additional yearly estimation using the following specification:[5]

$$\Delta\ln HP_{i,y} = \lambda_0 + \lambda_1 K_i \Delta\ln P_{i,y} + \lambda_2 \Delta Y_{i,y} + \lambda_3 \Delta U_{i,y} + \lambda_4 \Delta Sub_{i,y} + T_y + S_i + \varepsilon_{i,y} \quad (3)$$

We also conduct tests for potentially asymmetric effects of a rising log real gasoline price (i.e. instances of a positive change in the log real gasoline price) and a falling log gasoline price (instances of a negative change in the log real gasoline price). These variables equal zero if the price is not rising or falling. Using the yearly dataset we estimate the following first-differenced specification:

$$\Delta\ln HP_{i,y} = \rho_0 + \rho_1 \Delta\ln P^{+}_{i,y} + \rho_2 K_i \Delta\ln P^{+}_{i,y} + \rho_3 \Delta\ln P^{-}_{i,y} + \rho_4 K_i \Delta\ln P^{-}_{i,y} + \rho_5 \Delta Y_{i,y} + \rho_6 \Delta U_{i,y} + \rho_7 \Delta Sub_{i,y} + T_y + S_i + \varepsilon_{i,y} \quad (4)$$

[5] A first-differenced estimator is not estimated for a monthly dataset because a monthly window is narrow and, as will be presented, some results emerge with a lag of several months.

where the “+” variable equals the first difference of the log real gasoline price when this exceeds zero and zero otherwise. The “–” variable equals the first difference of the log real gasoline price when this is less than zero and zero otherwise. Note that the + and – variables sum to give the original variable.

3.3 Additional analysis and robustness checks

We next present estimations that vary along several other dimensions. First, heterogeneity analysis is carried out for cities that have high automobile ownership rates versus others; for densely populated cities versus others; and for cities that have high EV market shares versus others using the following model applied to monthly data:

$$\ln HP_{i,t} = \gamma_0 + \gamma_1 \ln P_{i,t} + \gamma_2 K_i \ln P_{i,t} \times D_1 + \gamma_3 K_i \ln P_{i,t} \times D_2 + M_t + S_i + \varepsilon_{i,t} \quad (5)$$

where D indicates a group dummy.

The impact of gasoline prices on housing purchases may take time to be fully realized, with delayed responses emerging for reasons including the need for time for searching, making decisions, negotiating, and transacting in housing. There is also typically a gap of more than a month between the transaction and registration dates according to Lianjia, one of the largest real estate agencies in China. Therefore, current housing prices might possibly be influenced by lagged gasoline prices. To capture delayed responses, we use monthly data to estimate the following distributed lag model:

$$\ln HP_{i,t} = \sigma_0 + \sum_{r=0}^{n} \varphi_r \ln P_{i,t-r} + K_i \sum_{r=0}^{c} \omega_r \ln P_{i,t-r} + M_t + S_i + \varepsilon_{i,t} \quad (6)$$

The coefficient for the contemporaneous log gasoline price terms are interpreted as short-run effects: they show how housing prices in a month are affected by the gasoline price in that same month, holding the other variables constant. The coefficient of the one-month lagged gasoline price terms measure any influence from the previous month’s gasoline price. The coefficients for deeper lags are interpreted in a similar manner. The sum of the coefficients measures how much housing prices will eventually change in response to a permanent change in the gasoline price occurring at a specific point in time.

Next, to address potential remaining endogeneity we instrument the log real gasoline price*distance to CBD with the log real world crude oil price*distance to CBD given that the cost of crude oil is the major contributor to the pump price of gasoline. This is done both for a monthly estimation using Eq. (1) and a yearly estimation using Eq. (2). The un-interacted log gasoline price is dropped from this specification and month fixed effects are included. This allows us to only instrument for one gasoline price term while also flexibly controlling for time-specific factors such as macroeconomic conditions. The world crude oil price measure is the West Texas Intermediate (WTI) price.

Some REAs in the sample are quite far from the CBD. In order to check the robustness of results from the main specification, we estimate Eq. (1) using different sub-samples of increasing size: ≤10 km driving distance of the CBD, ≤20 km, ≤30 km, and ≤40 km. We then explore for any potential effects on the housing transaction volume and housing transaction area in each month and REA. It may be the case that additional properties in the inner city are traded when the gasoline price is high, for instance. However we would expect that price responses would be more prominent than any quantity responses given the expectation that prices should change in response to underlying fundamentals.

4. Data

This study analyzes data for 19 large cities in China, the locations of which are shown in Figure 2. The principal reason for analyzing this group of 19 cities is that data on housing prices, gasoline prices, and subway lines are not sufficiently available for smaller cities. The cities were home to nearly 264 million residents in 2018, 17.6% of China's total population (National Bureau of Statistics of China 2019a). This is only slightly smaller than the total size of the US urban population in that year (World Bank 2020).

The 19 cities cover all "tier 1" and "new tier 1" cities in China according to a year-2019 list compiled by Diyicaijing. The Diyicaijing list classifies cities in mainland China into 6 tiers – tier 1, new tier 1, tier 2, tier 3, tier 4, and tier 5 – based on each city's business resources, potential to function as a hub, activities for residents, lifestyle diversity, and future adaptability (Chinadaily 2019). Tier 1 cities are the most developed and wealthiest cities in China: Beijing, Shanghai, Guangzhou, and Shenzhen. The new tier 1 cities are other important and fast-growing urban areas, generally provincial capitals, direct-administered municipalities, and cities of sizeable economic influence: Chengdu, Hangzhou, Chongqing, Wuhan, Xi'an, Suzhou, Tianjin, Nanjing, Changsha, Zhengzhou, Dongguan, Qingdao, Shenyang, Ningbo, and Kunming.[6] The list of cities includes four of the world's 20 most populous cities as of 2018: Shanghai, Beijing, Chongqing, and Tianjin (United Nations 2018).

REA-level housing price data are from the China Real Estate Information Corporation (CRIC), a widely-used source. CRIC's monthly housing price data are based on daily transaction information provided by real estate companies in each city, and are available at the REA level. Housing prices are measured as the average transaction price per square meter of private residential real estate, with prices covering ordinary residences, villas, and serviced apartments. Public housing is excluded.

A city is divided into several districts by China's government. CRIC then divides each district into several REAs according to their real estate market characteristics. REAs differ from suburbs. REAs are excluded from the sample if housing price data are not available for a whole year between 2010 and 2018. Linear interpolation is used to fill some data gaps of less than one year.[7] For estimations, we use a panel of monthly housing prices for 641 REAs in China's 19 large cities from January 2010 to December 2018. The REAs are from 186 districts.

[6] Cities are ordered by Diyicaijing's ranking. China's government does not officially issue city tiers, however Diyicaijing's classification is often referenced by media and citizens in China.
[7] Results are similar if this interpolation is not carried out.

Figure 2 Geographical distribution of the 19 cities

The oil market was among the first of the energy sectors for which market-oriented reforms were implemented in China. However, gasoline prices are not entirely determined by the market, with some government regulations still in place. Refined oil product prices are issued by the National Development and Reform Commission (NDRC) and adjusted every 10 trading days according to movements in world crude oil prices. Retail prices are not adjusted when the movement in the refined oil price is less than 50 CNY per ton (NDRC 2013). In 2016, NDRC set a floor of $40 USD and a cap of $130 USD per barrel for refined oil products (NDRC 2016). Within the allowed range, gasoline companies can determine prices independently according to their own operations and market situations. Thus different gasoline stations sell gasoline at different final pump prices.

Our analysis uses the monthly city-level gasoline pump price across weeks from Wind (2019). As gasoline price data are not available for every city in the sample, we use the price for the corresponding provincial capital city in some cases.[8] The 93-octane gasoline price is used given that this is currently the most commonly used fuel in China's road transport market. Movements in this price are highly correlated with movements in other fuel prices, such as the prices of premium gasoline and diesel, due to close integration of these related markets (Ma et al. 2009). Our focus is the use of temporal variation in city-level gasoline prices to examine

[8] Results remain similar for a sub-sample of 12 cities for which city-specific data of the monthly gasoline pump price are available.

effects on geographical patterns in housing prices over time. In their studies of the US, Molloy and Shan (2013) and Larson and Zhao (2017a) used national measures and Blake (2016) used a regional measure of the gasoline price.

The gasoline price data are not available at a more geographically-disaggregated level than the city, although temporal price movements should be expected to be quite similar across a city. An advantage of not using more spatially granular measures of gasoline prices is that these may be affected by local demand factors to some extent (Molloy and Shan 2013). Any effects of persistent (time-invariant) differences in average prices across REAs are removed by REA fixed effects.

Data for the driving distance, straight-line distance, and driving time were constructed from the business center of each REA to the center of each city's CBD. The straight-line distance is calculated based on latitude and longitude using the Pythagorean theorem. The driving distance and time were crawled using Python according to the recommended route of Baidu Maps, the most frequently used mapping application in China. They were measured as of 2021 given that they are only available in real-time when accessing Baidu Maps.

We use two measures of driving time to the CBD. The first is at a peak hour, approximately 8am on Wednesday 25 August 2021 (UTC+8:00). The second is at an off-peak hour, approximately 2pm on 25 August 2021 (UTC+8:00). We also provide estimates using data for peak (8am) and off-peak (2pm) weekend times measured as of Sunday 22 August 2021. Driving distance is measured at a peak hour (8am 25 August 2021), but the off-peak driving distance as recommended by Baidu Maps is highly similar. The average commute distance uses data from a survey conducted in 2017 by Jiguang (2019) and is available cross-sectionally at the district level, but only for 10 of the cities.

Shocks to housing prices are likely to be geographically correlated. A Pesaran (2004) test for cross-sectional ("spatial") dependence was conducted for the monthly estimations. The results suggest that the null of cross-sectional independence can be rejected at the 1% significance level. Therefore, Driscoll and Kraay (1998) standard errors, robust to general forms of cross-sectional as well as temporal dependence, will be presented (Hoechle 2007). In the yearly estimations, cluster-robust standard errors are preferred because Driscoll and Kraay (1998) standard errors tend to be invalid when the number of temporal units is small. As there are only 19 cities in the sample, the conventional cluster-robust standard errors may also be downwards biased (Cameron et al. 2008). Bootstrap procedures are thus used to obtain more accurate cluster-robust inference in the yearly estimations.

Table 1 presents summary statistics for the housing price data, gasoline price data, and five different road transportation cost proxies. Housing and gasoline prices are in real terms. The housing price dataset consists of about 69,000 observations (REA*month). The definition of a "city" refers to the administrative division. This includes neighbouring hinterland (non-urban) areas, although we will also present estimates for narrower sub-samples of REAs close to the CBD. For example, Beijing's size is 16,411 km^2. In 2018 this consisted of a built-up area of

1,485 km^2 and a non-built-up area of 14,926 km^2 (National Bureau of Statistics of China 2019b).

Table 1 Summary statistics

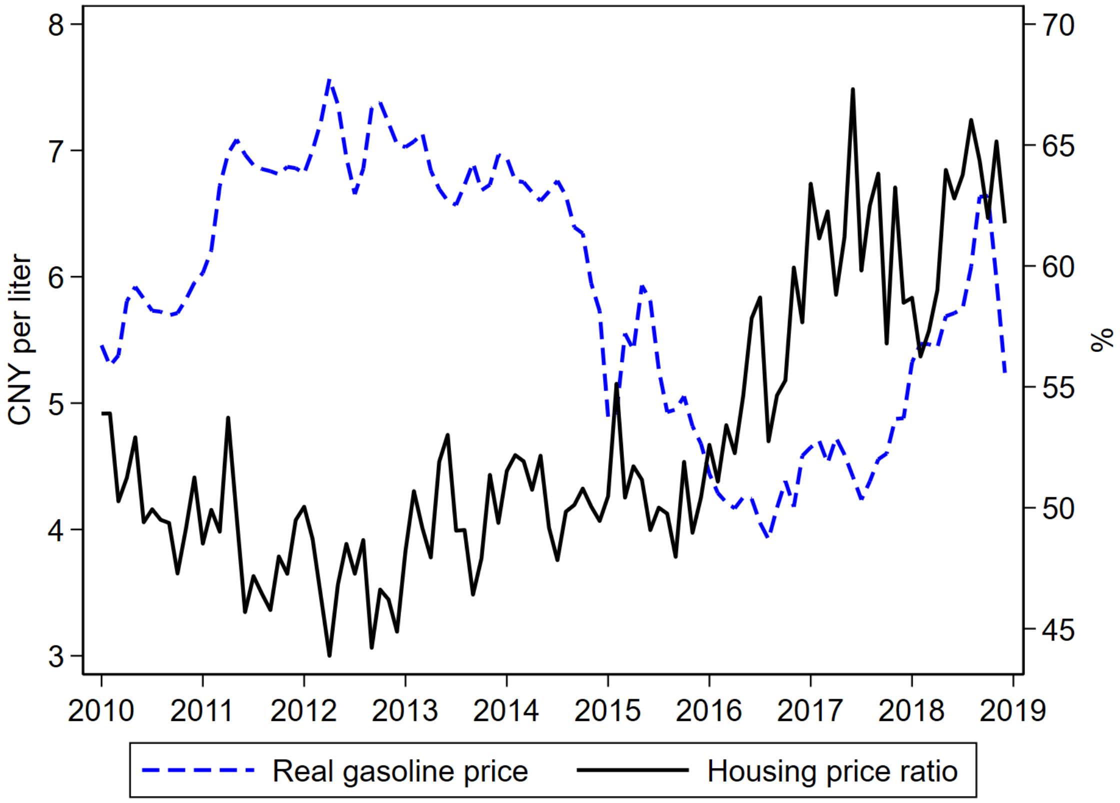
Variable	Observations	Mean	Std. dev	Max	Min
Real housing price (CNY/m^2, monthly)	69,228	16,921	17,924	300,905	1,064
Real gasoline price (CNY/liter, monthly)	2,052	5.8	1.1	7.8	3.4
Driving distance to the CBD (km)	641	19.7	15.7	98.4	0
Straight-line distance to the CBD (km)	641	15.0	12.5	79	0
Driving time to the CBD, peak hour (minutes)	641	35.6	18.9	107	0
Driving time to the CBD, off-peak hour (minutes)	641	31.5	18.9	102	0
Commute distance (km)	125	10.3	2.0	15.7	4.8

Source: Variable definitions and data sources are in the Appendix. *Notes*: 0 km or minutes refers to the REA that is the city's CBD. Driving distance was measured at 8am 25 August 2021 (UTC+8:00). Driving time was measured at a peak hour (8am 25 August 2021 (UTC+8:00)) and an off-peak hour (2pm 25 August 2021 (UTC+8:00)). Gasoline price is measured at the city level. Housing price, driving/straight-line distance, and driving time to the CBD are measured at the REA level. Commute distance is measured at the district level.

The average area of an REA in the sample is about 201 km^2, larger than the average postal code land area in the US (81 km^2) that was reported by Molloy and Shan (2013). Nevertheless, the sample still includes an average of 34 REAs per city. 89.3% of REAs in the sample are located within 40 km from the city's CBD in driving distance terms. Variable definitions and data sources are shown in the Appendix.

Figure 3 plots the average monthly real gasoline price across cities versus the ratio of outer-city to inner-city real housing prices. Theory would suggest that the ratio should decrease with an increase in gasoline prices because consumers' willingness to pay for outer-city housing will reduce relative to that for inner-city housing. A negative correlation is indeed observable during the period June 2014 to 2017, when the gasoline price exhibited a steep decline due to upward surprises in the global production of oil, weakening global demand, and a significant shift in OPEC policy (Baffes et al. 2015). During this time the ratio of outer- to inner-city housing prices presented an upward trend. A negative correlation between the series is not apparent for some of the other years, although Figure 3 only shows the unconditional association using average data and does not take other factors into account. The conditional effect will be estimated using econometric estimations for the full dataset.

Figure 3 Gasoline prices and housing prices



Source: CRIC (2019) and Wind (2019). *Notes*: Gasoline price are average monthly real gasoline prices across 19 cities. The housing price ratio is the ratio of outer-city (further than 20 km driving distance from the CBD) to inner-city (within 5 km driving distance of the CBD) housing prices.

5. Results

5.1 Initial results

Table 2 reports the results from the basic specification. In column 1, a negative coefficient, statistically significant at the 1% level, is found for the interaction between the log gasoline price and driving distance to the CBD. This implies that gasoline price increases tend to be associated with a reduction in the relative price of homes further from the CBD. Specifically, a 1% increase in gasoline prices on average leads to about a 0.004% reduction in the value of homes per extra kilometer of driving distance to the CBD relative to homes in the CBD. A negative and statistically significant coefficient for the interaction term, with a magnitude of –0.002, is also found when controlling for REA-specific time trends in column 2. Column 3 interacts the log gasoline price with the distance ring dummies. The base is the inner-city area, defined as < 5 km driving distance of the CBD. The coefficient on the interaction term between the log gasoline price and the distance ring dummy for REAs > 20 km from the CBD is –0.24, significant at the 1% level. This implies that a 1% increase in gasoline prices on average leads to about a 0.2% reduction in the value of outer-city relative to inner-city homes. The coefficient for mid-city REAs is –0.149, statistically significant at 1% level.

Table 2 Monthly estimations

Dependent variable: Ln housing price$_{i,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Driving variable used:	Driving distance to the CBD (km)	Driving distance to the CBD (km)	Driving distance to the CBD > 20 km (binary)	Straight-line distance to the CBD (km)	Driving time to the CBD at a peak hour (minutes)	Driving time to the CBD at an off-peak hour (minutes)	Commute distance (km)
Ln gasoline price$_{i,t}$	–0.054	0.074	0.023	–0.070	–0.003	–0.022	0.073
	(0.094)	(0.080)	(0.092)	(0.094)	(0.095)	(0.094)	(0.125)
Ln gasoline price$_{i,t}$ × Driving variable$_{i,2021}$	–0.004***	–0.002*	–0.236***	–0.004***	–0.004***	–0.004***	–0.025***
	(0.001)	(0.001)	(0.065)	(0.001)	(0.001)	(0.001)	(0.008)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
REA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
REA-specific time trend	No	Yes	No	No	No	No	No
Within-R^2	0.55	0.68	0.55	0.55	0.55	0.55	0.56
Observations	69,110	69,110	69,110	69,110	69,110	69,110	48,209

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Driscoll and Kraay (1998) standard errors are in parentheses. Column 3 also includes a category for mid-city REAs (5–20 km driving distance from the CBD), with the coefficients not shown. The point estimate on the interaction for the mid-city group is –0.149, statistically significant at the 1% level. Driving time at a peak hour (8am) in column 5 and an off-peak hour (2pm) in column 6 are measured on 25 August 2021. Column 7 uses the average commute distance from a survey conducted in 2017 by Jiguang (2019). The number of observations reduces in column 7 because Jiguang (2019) only reports commute distance data for 10 of the cities in the sample.

The results using the straight-line distance to the CBD in column 4 of Table 2 are similar to the main specification using driving distance to the CBD in column 1. The magnitudes of the interaction using the driving time in minutes at a peak hour in column 5 and at an off-peak hour in column 6 are also similar.[9] The similarity of these coefficients may be surprising given the different units of the variables (kilometers and minutes). This is related to the fact that vehicles typically drive at between 30 km/h and 50 km/h on China's urban roads (Baidu 2019), meaning that a trip's driving time in minutes and distance in kilometers are not of hugely dissimilar magnitudes despite the different units.

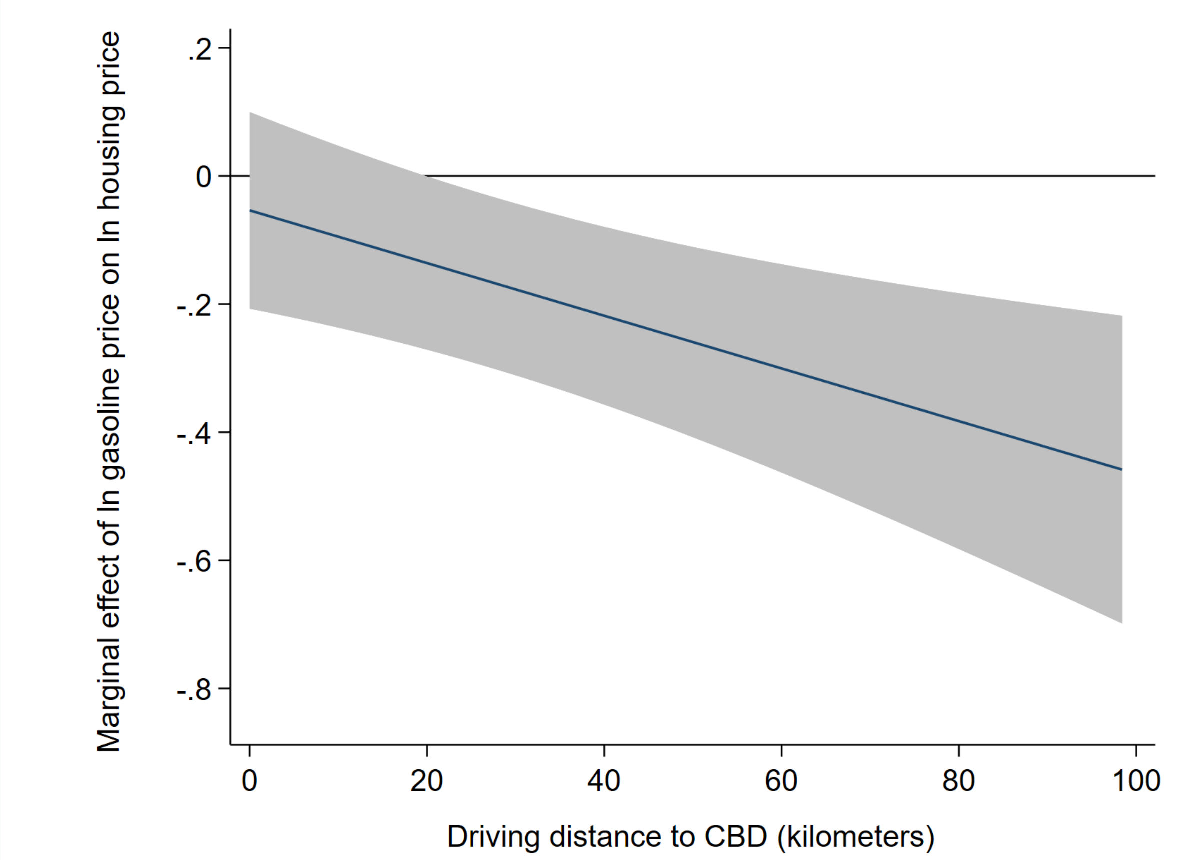
Column 7 of Table 2 shows the results using the average commute distance in kilometers, noting that many commuting journeys are not to the CBD. A negative and significant point estimate is again found for the interaction term, implying that gasoline price increases lead to a relative reduction in the value of homes in locations where people face longer average commute distances. The magnitude is larger than for the interaction terms in the earlier columns, perhaps because this measure of commuting distance is more pertinent than CBD-based measures. While some commutes are by public transport and so are unaffected by retail gasoline price movements, it is interesting that overall effects are still observed.

Figure 4 plots the marginal effect of the log gasoline price on the log housing price as a function of the driving distance to the CBD, using the estimate in column 1 of Table 2. The effect declines with driving distance and remains insignificantly different from zero for up to 18 km of driving distance from the CBD. It becomes significantly different from zero for greater distances, and increasingly negative the further one moves out. Note that some residents do commute long distances in large Chinese cities.

Figure 5 shows simulated housing price-distance trade-offs for different gasoline prices using the estimates in column 1 of Table 2. The dashed line is the housing price gradient with respect to distance to the CBD for the minimum gasoline price in the sample (3.4 CNY per liter). Higher gasoline prices lead to the fitted line rotating and becoming steeper, implying that when gasoline prices increase, price differentials between homes in distant areas and the CBD increase.

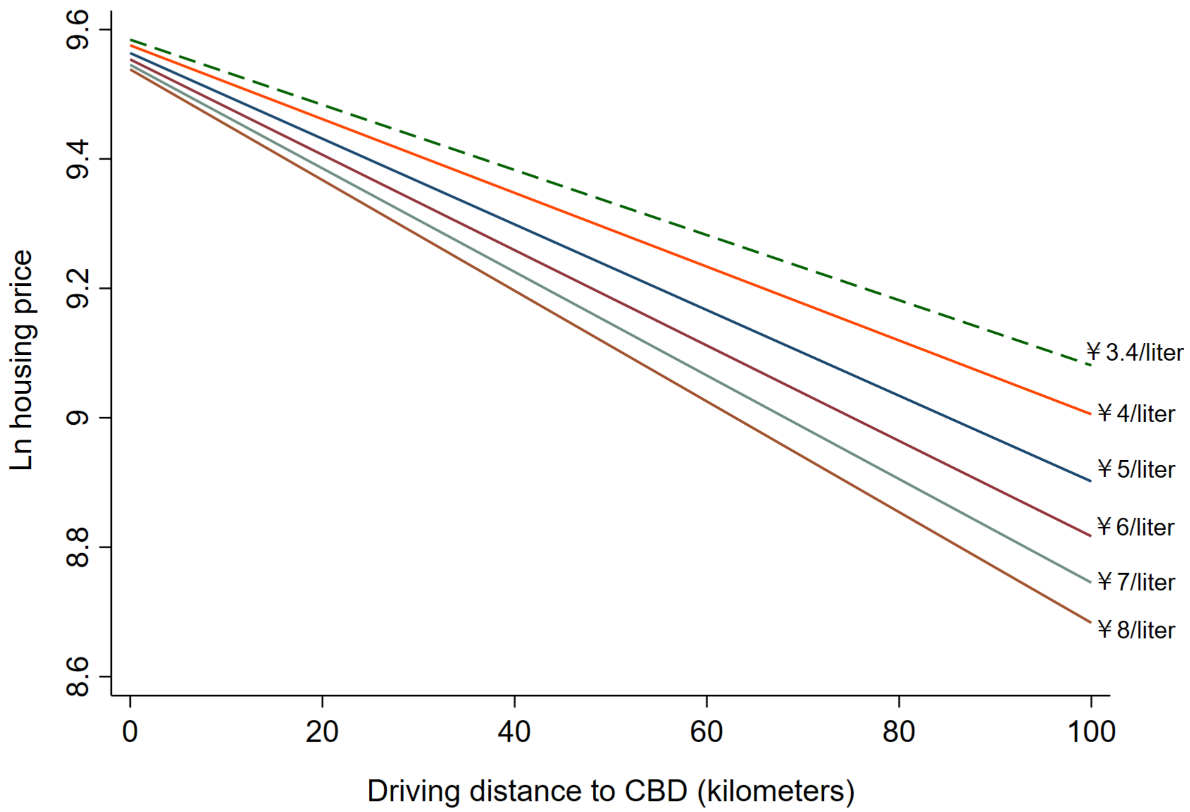
[9] The coefficients on the interaction terms using the driving time at a peak hour (8am) and an off-peak hour (2pm) on Sunday 22 August 2021 also remain similar to those in columns 5 and 6.

Figure 4 Marginal effect of gasoline price on housing price by distance to the CBD



Source: CRIC (2019) and Wind (2019). *Notes:* The regression uses monthly data and the driving distance to the CBD as the proxy of road transport costs in the interaction term. The grey areas show the 95% confidence intervals.

Figure 5 Trade-offs between housing prices and distance for different gasoline prices



Source: CRIC (2019) and Wind (2019). *Notes:* The regression uses monthly data and the driving distance to the CBD as the proxy of road transport costs in the interaction term. This graph is plotted using the "margins" and "marginsplot" commands in Stata 16 for the specification in column 1 of Table 2. The "margins" command estimates statistics calculated from predictions using average values for the other covariates.

5.2 Yearly estimations

Table 3 reports estimations using yearly data. In column 1, the point estimate on the interaction between the log gasoline price and distance is slightly larger in absolute value than in the monthly specification. There are no significant findings for the income level and the unemployment rate. More district-level subway lines are associated with higher housing prices holding the other variables constant, as expected. Column 2 controls for interactions between the distance variable and both log income and the unemployment rate. The estimation produces a smaller estimate for the interacted log gasoline price variable, and one that is similar to that in the monthly specification. Column 3 controls for the un-interacted log gasoline price and the national GDP growth rate, and excludes the year fixed effects. The coefficient on the interaction between log gasoline price and distance is similar to that in column 1.

Table 3 Yearly estimations

Dependent variable: Ln housing price$_{i,y}$			
	(1)	(2)	(3)
Ln gasoline price$_{i,y}$			0.031
			(0.040)
Ln gasoline price$_{i,y}$ × Driving distance (km)$_{i,2021}$	–0.006***	–0.002*	–0.006***
	(0.001)	(0.001)	(0.002)
Ln per capita income, city$_{i,y}$	–0.076	–0.154*	0.766***
	(0.085)	(0.084)	(0.021)
Ln per capita income, city$_{i,y}$ × Driving distance (km)$_{i,2021}$		0.006***	
		(0.001)	
Unemployment rate (%), city$_{i,y}$	0.000	0.0003***	–0.0003***
	(0.000)	(0.0001)	(0.000)
Unemployment rate, city$_{i,y}$ × Driving distance (km)$_{i,2021}$		–0.00002**	
		(0.000)	
Number of subway lines, district$_{i,y}$	0.025***	0.030***	0.035***
	(0.008)	(0.008)	(0.008)
National GDP growth rate (%)$_y$			–0.599***
			(0.028)
Year fixed effects	Yes	Yes	No
REA fixed effects	Yes	Yes	Yes
Within-R^2	0.67	0.67	0.61
Observations	5,767	5,767	5,767

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Bootstrapped standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables.

5.3 First-differenced yearly estimator

Table 4 reports the results using a yearly first-differenced estimator (using annual data) and also tests for asymmetric effects. The coefficient on the interaction term using the full sample in column 1 is negative and statistically significant, with a similar magnitude to earlier results. The coefficient on the interaction terms for the rising log gasoline price term in column 2 is negative and statistically significant. The coefficient for the falling log gasoline price term is not statistically significant, and the hypothesis of equivalent coefficients on the interaction terms is able to be rejected at the 5% level. There is thus evidence of asymmetry in the effect: the effect of rising gasoline prices tends not to be reversed if and when gasoline prices decline again.

Table 4 Results using differences and asymmetric effect tests, yearly data

Dependent variable: d.Ln housing price$_{i,y}$		
	(1)	(2)
d.Ln gasoline price$_{i,y}$ × Driving distance (km)$_{i,2021}$	–0.002*	
	(0.001)	
Positive d.Ln gasoline price$_{i,y}$		0.100
		(0.194)
Negative d.Ln gasoline price$_{i,y}$		–0.467***
		(0.120)
Positive d.Ln gasoline price$_{i,y}$ × Driving distance (km)$_{i,2021}$		–0.005**
		(0.002)
Negative d.Ln gasoline price$_{i,y}$ × Driving distance (km)$_{i,2021}$		0.002
		(0.002)
		[0.012]
d.Ln per capita income, city$_{i,y}$	0.017	0.005
	(0.044)	(0.049)
d.Unemployment rate (%), city$_{i,y}$	0.0001***	0.000***
	(0.000)	(0.000)
d.Number of subway lines, district$_{i,y}$	–0.010*	–0.010*
	(0.006)	(0.006)
Year fixed effects	Yes	Yes
REA fixed effects	Yes	Yes
Within-R^2	0.13	0.14
Observations	5,126	5,126

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Bootstrapped standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables. The number in the square bracket is a p-value for a test of parameter equality for interaction terms.

5.4 Heterogeneity analysis across cities

We now investigate potential heterogeneity in effects. Table 5 presents point estimates for interaction terms for different city groups. Cities are first categorized by automobile ownership rates, with a high ownership rate being defined as ≥ the median number (301) of automobiles per 1,000 people in the sample in 2017. Panel A reports that the point estimate for an interaction between log real gasoline price and distance for cities with a high automobile ownership rate (–0.007) is higher than for cities with a low vehicle ownership rate (–0.003). The null that effects for these two groups are equal can be rejected at the 1% significance level. This suggests that gasoline prices tend to have a larger effect on spatial differentials in housing prices in cities with higher automobile ownership rates.

Panel B of Table 5 presents effects for cities with high and low population densities. Cities are categorized based on their density ranking in 2017. The high density group consists of 10 cities and the low density group has 9 cities. In absolute value terms, a smaller point estimate is obtained for high-density (–0.003) than for low-density cities (–0.008), with a p-value for a test of equality of 0.014. Densely populated cities in our sample typically have better public transport connectivity (Gaode Map 2018), so this result makes intuitive sense.

Table 5 Heterogeneity analysis by city group, monthly data

Dependent variable: Ln housing prices$_{i,t}$	Number of REAs	Number of cities	Point estimates for the interaction term
A. By automobile ownership rate			
High automobile ownership rate	271	10	–0.007***
Low automobile ownership rate	370	9	–0.003***
			[0.000]
B. By population density			
High density	447	10	–0.003***
Low density	194	9	–0.008***
			[0.006]
C. By EV market share			
High EV market rate	369	10	–0.004**
Low EV market rate	272	9	–0.004***
			[0.593]

Notes: Coefficients on controls and constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Each cell shows the point estimates for that category. Point estimates are the coefficients for the interaction terms between the group dummy and the log real gasoline price*distance interaction. All regressions use driving distance as the proxy for transport costs and control for month fixed effects and REA fixed effects. Group is controlled for separately. Figures in square bracket are p-value for test of equality to the coefficient for the other group in the same panel.

Panel C of Table 5 presents separate effects for cities with high and low EV market shares. Cities are categorized based on having ≥ or < median EV market share (5.2%) in new vehicle sales in the sample in 2017. The coefficients on the two interaction terms are negative and statistically significant, and the p-value for a test of equality of the coefficients on the two interaction terms is not able to reject the null of parameter equality. Perhaps the EV market share also remains too low to have much influence. Also, many cities have a similar EV market share, so perhaps any potentially differential effects are difficult to detect.

5.5 Distributed lag model

Table 6 includes up to five monthly lags of the gasoline price variable.[10] The coefficients on the interaction between the log gasoline price$_t$ and the driving distance are not statistically significant in each column but some of those on the interaction between the log gasoline price$_{t-n}$ and driving distance are negative and statistically significant, with the coefficients suggesting that the effect operates with a lag of several months. This distributed lag analysis does not change the overall result substantially. Specifically, the summed coefficients for the interaction terms are shown at the base of Table 6. The total effect for the interaction term is

[10] There is no single correct way to identify the number of lags to include. In order to not lose too many degrees of freedom, lags back to five months are used. The sum of the coefficients on the interaction terms remains similar when adding additional lags.

estimated to be –0.005 in column 5, only slightly larger in absolute value than in the static estimation.

Table 6 Distributed lag estimates, monthly data

Dependent variable: Ln housing price$_{i,t}$					
	(1)	(2)	(3)	(4)	(5)
Ln gasoline price$_{i,t}$	–0.030	–0.007	–0.004	–0.022	–0.005
	(0.080)	(0.081)	(0.084)	(0.089)	(0.094)
Ln gasoline price$_{i,t-1}$	–0.047	–0.071	–0.052	–0.025	–0.064
	(0.108)	(0.092)	(0.089)	(0.094)	(0.093)
Ln gasoline price$_{i,t-2}$		–0.015	–0.035	–0.032	–0.004
		(0.093)	(0.067)	(0.063)	(0.069)
Ln gasoline price$_{i,t-3}$			–0.024	–0.013	–0.001
			(0.113)	(0.072)	(0.075)
Ln gasoline price$_{i,t-4}$				–0.051	–0.063
				(0.098)	(0.068)
Ln gasoline price$_{i,t-5}$					–0.026
					(0.095)
Interactions with Driving distance (km)$_{i,2021}$					
Ln gasoline price$_{i,t}$	–0.001	–0.002	–0.002	–0.001	–0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln gasoline price$_{i,t-1}$	–0.003	0.002	0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln gasoline price$_{i,t-2}$		–0.004**	0.002	0.000	0.000
		(0.002)	(0.002)	(0.002)	(0.002)
Ln gasoline price$_{i,t-3}$			–0.005**	0.000	–0.001
			(0.002)	(0.001)	(0.001)
Ln gasoline price$_{i,t-4}$				–0.005**	0.001
				(0.002)	(0.001)
Ln gasoline price$_{i,t-5}$					–0.004**
					(0.002)
Month fixed effects	Yes	Yes	Yes	Yes	Yes
REA fixed effects	Yes	Yes	Yes	Yes	Yes
Within-R^2	0.55	0.54	0.52	0.54	0.53
Observations	68,492	67,870	67,246	66,616	65,985
Sum of coefficients on interaction terms	–0.004***	–0.004***	–0.005***	–0.005***	–0.005***

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Driscoll and Kraay (1998) standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables. The sample size reduces when adding each additional lag.

5.6 Instrumental variable estimations

The IV elasticities are reported in Table 7. They are similar to the OLS results, with the point estimates for the interactions between the log gasoline price and driving distance to the CBD remaining negative and statistically significant. Montiel Olea and Pflueger (2013) tests suggest that the log crude oil price*distance to the CBD provides adequate identification strength. Because the temporal variation in Table 7 comes from the world crude oil price (as measured in the US), the IV results strengthen our confidence that we are estimating a causal effect of gasoline prices on local intra-city housing price patterns.

Table 7 IV results

Dependent variable: Ln housing price$_{i,t}$		
	Monthly	Yearly
	(1)	(2)
Ln gasoline price$_t$ × Driving distance (km)$_{i,2021}$	–0.005***	–0.007***
	(0.000)	(0.001)
Ln per capita income, city$_{i,t}$		–0.072
		(0.060)
Unemployment rate (%), city$_{i,t}$		0.0001
		(0.0001)
Number of subway lines, district$_{i,t}$		0.026***
		(0.005)
Month fixed effects	Yes	No
Year fixed effects	No	Yes
REA fixed effects	Yes	Yes
Within-R^2	0.55	0.67
Observations	69,110	5,767
Instrumented variable: Ln gasoline price$_{i,t}$ × Driving distance $_{i,2021}$		
Instrumental variable: Ln world crude oil price$_{i,t}$ × Driving distance $_{i,2021}$		
Coefficient on instruments	0.493***	0.516***
F statistic on instrument	22,773.5	2,987.5

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Column 1 uses monthly data and column 2 uses yearly data. Clustered-robust standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables. The null of weak instruments is rejected if the *F* statistic on the instruments exceeds the Montiel-Pflueger critical value. The Montiel-Pflueger critical value for 10% of the worst case bias is 23.11.

5.7 Distance-based sub-samples

Table 8 reports results for various sub-samples. The magnitude of the point estimate on the interaction term reduces in absolute value as the sample size increases. This means that the per-kilometer effect appears to be largest for the first kilometers of distance from the CBD. This is perhaps because households living in REAs outside 20 km from the CBD are less likely to travel to the CBD.

Table 8 Results for sub-samples, monthly data

Dependent variable: Ln housing price$_{i,t}$				
Driving distance to the CBD:	0–10 km	0–20 km	0–30 km	0–40 km
	(1)	(2)	(3)	(4)
Ln gasoline price$_{i,t}$	–0.094	–0.105	–0.092	–0.078
	(0.154)	(0.130)	(0.122)	(0.109)
Ln gasoline price$_{i,t}$ × Driving distance (km)$_{i,2021}$	–0.013*	–0.015***	–0.009***	–0.006***
	(0.007)	(0.003)	(0.002)	(0.002)
Month fixed effects	Yes	Yes	Yes	Yes

REA fixed effects	Yes	Yes	Yes	Yes
Within-R^2	0.48	0.52	0.53	0.54
Observations	21,272	44,688	56,121	61,692

Notes: Coefficients for controls and constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Driscoll and Kraay (1998) standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables.

5.8 Housing sales numbers and area sold

Table 9 reports the results for the alternative dependent variables measuring housing transaction volumes and areas. We did not have any expectations on the signs of the coefficients. The coefficient on the interaction term in the log housing transaction volume regression in column 1 is negative, however the effect is not statistically significant. A similar result is obtained when examining the log housing transaction area in column 2.

In interpreting the results in Table 9, it is important to note that it is highly possible for house pricing effects to exist even when significant quantity effects do not. When the gasoline price rises, the number of residences that change hands in outer-city areas may not change much, for instance, yet the price paid for these residences may fall on account of the reduction in the expected utility that would be experienced from owning them over the future time horizon. This is because living in the outer city means that residents generally face greater exposure to road transport costs and less opportunity to participate in inner-city activities when these costs are high.

Table 9 Results using housing sales, monthly data

Dependent variable:	Ln housing transaction volume$_{i,t}$	Ln housing transaction area$_{i,t}$
	(1)	(2)
Ln gasoline price$_{i,t}$	–0.231	–0.212
	(0.527)	(0.510)
Ln gasoline price$_{i,t}$ × Driving distance (km)$_{i,2021}$	–0.005	–0.004
	(0.004)	(0.004)
Month fixed effects	Yes	Yes
REA fixed effects	Yes	Yes
Within-R^2	0.11	0.11
Observations	69,110	69,110

Notes: Coefficients for controls and constants are not reported. *** p<0.01. ** p<0.05. * p<0.1. Driscoll and Kraay (1998) standard errors are in parentheses. The within-R^2 measures the explanatory power of the time-varying explanatory variables.

6. Discussion

In this study of 19 large Chinese cities, a 10% increase in the gasoline price has been found to on average be associated with about a 0.04% relative reduction in home values for every additional driving kilometer from the CBD. A home in an REA that is one standard deviation further from the CBD (15.7 km) would thus be expected to cost 0.6% less relative to homes in the CBD as a result of this effect. This is a reasonably-sized effect, although gasoline prices are only one of many factors affecting housing prices. The 19 large cities in the sample each ranked in the top 30 cities with the highest automobile ownership rate in China (Diyicaijing 2021). Given that the estimated spatial effect is larger for cities with higher automobile dependence (see Table 5), the effect might be smaller if the sample were expanded to include smaller cities.

While relatively few households may consciously decide to sell or buy because of fuel price changes alone, the results in this study indicate that there can nevertheless be effects on overall relative market price valuations. It is not surprising that the effect of gasoline prices on housing prices differentials across cities is not found to be much larger than estimated here, as there are various ways to respond to increases in gasoline prices, such as buying more fuel-efficient vehicles. Residential property prices are also high in China and represent a large share of household assets, with residences tending to be held for multiple years.

The findings in this study are consistent with the negative relationship between transport costs and housing prices reported in studies of the US. Coulson and Engle (1987) found that increases in gasoline prices steepen the housing price gradient with respect to distance from the CBD in the US. Blake (2016) found that a $1 increase per gallon of gasoline tends to reduce home values by about 0.143% for every additional commute mile. Larson and Zhao (2017a) found that a 1% increase in oil prices tends to cause a 0.004% relative reduction in home values for every additional mile from the CBD after five years. Morris et al. (2020) found that a 10% increase in gasoline prices causes home values beyond 5 miles from the city center to fall by an average of about US$1,000, or about 0.4% relative to that in the city center in Clark County. In our study, the –0.004 coefficient for the interaction term implies that a 10% increase in gasoline prices causes home values at 5 miles from the city center to fall by about 0.3% relative to prices in the city center (noting that 1 mile = 1.61 km). The results are thus of a similar magnitude to the recent results of Morris et al. (2020).

Similarity in findings for China and the US is of interest given that Chinese cities tend to be more reliant on public transport. It is however also relevant to note that gasoline pump prices are higher in China than the US, at US$0.96 per liter in 2016 versus US$0.71 per liter in the US (World Bank 2020). Gross national income levels are lower, at US$15,320 per capita versus US$63,780 per capita in the US in 2018 (World Bank 2020). Chinese cities are also becoming increasingly car-reliant over time, so road transport costs are an increasingly important consideration for many residents.

7. Conclusion

This study has used a newly-constructed REA-level dataset to estimate the effect of gasoline prices on housing prices in China’s 19 large cities. The findings indicate that higher gasoline prices on average result in a decline in housing prices in outer urban areas relative to housing prices in or near the city center. Specifically, every 1% increase in gasoline prices is on average estimated to lead to a 0.004% reduction in relative home values for every additional kilometer of driving distance from the CBD. Gasoline prices are found to have a larger effect on spatial differentials in housing prices in cities with high automobile ownership rates and with relatively low population densities. This is the first study to estimate the effect of gasoline prices on spatial patterns in real estate prices for Chinese cities. The estimated effects are quite similar to those obtained for the US.

According to Finder (2020), the price differential between a square meter of city-center housing and a square meter of suburban housing in China was 50%, higher than the global average (35%). This study reveals that among the underlying contributors may be China's relatively high fuel price, at least in comparison to the US. The estimated housing price effect contributes to an exacerbation of asset inequality at times of high fuel prices given that the well-off tend to own properties closer to city centers.

An interesting extension is to consider the implications of the rise of EVs and other new-energy vehicles (NEVs), autonomous vehicles, and working from home for housing price differentials within cities. The marginal fuel cost of driving NEVs is typically lower than for conventional vehicles. Autonomous driving features also reduce the time cost of driving, while working from home reduces driving demand. The estimates in this paper would suggest that, all else equal, these processes should tend to narrow the gap between housing prices in distant urban areas versus inner-city areas, as the importance of road transport costs in locational decisions declines (Larson and Zhao 2017b, 2020). A general move away from gasoline use for road transport will also mean that the mechanism studied in this paper is likely to decline in importance over time.

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Appendix

Location of each city’s CBD

Beijing: Beijing CBD; Shanghai: Lujiazui CBD; Guangzhou: Tianhe CBD; Shenzhen: Futian CBD; Dongguan: Hongfulu; Nanjing: Xinjiekou; Tianjin: Xiaobailou CBD; Ningbo: Tianyi Square; Chengdu: Chunxilu; Kunming: Jinmafang; Hangzhou: Wulin Square; Wuhan: Wuhan CBD; Shenyang: Xindizhongxin; Suzhou: Guanqianjie; Xian: Zhonglou; Zhengzhou: Erqi Square; Chongqing: Jiefangbei CBD; Changsha: Furong CBD; Qingdao: Shinanqu.

Variable definitions and sources

Housing price (real): The average private residence transaction price per square meter in CNY in each REA. Measured as a monthly average. Source: CRIC (2019). The consumer price index (CPI) for all goods in each city was used to adjust the price to a 2010 base. Source of CPI: Wind (2019).

Gasoline price (real): Pump price per liter for gasoline (93-octane gasoline) in CNY in each city. Measured as a monthly average based on the weekly raw dataset. The raw pump price was reported on a specific, non-fixed date in the week. If a week crosses over months, it is counted for the month in which the specific reported date is. Source: Wind (2019). The CPI in each city was used to adjust the price to a 2010 base. Source of CPI: Wind (2019).

Driving distance to the CBD: Driving distance on the recommended route by Baidu Maps from the business center of each REA to the center of each city’s CBD, in kilometers. Measured at the REA level and accessed at approximately 8am 25 August 2021 (UTC+8:00).

Straight distance to the CBD: Straight-line distance from the business center of each REA to the center of each city’s CBD, in kilometers. Measured at the REA level.

Driving time to the CBD at a peak hour: Peak period travel time on the recommended route by Baidu Maps from the business center of each REA to the center of each city’s CBD, in minutes. Measured at the REA level and accessed at approximately 8am 25 August 2021 (UTC+8:00).

Driving time to the CBD at an off-peak hour: Off-peak period travel time on the recommended route by Baidu Maps from the business center of each REA to the center of each city’s CBD, in minutes. Measured at the REA level and accessed at approximately 2pm 25 August 2021 (UTC+8:00).

Commuting distance: Average commute distance for a one-way trip to work for all workers in each district, in kilometers. Measured at the district level in 2017. Source: Jiguang (2019).

Per capita income: Per capita disposable income of urban households in CNY in each city. Measured yearly. Source: Wind (2019). The CPI for all goods in each city is used to adjust the income level to a 2010 base. Source of CPI: Wind (2019).

Unemployment rate (%): Unemployment rate in each city. Measured yearly. Source: Wind (2019).

Number of subway lines: The number of subway lines in each district. Measured yearly. Source: The subway strategic planning from each city's government.

National GDP growth rate (%): The rate of change in the real national GDP from the current year to the previous year. Measured yearly. The national GDP deflator is used to adjust to a 2010 base. Source of GDP and GDP deflator: Wind (2019).

Automobile ownership rate: Number of civil automobile per 1,000 people in 2017. Measured at the city level. Vehicle and population source: Each city's Bureau of Statistics.

Population density: Number of people per square kilometer in 2017, measured at the city level. Source: Chyxx (2017).

EV market share: The share of new EV sales in total new automobile sales in 2017. Measured at the city level. Vehicle stock source: Each city's Bureau of Statistics.

World crude oil price (real): Cushing, Oklahoma West Texas Intermediate (WTI) Spot price (US$ per barrel). Measured monthly or as a monthly average. Source: U.S. Energy Information Administration (2019). To obtain the real crude oil price, the US CPI from the Federal Reserve Bank of St. Louis (2020) was used as a deflator. Then the unit was converted from US$/barrel to CNY/liter based on the monthly USD/CNY exchange rate and a barrel-to-liter conversion. Exchange rate source: Wind (2019).

Housing transaction volume: The number of residences sold in each REA. Measured monthly. Source: CRIC (2019).

Housing transaction area: The total areas of residences sold in each REA, in m^2. Measured