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Valuing consumption services as technology transforms accessibility: Evidence from Beijing

Ying Chen
Paul Cheshire
Xiangqing Wang
You-Sin Wang

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
Home delivery reduced the value of cities as locations to access variety in durable consumption goods. Food delivery services (FDS) are doing the same for restaurants. Home-streaming of sports or home-delivered restaurant meals are close but not perfect substitutes for the live experiences. Here we investigate the impact of FDS in Beijing. Employing a Bartik IV strategy, we find that a one standard deviation increase in the number of FDS-accessible restaurants generates a 7.1% increase in property values. The premium is estimated as equivalent to half a top-quality school. FDS appears to be changing how cities deliver welfare from consumption services and so modifies urban land rents and housing attributes. Its value and that of restaurant variety increase with household size but seems to reduce the value of well-equipped kitchens.

Keywords: food delivery services, impact of choice in consumer services, hedonic analysis, changing urban consumption patterns
JEL: D21; R21; O33

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Ying Chen, Xiamen University. Paul Cheshire, London School of Economics and Centre for Economic Performance at LSE. Xiangqing Wang, Xiamen University. You-Sin Wang, Beike Zhaofang (Beijing) Technology Co., L.

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"…cities of the future will either be car cities with decentralized employment or walking public transport cities with extremely high levels of density…cities will only succeed when they provide amenities that are attractive to high human capital residents." (Glaeser et al., 2001)

1 Introduction

As Glaeser et al. (2001) wrote "too little attention has been paid to the role of cities as centers of consumption". This paper sets out in some part to redress that omission. There is now an ample body of rigorous research demonstrating the vital role played by cities in production, especially for growing sectors such as traded services, cultural services or public administration (Graham, 2007; Melo et al., 2009; Li et al., 2022; Liu et al., 2024). There is evidence of how urban agglomeration economies contribute to the economy and how they could contribute more (Duranton and Puga, 2023). There is still scant evidence estimating the significance of consumption externalities in the success of cities although increasing evidence that consumption opportunities are a central function of cities (Miyauchi et al., 2021).

A starting point for the pioneering study of Glaeser et al. (2001) was the distinction between consumer goods and consumer services. Larger cities provided a better and more diverse supply of both but the internet and Amazon had converted consumer goods into 'national goods' that could, via the internet, be consumed anywhere. The distinctive consumer offer of cities was access to theaters, an attractive mix of social partners or restaurants.

In fact consumer goods can be thought of as having (at least) two components generating utility: the physical goods themselves and the 'shopping experience'. Indeed we casually talk about 'retail therapy' – the enjoyment derived from the shopping experience. For some this is of comparable value as the goods themselves.

Since 2010 a comparable transformation has moved to the restaurant experience. A meal in a restaurant remains a different experience (consumer service) to eating a take-out meal from the same restaurant at home. But delivery apps and their associated physical networks have transformed the transport costs associated with restaurant meals. Home delivery is not confined to the mass market – simple hamburger and chips – but has reached the fine dining and ethnic restaurant world. While these delivery systems can be conceptualized as having reduced the transport costs associated with restaurant meals, unlike physical goods, proximity to the origin – in this case the restaurant kitchen – remains important because fresh cooked meals have a short life. A cold congealed boeuf stroganoff, Shanghai dumplings or Beijing duck is not very palatable and a very poor substitute for straight from the pan, even ignoring the restaurant experience itself.

What we take advantage of in this paper is the advent of home delivery for restaurants in Beijing. This did not transform them into national goods but made close physical presence no longer necessary by greatly extending the distance over which their services could be consumed. While not an exact substitute for eating in a restaurant, home delivery can be thought of as flattening the kinks in the urban land rent surface as the value of proximity to restaurants was reduced.

We employ a unique and comprehensive dataset to investigate the impact of food delivery services (FDS) on property values in Beijing, China of over 0.7 million property transactions and more than 3 million service establishment records, spanning the period from 2012 to 2019. This rich geolocated data allows us to examine the relationship between the accessibility of consumption services and house prices at a granular level.

We start by exploring the descriptive relationship between house prices and the total number of consumption services within walking distance of the property. We find that properties with access to a greater variety of consumption services command higher prices, while the sheer count of establishments does not. This pattern aligns with the notion that households value diversity and convenience in their consumption options when choosing locations. However, this descriptive evidence does not necessarily imply causality. Different types of consumption services tend to co-locate, and residents may value proximity to restaurants differently than proximity to legal services, making it challenging to disentangle the specific effects of each type of service on house prices (Su, 2022b). Moreover, the location of consumption services may be endogenous to house prices due to unobserved local characteristics or sorting of households and businesses, further complicating the interpretation of the observed relationship.

Focusing on how FDS-induced accessibility to restaurants affects house prices addresses the aforementioned empirical challenges. First, with FDS, the accessibility to deliverable consumption services is clearly defined by the range of delivery services, providing a more precise measure of accessibility compared to the general co-location of various consumption services.[1] To address potential endogeneity concerns, we employ a Bartik instrumental variable (IV) strategy that uses the exogenous variation brought about by the rapid nationwide expansion of food delivery platforms and the predetermined local restaurant density to construct a valid instrument for the number of delivery-accessible restaurants.[2] Our falsification tests show that prior to the advent of FDS, the spatial distribution of hypothetical accessible restaurants via FDS is not correlated with house price trends at the neighborhood

[1] Additionally, we would expect there to be a distance decay effect since restaurants are still accessible to more distant residents: they just have to travel further so the cost to them is higher (Glaeser et al., 2001).

[2] We define "delivery-accessible" restaurants as those located within a 2 to 5 kilometer radius of a given property. This distance range aligns with the typical delivery radius of major food delivery platforms in Beijing during the study period. We exclude restaurants inside the 2-kilometer radius to conservatively exclude any restaurants might be thought to be within walking distance so not necessarily dependent on FDS for accessibility.

level, supporting the validity of our instrument. By using this IV strategy, we can isolate the causal effect of FDS on property values, overcoming the limitations of the descriptive analysis.

We find that a one standard deviation increase in the number of restaurants accessible through FDS within a 2-5km radius results in a 7.1% increase in property values. This substantial effect highlights the significant role that consumption services, particularly those made more accessible through technology, play in shaping urban housing markets.

We further investigate the potential mechanisms driving this net effect. First, we examine the enhanced accessibility channel, whereby FDS expands the set of restaurants available to households without the need for physical proximity. Second, we explore the FDS-induced competition effect among restaurants, as they may strive to differentiate themselves in a more competitive market. Third, we present evidence that since FDS allows households to access a wider range of cuisines and restaurant types that cater to a variety of tastes it induces better matching of consumer preferences.

Our study contributes to the broader discussion on how technology is transforming urban functions and shaping cities' futures by being the first to quantify the hedonic valuation of deliverable consumption services. As FDS and similar gig economy platforms, such as ride-sharing and space-sharing, continue to grow and evolve, they have the potential to significantly alter how households value and interact with consumption amenities (Cohen et al., 2016; Zervas et al., 2017; Berger et al., 2018; Hall et al., 2018; Garcia-López et al., 2020; Barron et al., 2021; Koster et al., 2021; Farronato and Fradkin, 2022; Buchak, 2024). This shift carries profound implications for urban housing markets, land use patterns, infrastructure planning, and the overall livability of cities. Our research provides a framework for understanding and quantifying these effects, which can inform policymakers and urban planners as they seek to harness the benefits of technological innovations while mitigating potential challenges.

We build upon existing literature that aims to evaluate how people value consumption amenities (e.g., Kuang, 2017; Su, 2022a; Rappaport, 2008; Boualam, 2014; van Vuuren, 2023) in several ways. First, by detailed data on a very large number of establishments, we provide a comprehensive analysis of the impact of both walkable[3] and deliverable consumption services on property prices (Glaeser et al., 2018). Second, we exploit the sudden expansion of FDS as a natural experiment to identify the causal effect of deliverable consumption services on property values. This approach addresses potential endogeneity concerns and allows us to decompose the underlying mechanisms. Third, we employ a combination of two-way fixed effects with granular fixed effects and nonparametric random forest methods to assess the descriptive

[3] We define "walkable" consumption services as those located within a 1 kilometer radius of a given property. Establishments within this radius are considered easily accessible on foot, making them a distinct category from those primarily accessible through delivery services.

patterns of the quantity and diversity of walkable consumption services on house prices. These complementary methods provide consistent results, reinforcing the robustness of our findings.

2 Background, Conceptual Framework, and Data

2.1 Consumption and Food Delivery Services in Beijing

Consumption services refer to the various amenities and experiences provided by establishments that cater to the needs and desires of residents and visitors in a given location. These services are essential features or attributes of a location that enhance the quality of life and overall attractiveness of the area. They are a particular offer of cities and their diversity and accessibility underlie the welfare advantages of urban life; moreover the larger the city, the richer its available set of consumer services is likely to be. Examples of establishments that provide consumption services include shopping centers, restaurants, entertainment venues, and cultural, sporting, or tourist attractions. The availability and diversity of these consumption services play a crucial role in determining the appeal of a location to potential residents and visitors. Given this the value of these services should be reflected in local property values, as areas with a richer array of consumption services tend to command higher prices.

As China's capital and a high-density metropolitan area – a high density, walking and public transport city – Beijing serves as an ideal case study to investigate people's valuation of consumption services. The city boasts great diversity, extensive coverage and a large number of service establishments, making it a diverse and vibrant consumption landscape. Figure 1 illustrates the concentration of consumption services within a 500-meter radius of the China World Trade Center, located in central Beijing, highlighting the abundance and variety of options available to residents and visitors in the area.

To quantify the causal valuation of consumption services, we zoom into the specific categories the accessibility of which greatly increased because of the expansion of food delivery services (FDS): deliverable meals represented by the number of restaurants accessible through food delivery apps.

The introduction of platform-based FDS in China, such as Ele.me and Meituan, revolutionized the traditional market for restaurant and food buying services. Ele.me and Meituan are two of the largest FDS platforms in China, offering a wide range of food delivery options. Powered by advanced technologies such as mobile payment, user-friendly apps, and algorithmic optimization, FDS platforms like Ele.me and Meituan quickly expanded their coverage nationwide between 2014 and 2016. This rapid growth was fueled by intense competition to acquire a larger market share. We illustrate this explosive expansion using Baidu Search Index (the Chinese version of Google Search Index) in Appendix Figure A1. The figure shows sharp increases in searches in late 2014 and mid-2015, corresponding to the rapid expansion of the food delivery industry.

The sudden adoption and rapid expansion of FDS in China have significantly impacted the urban consumption landscape. As FDS has grown to encompass meals and beverages, consumers have become less reliant on physical visits to establishments for these experiences. This shift provides a unique opportunity to explore the causal effect of delivery services on how people value and interact with consumption services.

2.2 Conceptual Framework

Hedonic price theory posits that the value of a heterogeneous or complex good, such as housing, is determined by its utility-bearing attributes (Rosen, 1974). These attributes encompass physical and structural characteristics, but also, as has been repeatedly confirmed by research, a house's precise location and the access that gives not just to jobs (the basic urban economics monocentric model) but to local public services such as schools, and neighborhood features. Access to consumption services, particularly restaurants, has been shown to significantly influence house prices (Glaeser et al., 2001; Kuang, 2017).

The advent of food delivery services (FDS) has several potential impacts on the spatial distribution of consumption services and the perceived value of a location. First, FDS platforms reshape the spatial dynamics of consumption services by transforming households' access to a wider range of restaurants and variety of cuisines,[4] reducing the importance of physical proximity to establishments. This shift diminishes the significance of the physical distance between restaurants and residents, allowing households to enjoy a diverse range of culinary options from home, even when the restaurants are not in close proximity.

The increased accessibility and convenience provided by FDS can be seen as an improvement in the consumption services offered by a location. Households can now enjoy a given set of consumption services while incurring lower transportation costs or time, as FDS reduces both the monetary and time costs associated with trips to restaurants and waiting for meals. As a result, households may place a higher value on living in areas with better access to FDS, as they can take advantage of the enhanced consumption opportunities without the traditional constraints of physical proximity: in effect a flattening and smoothing of the rent surface as access to restaurant-cooked meals becomes more accessible and so in effect cheaper.

Moreover, the presence of FDS can have supply-side effects on the local business landscape. As FDS lowers entry cost and more households utilize these services, it may incentivize the establishment of new restaurants or the adaptation of existing ones to cater to the growing

[4] Having more choices, all else being equal, can be utility-increasing (Krugman, 1980; Costa and Kahn, 2000) but the effect likely varies with household size.

demand for delivery. Kitchen only rather than dine-in restaurants emerge. The resulting supply-side competition effect can further change the number of restaurants, variety, and quality of consumption services available in a given location, and reduce their prices (as less space is needed or competition squeezes margins). In so far as these changes make the location more attractive to residents, they will be reflected in changes in hedonic prices.[5]

In the longer horizon, the growing popularity of FDS may lead to a shift in household preferences regarding housing attributes. Conventionally, a well-equipped kitchen has been considered a desirable feature in a home. However, as FDS makes it more convenient for households to access a variety of food options without cooking facilities, the value placed on having a kitchen may diminish. A report by The Economist (Ryder, 2019) suggests that a significant proportion of survey respondents in China were willing to rent a flat without a kitchen at all. This change in preferences could further influence the hedonic value of housing, with properties offering better access to FDS potentially commanding a premium while the hedonic price of kitchens falls.

Drawing upon the concept of spatial equilibrium (Glaeser and Gottlieb, 2009), we argue that the increased accessibility and convenience provided by FDS can influence households' willingness to pay for housing in a given location. Given that households value access to a diverse set of consumption services, the ability to enjoy a wide range of food options through FDS can make a location more desirable, leading to higher house prices.

In summary, our conceptual framework suggests that the emergence of food delivery services can change house prices by altering the distribution across urban space of the cost of accessing consumption services. FDS enhances the value of those neighborhoods benefiting from a wider variety of restaurants and cuisines more accessible, reflected in house prices but because strictly related to the house’s location, capitalized into land prices. This framework provides a theoretical foundation for our empirical analysis, which aims to quantify the impact of FDS on housing values and explore the underlying mechanisms driving any observed relationship.

In our empirical analysis, we use the available data to explore the channels through which FDS can affect house prices:

1. The accessibility effect on consumption service choices: We examine how the expansion of FDS, as it increased the number of restaurants accessible to households, influenced house prices.

[5] On the flip side, if the competition is asymmetric in increasing the market power of particular types of restaurants, the quantity, diversity, and quality could move in the opposite direction. However, disentangling the supply-side channels is beyond the scope of this paper.

2. Supply-side effects that may affect the provision of delivery-accessible restaurants: We disentangle the potential supply-side competition effect from the demand-side accessibility effect in the hedonic premium of increased delivery-accessible restaurants.

3. Heterogeneity by housing attributes: We analyze how the convenience of FDS may lead to differential impacts on key housing attributes, reflecting varying household preferences. For example, larger properties that house larger households may value the increased choices of restaurants brought about by FDS more, due to greater variation in tastes among household members. Additionally, the potential diminished value placed on having a well-equipped kitchen may be reflected as a lower premium for properties with kitchens, while the premium for houses with well-equipped kitchens may fall.

4. Valuing other attributes of the deliverable consumption services: FDS may also alter the number of cuisine types, quality, and price levels of the restaurant experience accessible through delivery service. We explore the FDS impact on these attributes with the best data possible but since the results are not conclusive they are reported in the Appendix.

2.3 Data Sources

To conduct the empirical analysis, we collect various types of data, including web-scraped Point of Interest (POI) data on DaZhongDianPing (DZDP), housing transaction data from a major real estate listing company in Beijing (Lianjia.com), satellite remote-sensing data on nighttime lights, population, and various official statistical data. Our main sample contains 762,667 property transactions and 3.5 million service establishments from 2012 to 2019 distributed across 239 neighborhoods in central Beijing. The neighborhood (jiedao) is a granular administrative and statistical unit that determines some of the social benefits of its residents within its jurisdiction. The population share of neighborhoods in Beijing is similar to that of the Neighborhood Tabulation Areas in New York City.[6] Given the available data, Beijing neighborhoods represent the most granular spatial unit for which we could obtain unit-year variation in demographic variables.

Housing Transaction Data. This dataset contains 762,667 records of second-hand property transactions sourced from Lianjia.com, covering all urban districts in Beijing from 2012 to 2019. Each record includes the transaction price, date of sale, coordinates, floor area (in square meters), address, building height (short, middle, or tall), floor level, internal condition (finished or not), and number of bedrooms. Figures 2a and 2b depict the average housing transaction price at the neighborhood level. The mean house price was 61,004 RMB per m^2 in 2019. The average usable floor area is 85.31 m^2.

[6] The average neighborhood population share in Beijing is 0.3% using 2020 census data, and the figure is 0.38% in NYC using 2020 census data.

DZDP Establishment Data. To measure the provision of local consumption services, we scraped establishment-level information from DaZhongDianPing (DZDP) each year from 2012 to 2019. Established in 2003, DZDP is China's most widely used social media and reviews app for local consumption services, similar to platforms such as Google Reviews, Yelp, TripAdvisor, and Foursquare. Due to its popularity, DZDP provides the most complete coverage of consumption services. The key information we use in this paper includes establishment coordinates, business status, and product and service types. We focus on two main categories of establishments: (1) restaurants,[7] which are directly related to food delivery services, and (2) the rest categories of consumption services (retail, personal care services, lifestyle and convenience services, entertainment and recreation, home improvement, automotive services, wedding services, childcare services, fitness and wellness, educational services, hospitality, tourism, pet care, and other professional services.), which represent other types of consumption services. Figures 2c and 2d (Figures 2e and 2f) depict the number of all service establishments (restaurants) at the neighborhood level in 2012 and 2019. Visually, a clear spatial correlation exists between average house prices and consumption services although causation could go either (or both) way(s).

Food Delivery Service Growth. We employ a Bartik type Instrumental Variable (IV) strategy for identification. Issues with this approach are discussed below but to construct the "shift" component of the Bartik IV in our empirical strategy, we measure the growth of the Chinese food delivery industry by its national market size. We use data from iResearch, a well-known market research and consulting firm specializing in the Chinese commercial market, to obtain the national market size of the food delivery industry.[8] According to iResearch, the national market size of the food delivery industry grew from 3.6 billion RMB in 2012 to 12.5 billion RMB in 2015, while total users increased from 80 million to 209 million during the same period. This national market size data is used to construct the time-varying "shift" component of the Bartik instrument, which captures the time trend of the food delivery industry at the national level.

Auxiliary Data. We utilize a set of auxiliary data sources to construct locational characteristics at the property- and neighborhood-level:

Pollution levels: We obtain the property-level particulate matter 2.5 (PM2.5) exposure by processing the remote-sensing data from Tracking Air Pollution in China (TAP) website[9] (Geng et al., 2021; Xiao et al., 2021a and b, 2022). This is to control for pollution levels.

Top elementary schools: To better capture the premium from access to high-quality elementary schools, we manually collect the catchment area information in 2018[10] for the 15 top

[7] This category includes establishments that serve food and beverages (restaurants, cafes, bakeries, and eateries).

[8] To ensure the credibility of the data, we compare their estimated market size values with those obtained from the China Internet Network Information Center (CNNIC), an official source in China, and find that they are nearly identical.

[9] http://tapdata.org.cn/

[10] Accessible at: https://www.ysxiao.cn/, accessed on Jul 31, 2024

elementary schools, altogether 22 campuses at the community level, and construct the top elementary school dummy for each property.[11] We emphasize the quality of elementary schools because enrollment is based on housing locations. In contrast, enrollment in secondary schools and beyond is merit-based.

Infrastructure: As the role of subways becomes more important in larger, high-density, public transport cities, we obtain geo-coded subway station data from the web-scraped Gaode POI dataset for the years 2012-2017, with manual additions[12] for 2018 and 2019.

Economic growth: To best capture neighborhood time-varying economic growth, we use nighttime light intensity by processing satellite data from Chen et al. (2020).

Urban planning: We use geo-coded records from the Chinese Land Transaction Monitoring System[13] to analyze changes in local urban planning. This system tracks the sale of land parcels across China, providing detailed information on the location and intended use of each parcel. By aggregating the number of land parcels sold by land-use types (e.g., residential, commercial, industrial) to the neighborhood-year level, we capture trends and shifts in local urban development patterns.

Demographics: We calculate the neighborhood mean population from the interpolated population census data from Worldpop.[14]

These auxiliary data sources help control for factors at both the granular property level and the neighborhood level that may influence house prices and the provision of consumption services, allowing for a more robust analysis of the relationship between food delivery services and the valuation of consumption services.

2.4 Variable Definitions and Summary Statistics

Walkable and Deliverable Consumption Services. We define "walkable" consumption services as the DZDP establishments within a 1km buffer of each property, which is a 10 to 12-minute walk. We define "deliverable" restaurants as those offering delivery service as an option within the 2-5km buffer of each property. The quantities of walkable and deliverable consumption services are calculated as the total number of establishments within the 1km or 2-5km buffers for each property. The quantity of walkable consumption services is calculated annually for 2012 through 2019. That of deliverable consumption services is computed annually

[11] There is no official ranking of all elementary schools. We follow Cheshire and Sheppard (2004) and focus on the set of "known" star schools.

[12] We use various data sources including BaiduBaike and subway maps.

[13] https://www.landchina.com/, accessed on Jun 15, 2022.

[14] https://hub.worldpop.org/, accessed on Dec 4, 2022.

from 2015 to 2017, because the FDS industry expanded in late 2014 and DZDP only provides delivery information for up to 2017.

Diversity of Consumption Services. We use the fractionalization index to measure the diversity of all consumption services. The index is defined as $\mathrm{Frac}_i = 1 - \sum_c \pi_{ic}^2$, where π_{ic} denotes the proportion of the number of establishments in category[15] c to the total number of establishments in all categories within a 1km buffer around the property i. The value of Frac_i ranges from 0 to 1 by construction, with a larger value indicating a higher diversity of establishment categories within walking distance. The fractionalization index is a suitable measure for diversity because it takes into account both the number of different categories and their relative abundance (Montalvo and Reynal-Querol, 2005; Eberle et al., 2020).

Cuisine Diversity. We use the number of delivery-accessible cuisine types as a proxy to capture the impact of food delivery platforms on the diversity of accessible restaurants. In the monopolistically competitive restaurant industry, a higher number of restaurants is expected to result in a more differentiated product offering, with the number of restaurants itself serving as a measure of product diversity. Data limitations mean we cannot identify the specific dishes offered by each restaurant.

While the number of restaurants serves as a proxy for product diversity, the number of cuisine types provides a broad indication of market diversity. It is important to note that the latter is a relatively coarse measure that may not fully capture the granular variations in product offerings, as two restaurants within the same cuisine type may still offer significantly different dishes. Therefore, we distinguish between "product diversity", which encompasses the variety of dishes offered, and "cuisine diversity", which refers to the number of distinct cuisine types available.

In the absence of more detailed data on individual dishes, we rely on the number of cuisine types as a proxy measure to assess restaurant diversity. However, we interpret the results with caution, acknowledging that this measure may not fully capture the true extent of product diversity in the market.

Restaurant Quality and Price. To assess the average restaurant quality and price levels accessible via FDS, we employ the best available data. However, both proxies have notable data limitations, which we discuss in detail in Appendix A2.1.

Table 1 presents summary statistics for key variables in our sample of 762,667 housing transactions across 239 neighborhoods. The table is organized at the property and neighborhood levels, respectively. Summary statistics are calculated for the years 2012, 2015 (the year of FDS national expansion), and 2019. The transaction price of an average property

[15] The list of these categories is presented in Section 2.3.

went up from two million RMB to five million RMB between 2012 and 2019. There is also a sharp increase in the provision of consumption services during the sample period, with the number of walkable restaurants around a typical property increasing almost six times.

3 Estimation Methodology

We begin with a standard hedonic price function with panel fixed effects and discuss the potential empirical challenges related to multicollinearity, interactions, and identification bias. We then demonstrate how we employ rich and granular data with nonparametric estimation to descriptively quantify the hedonic premium of the quantity and diversity of all consumption services. Finally, we present our instrumental variable approach that exploits the sudden expansion of food delivery services to identify the hedonic premium of deliverable consumption services.

3.1 Baseline Model

We begin with the following hedonic price function with two-way fixed effects (TWFE):

$$\ln p_{int} = \alpha S_{it} + \beta D_{it} + X_{it}\gamma + W_{nt}\delta + \mathrm{nbhd}_n + \mathrm{ym}_t + \varepsilon_{int} \tag{1}$$

where p_{int} represents the unit transaction price of property i in neighborhood n in year t over the period of 2012-2019. S_{it} is the standardized number of all consumption service establishments within walking distance of property i (quantity), and D_{it} is the standardized fractionalization of total consumption services within walking distance, indicating the diversity of service establishments around property i.

X_{it} captures observable housing features at a granular level, including both physical attributes and locational characteristics. The standard hedonic model emphasizes housing attributes,[16] but studies have increasingly highlighted the importance of locational features (Cheshire and Sheppard, 1995; Gibbons and Machin, 2008). To account for these locational features, we include several property-level measures. First, we incorporate property-level particulate matter 2.5 (PM2.5) to capture the significant effects of air quality on housing markets, as revealed by recent studies (Chay and Greenstone, 2005). Second, to better capture the impact of top elementary schools on housing values (Cheshire and Sheppard, 2004; Chan et al., 2020), we generate a dummy variable indicating whether a property falls within the catchment area of one of the top 15 elementary schools in Beijing. Finally, we generate three dummies to indicate whether there are subway stations specifically within 500m, 500-1000m,

[16] We include the following housing physical attributes: the logarithms of internal floor area, age, age square, floor level, number of bedrooms, building height, and internal condition.

and 1000-1500m distance bands to create nonlinear measures of this increasingly valued infrastructure (Xu et al., 2015; Du and Zheng, 2020).

In addition to accounting for the significant demand for urban features at the property level, we include a vector of observable time-varying characteristics (W_{nt}) at the neighborhood level to capture people's willingness to pay for specific property locations. Nighttime light intensity serves as a proxy for local economic development (Henderson et al., 2012; Nordhaus and Chen, 2015), while three types of land auctions reflect city expansion and gentrification. We also incorporate neighborhood-year level population data to capture potential changes in local demand. Our preferred specification includes neighborhood and year-month fixed effects. The error term is denoted by ε_{int}, and we cluster standard errors at the neighborhood level to address potential spatial correlations within neighborhoods.

To address potential omitted variable concerns, we collect data on property- and neighborhood-level observables in a considered way trying to reflect the findings of past studies. Changes in neighborhood nighttime lights, land use patterns, and population can capture potential omitted local trends such as gentrification. The neighborhood fixed effects also aid in identification at a fine granularity. For example, neighborhoods are generally the spatial units delineating social benefit eligibilities. Hence, our coefficients of interest, α and β, are less likely to be confounded by other neighborhood amenities.

There are two remaining empirical concerns specific to our research question. The first relates to the multicollinearity and interaction between the quantity and diversity of consumption services. Given the high-dimensional nature of housing characteristics and locational features, multicollinearity can inflate the variance of the coefficient estimates, making the key estimates unstable and difficult to interpret. Moreover, we are interested in how the interaction between quantity and diversity of consumption services affects house prices. The TWFE specification would require manually creating interaction terms and specifying functional forms. Thus, we use the non-parametric Random Forest model to improve our estimates. We discuss the details in Section 3.2.

Lastly, our estimates may still be biased by omitted variables. We do not have data to measure neighborhood time-varying crime and safety trends, which may affect both house prices and establishment openings. While we are unable to tackle this bias in the estimation of all types of consumption services, we exploit the sudden expansion of FDS to identify the hedonic pricing of deliverable consumption services. We discuss the details of this IV strategy in Section 3.3.

3.2 Nonparametric Method: Random Forests

We implement Random Forest in addition to the TWFE specification to address the potential multicollinearity concern and uncover the interaction between the quantity and diversity of consumption services in a flexible manner. The Random Forest algorithm is an ensemble learning method, which combines multiple decision trees to make predictions, and is effective in detecting nonlinear structures (Tabuchi and Yoshida, 2000; Huck, 2009, 2010; Krauss et al., 2017). Compared to our TWFE models, the Random Forest algorithm is less sensitive to multicollinearity because it uses a random subset of features for each split in the trees. The tree-based structure allows the algorithm to model complex interactions. We rely on it to automatically capture the interaction between the quantity and diversity of consumption services without the need to explicitly specify them. We discuss the implementation details in Appendix A1.

3.3 Valuing Deliverable Consumption Services: An Instrumental Variable Approach

3.3.1 IV Construction

The swift growth of food delivery services enables us to overcome the limitations in establishing a causal relationship between consumption services and house prices by focusing on delivery-accessible restaurants. We employ an adaptation of the Bartik shift-share IV approach to identify the causal effect of deliverable consumption services on house prices, conditional on walkable consumption services. The instrumental variable exploits two sources of variation, as shown in Equation 2: i) aggregate time variation in the FDS sector and ii) cross-sectional variation in pre-existing consumption services across locations.

$$Z_{it} = g_t \times r_{i,2012} \quad (2)$$

As discussed in Section 2.2, the explosive national expansion of FDS platforms occurred at the end of 2014 when it engaged in and won an intensely competitive battle between internet giants. The timing of this growth is likely uncorrelated with the FDS growth across Beijing neighborhoods, making it a suitable time-varying ‘shift’ component of our IV, denoted as g_t. For the instrument’s cross-sectional ‘share’ component, we count the total number of restaurants within the 2-5km radius of each property in 2012 (the first year of our sample period), denoted as $r_{i,2012}$. As existing restaurants had an advantage over new entrants in offering delivery services, $r_{i,2012}$ serves as a proxy for the potential number of delivery-accessible restaurants around property i following the FDS expansion.[17]

In summary, the instrument $Z_{it} = g_t \times r_{i,2012}$ operates as follows: The national trend in FDS market size (g_t) predicts the annual growth of delivery-accessible provisions across Beijing, while the number of pre-FDS restaurants around each property ($r_{i,2012}$) distributes this aggregate

[17] To test the robustness of our results, we explore two alternative definitions of the “share” component in the instrument. These alternative definitions and their results are discussed in detail in Section 4.2.5.

growth to each property. Therefore, Z_{it} serves as a predictor for the annual provision of delivery-accessible restaurants around each property from 2015 onward.

To reveal people's valuation of deliverable consumption services, we model the premium on house prices using the following specification:

$$DCS_{int} = \xi Z_{it} + X_{it}\gamma + W_{nt}\delta + \text{nbhd}_n + \text{ym}_t + \epsilon_{int} \tag{3}$$

$$\ln p_{int} = \alpha WCS_{it} + \beta \widehat{DCS_{it}} + X_{it}\gamma + W_{nt}\delta + \text{nbhd}_n + \text{ym}_t + \varepsilon_{int} \tag{4}$$

where Equation 3 represents the first-stage regression, and Equation 4 represents the two-stage least squares (2SLS). Z_{it} denotes the Bartik instruments constructed as defined in Equation 2. In the context of restaurant accessibility, DCS_{it} denotes the observed number of delivery-accessible restaurants within a 2-5km radius of each property, capturing the area served by delivery services. Meanwhile, WCS_{it} accounts for the count of restaurants within walking distance, defined as a 1km buffer around each property. When assessing the hedonic premium of cuisine types, quality, and prices, these two variables are replaced by their corresponding measures. The error terms ϵ_{int} and ε_{int} correspond to the errors from the first-stage and second-stage regressions, respectively. The model design is consistent with the baseline hedonic price model discussed earlier, incorporating the same housing physical attributes, property-level locational features, and neighborhood-level characteristics.

3.3.2 Identifying Assumptions and Supporting Evidence

In this section, we discuss the key assumptions for the validity of our instrumental variable (IV) approach: first-stage predictability and the exclusion restriction. First-stage predictability follows from the idea that locations with more restaurants before the advent of FDS technology will have higher numbers of delivery-accessible restaurants post-FDS. Related to this, these locations may also have more cuisine types. Similarly, the average quality and price of delivery-accessible restaurants may also change as a mechanical result of increased accessibility. The first-stage regression results (Panel A of Table 4 and Appendix Table A4), which we discuss further in Section 4.2, demonstrate the validity of this assumption so reassuring us that it is valid as an instrumental variable for this purpose.

Regarding the exclusion restriction, recent literature on shift-share instruments suggests that either the 'shift' or 'share' component can be independent of the error term under certain assumptions (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In our design, we argue that the timing and growth trends of the national FDS expansion, which constitute the 'shift' component, are driven by intense competition among internet oligopolies seeking to capture greater market share nationwide. The pre-existing spatial variation in the provision of restaurants across Beijing neighborhoods then serves as the 'share' component, determining how the common shock of national expansion is distributed across these neighborhoods.

In our panel setting, the crucial assumption is that the differential local exposures to the common national expansion of FDS are uncorrelated with house price growth trends across Beijing neighborhoods without FDS. In addition to the previously discussed endogeneity concern of not having data on local crime rates, another potential issue is the spatial correlation of amenity provision. For instance, the number of restaurants within a 2-5km radius of a property may be correlated with the number of restaurants within its walking distance of 1km or other unobserved local characteristics that contribute to the house price premium. The direction or functional form of this spatial correlation for all the transaction properties cannot be quantified.

To address potential bias arising from this unobserved spatial correlation, we exploit the availability of pre-FDS expansion housing transaction data to conduct falsification tests. Specifically, we examine whether the future provision of deliverable consumption services for properties transacted during the pre-FDS period (2012-2014) is correlated with concurrent house price changes. If our identification strategy is valid, we expect to find no significant relationship between the future provision of deliverable consumption services and house price changes in the pre-FDS period.

To do so, we first regress the logarithms of property transaction prices on time-varying property-level features, year-month fixed effects, and neighborhood fixed effects to obtain the price residuals for 2012-2014. We then calculate the median and mean values of residual house prices, neighborhood-level characteristics, and the three types of consumption services within walking distance for each year from 2012 to 2014. The neighborhood-level price residuals essentially capture the unobserved components of location prices.

To assess the hypothetical impact of FDS on these pre-FDS transacted properties, we compute the potential delivery-accessible restaurants, cuisine types, average quality, and price, assuming that FDS were available in 2012-2014. By aggregating all variables to the neighborhood median and mean level,[18] we then regress the change in house price residuals between 2012 and 2014 on this measure of their hypothetical quantity, diversity, quality, and price of deliverable consumption services in 2015. This analysis allows us to examine whether the future provision of deliverable consumption services is correlated with house price changes during the pre-FDS period.

Table 2 presents the results from OLS and IV specifications using neighborhood median and mean values for the quantity of delivery-accessible restaurants. The OLS estimates in Columns 1 and 3 show that the hypothetical 2015 quantity of deliverable consumption services is not correlated with the 2012-2014 change in local median house prices, but is negatively correlated with the change in mean house prices. However, when we instrument the 2015

[18] As the housing transaction data includes both repeated sales and properties sold only once, we aggregate the level of analysis to the neighborhood level to track changes in local house prices over the pre-FDS period.

delivery-accessible restaurants using the neighborhood aggregate of the Bartik IV, the relationship becomes insignificant for both median and mean house prices, with smaller coefficients compared to the OLS estimates (Columns 2 and 4). These findings suggest that the future provision of deliverable consumption services does not systematically influence house price changes during the pre-FDS period, supporting the validity of our identification strategy.

Appendix Table A1 demonstrates that these patterns also hold for neighborhood means and medians of delivery-accessible cuisine types, average quality, and price. These results further support the validity of our instrumental variable approach by confirming that not only the quantity but also the diversity, quality, and price of future deliverable consumption services are not correlated with concurrent house price changes.

4 Valuing Walkable and Deliverable Consumption Services

Building upon the methods outlined in the previous section, we present our empirical findings in two parts. First, we examine the valuation of consumption services within walking distance, defined as being within 1km of a property. We focus on three key aspects: the quantity (measured by the number of service establishments), diversity (assessed using the fractionalization of all consumption services), and their interaction. To better investigate potential interactions between quantity and diversity, we employ the nonparametric random forest algorithm, which allows for a more flexible and data-driven approach to capturing complex relationships.

We then proceed to investigate the causal effect of deliverable consumption services on house prices using the Bartik IV approach. By leveraging the exogenous variation in the provision of delivery-accessible restaurants across locations, we can identify how the FDS-enabled access to deliverable consumption services affects house prices. We disentangle the accessibility, competition, and long-term effects of the FDS, as well as exploring other potential channels at work and heterogeneity. This approach enables us to provide robust and comprehensive estimates of the causal impact of deliverable consumption services on property values.

4.1 Valuing the Quantity and Diversity of Walkable Consumption Services

4.1.1 TWFE Estimates

Table 3 presents the estimation results for various specifications of Equation 1, focusing on the effects of quantity, diversity, and their interaction on house prices. Column 1 shows that, conditional on the full set of controls and fixed effects, house prices are not correlated with the number of nearby service establishments. In contrast, Column 2 reveals a significant and positive correlation between house prices and the diversity of nearby consumption services. Just more nearby service establishments do not appear to be a valued amenity but more local variety is. Specifically, a one standard deviation increase in the fractionalization index is associated with a 0.6% increase in house prices. The magnitude and statistical significance of these coefficients remain unchanged when both measures are included simultaneously (Column 3).

To explore potential interactions between quantity and diversity, we include the product of the standardized quantity and diversity measures in Column 4. However, the interaction term is statistically insignificant, presenting what appears to be a puzzle that we investigate further using the nonparametric Random Forest analysis.

4.1.2 Using Random Forest to Investigate the Interaction between Quantity and Diversity

The results of the nonparametric Random Forest method exploring potential nonlinearities in the relationship between house prices and the quantity, diversity, and interaction of consumption services within walking distance are discussed in Appendix A1. They are not reported in detail here since they largely confirm the TWFE result. Specifically they indicate that higher house prices are primarily driven by a greater diversity of consumption services rather than the quantity of service establishments. Conditional on the variety of consumption services, an increase in the count of service establishments almost always reduces house prices. This finding suggests that residents value greater variety in consumption services, while the quantity itself is not utility-enhancing.

4.1.3 Robustness and Sensitivity

We further investigate the robustness of our findings by conducting sensitivity checks on the TWFE specifications. Specifically, we address potential concerns about the completeness of the consumption services data in earlier years by limiting the sample period to later years when most vendors would have been listed on DZDP, the data platform for our consumption services measure. We re-run the regression for our baseline sample period (2012-2019) to evaluate the effect of consumption services on house prices using the quantity and diversity measures. We then limit the sample periods to 2013-2019, 2014-2019, and 2015-2019. These results are shown in Table A2 in the Appendix. We find that the signs and magnitudes of our coefficients of interest are similar to the baseline results. This indicates that our findings are robust and not affected by data-related concerns.

4.2 Valuing Deliverable Consumption Services

We now turn our attention to the valuation of deliverable consumption services. In this section, we present IV estimates to address potential endogeneity concerns and quantify the impact of deliverable consumption services on house prices. Furthermore, we investigate the potential channels through which this effect operates, including enhanced accessibility, intensified competition among restaurant service providers facilitated by FDS, and better matching of preferences, as proposed in Section 2.2.

4.2.1 Valuing Delivery-Accessible Restaurants

We begin by presenting the first-stage results of our IV estimation (Equation 3) in Column 1 of Table 4 Panel A. The result shows that our instrument effectively predicts the provision of deliverable consumption services. Having a higher stock of restaurants in the delivery range before the advent of FDS increases the number of restaurants available through delivery platforms after the introduction of FDS.

Next, we proceed with the two-stage least squares (2SLS) regression (Equation 4) in Panel B Column 1, examining the hedonic premium for the count of delivery-accessible restaurants. A one standard deviation (813) increase in the number of restaurants accessible through food delivery apps within a 2-5km radius leads to a 7.1% increase in property values, equivalent to 3,357.03 RMB per m^2 for an average property. The magnitude of this price premium is comparable to the presence of half an additional tournament superstar school in Shanghai (Chan et al., 2020). When comparing our results to the estimated hedonic premium of the concurrent technology platform Airbnb (e.g., Garcia-López et al., 2020; Barron et al., 2021), we find that the impact of enhanced food delivery services on house prices is similar in scale.[19] However, it is important to note that this comparison is intended to provide a sense of scale rather than directly compare the impacts of different platforms, as the mechanisms underlying food delivery services and house-sharing platforms are fundamentally different.

We can further explore the quantitative impact of food delivery services on house prices through a back-of-the-envelope calculation assuming an average apartment size of 80 m^2. Each additional restaurant accessible via FDS is valued at 3,357*80/813 = 330 RMB in total house price. Given the average delivery cost of 6 RMB per order, this premium is equivalent to approximately 55 restaurant trips saved. If a household orders approximately four delivery meals per month through FDS, they would recoup this premium in slightly over one year. However, it is important to note that this interpretation is over simplified, since it attributes the entire effect to accessibility and ignores potential heterogeneity in household preferences and the valued increase in product variety. We return to this discussion in Section 4.2.3.

To illustrate how our IV estimates address potential bias in the OLS specification, we present both OLS and IV estimates in Appendix Table A3. The OLS estimate in Panel A of Column 1 are substantially smaller than the corresponding IV estimate, suggesting the presence of endogeneity. One potential source of bias is unobserved location characteristics. Consider a scenario where a location has undesirable features that are unobservable to researchers (e.g., high rates of petty crime) and also has limited access to restaurants. However, suppose this

[19] Our point estimate can be re-estimated using a log-log specification, which indicates that a 100% increase in deliverable amenities leads to a 2.4% increase in house prices. To provide context, in the Airbnb literature, Barron, Kung and Proserpio (2021) reports a similar estimate of a 2.6% increase in house prices for a 100% increase in Airbnb listings, while Garcia-López et al. (2020) estimates a semi-elasticity of 3.1%.

location is situated 3km away from a desirable street with attractive restaurants and grocery stores. With the introduction of FDS, the access to deliverable consumption services for this location improves, increasing house prices within it. In this case, the OLS estimate will attenuate the true effect due to the presence of the unobserved, undesirable location features that are negatively correlated with the provision of deliverable consumption services.

4.2.2 Food Delivery Service, Accessibility and Competition

As argued in the conceptual framework, Section 2.2, the IV baseline coefficient of 0.071 can be decomposed into three main components: the sudden increase in demand-side accessibility in 2015 (short-term), its longer-term effect (2016-2017), and the FDS-intensified supply-side competition. To decompose this coefficient into these three channels, we modify the baseline IV specification (Equations 3 and 4). In Column 2 of Table 4, we limit the sample to 2015. This specification yields the short-term demand-side accessibility effect in the year of FDS national expansion, which is 0.292.

Next, in Column 3 of Table 4, we run the IV specification using the full sample (2015-2017) but fix the treatment intensity to its 2015 level. This approach allows us to isolate the supply-side competition channel. We assume that the number of delivery-accessible restaurants only begins to change after 2015 due to FDS-induced competition. Under this assumption, the 2016 and 2017 levels of delivery-accessible restaurants reflect the equilibrium outcomes of both demand-side accessibility and supply-side competition. As a result, the Column 3 estimate captures both the short-term accessibility effect and the long-term effect, which is 0.129. Comparing the estimates from Columns 2 and 3 reveals that, over the longer run, the initial accessibility effect diminishes.

Furthermore, by comparing the coefficients across all three columns, we can infer the direction and magnitude of the supply-side competition effect. The difference between the baseline coefficient in Column 1 and the sum of the short-term accessibility effect (Column 2) and the long-term effect (Column 3 minus Column 2) represents the supply-side competition effect. This comparison suggests that the supply-side competition effect is negative, indicating that the national expansion of FDS leads to a "crowding out" in the number of restaurants. In other words, the increased competition among restaurants due to FDS led to a reduction in the overall number of delivery-accessible restaurants.

It is crucial to recognize the potential limitations of our decomposition approach. First, the channels we have identified may not be exhaustive. Although we have used varying neighborhood night time lights to control for varying incomes, there could still be other mechanisms through which FDS affects house prices that we have not accounted for. Second, the dynamics among the three channels – short-term accessibility, long-term effect, and supply-side competition – are likely to be more complex than the simple algebraic decomposition assumes. Despite these limitations, this exercise provides valuable insights into the key channels through which FDS influences house prices. It allows us to assess the relative importance and direction of each effect, contributing to a more comprehensive understanding of the impact of FDS on the housing market.

To illustrate the accessibility mechanism further, we explore heterogeneous effects across properties with different initial accessibility to restaurants within walking distance. We split the sample into three sub-samples based on the property-level accessibility to restaurants within walking distance in 2012. The results, presented in Table 5 Panel A, reveal that the hedonic premium is larger for properties with initially low counts of restaurants within walking distance, indicating that people place a higher value on deliverable consumption services in areas that initially lacked access to these services.

This finding provides additional evidence that enhanced accessibility to restaurants is the primary mechanism through which greater FDS exposure increases house premiums. Moreover, FDS can help mitigate spatial inequality in amenities provision by offering access to a wider variety of dining options in previously relatively underserved areas. On the other hand, neighborhoods with the highest initial amenities may already have a wide variety of dining options within walking distance. In these areas, the convenience and variety offered by FDS may not provide a significant additional benefit. As a result, the valuation of deliverable amenities in these neighborhoods is lower, as the marginal utility gained from FDS is diminished.

Next, we examine how the valuation of delivery-accessible restaurants varies across distance bands. To avoid confounding coefficients, we exclude the 500m ring from our analysis and focus on the 0.5-2km range as our reference distance band for consumption services within walking distance. For the remaining distance ranges, we split the deliverable distance into 1km increments and include the 5-10km range for comparison. The specifications are similar to the previous regressions. Specifically, within the 2-3km distance band, we create a new treatment variable that measures the number of restaurants accessible through food delivery apps within this range. We also use the number of restaurants within the same 2-3km range from 2012 as the share component of the instrument. We then estimate IV regressions for the post-FDS periods (2015-2017) to assess the impact of deliverable services. For comparison, we run two-way fixed-effects regressions for the number of restaurants within the same distance bands for the pre-FDS periods (2012-2014). This approach allows us to analyze how the expansion of FDS affects people's valuation of restaurants across different distance ranges.

Figure 3 presents the results of this analysis. The blue solid line represents the two-way fixed-effects regression coefficients for the standardized number of restaurants within different distance bands for the pre-FDS period (2012-2014). The red dashed line illustrates the IV regression coefficients for standardized restaurants accessible through food delivery apps within different distance bands for the post-FDS period (2015-2017), using the corresponding share component of the instrument. The figure reveals that the FDS expansion significantly enhances the valuation of restaurants within the delivery range, with the highest valuation observed within the 3-4km band. This finding supports our reasoning that the availability of food delivery allows people to enjoy dining options from more distant locations, capturing the impact of these services on property values through enhanced accessibility to consumption services.

4.2.3 Other Potential Impacts

In addition to the primary effects of enhanced accessibility, we explore other potential factors that may contribute to the increase in property values associated with FDS.

Variety and Household Size. Given consumers' love for variety and the fact that tastes may vary between individuals, one would expect larger households would value more highly a wider range of choices. To test this we examine how the hedonic premium of FDS varies across properties with different numbers of bedrooms. Since we already control for the total floor area of apartments, we should have offset for any household income effect to focus on a specific proxy for household size. Consistent with this expectation the estimates in Table 5 Panel B suggest that properties with more bedrooms place higher hedonic premiums on greater restaurant choices. The coefficient for properties with 3 or more bedrooms is 0.077 (significant at the 1 percent level), 40% larger than that for properties with only 1 bedroom (0.54, significant at only the 5 percent level).

Internal Conditions and Appliances. We also investigate whether the value of increased accessibility to delivery restaurants varies across households that purchase properties with different kitchen conditions. We infer this using the property renovation conditions: bare shell/unfinished apartment, finished without appliances, and finished with appliances. Table 5 Panel C shows that finished properties without appliances have the highest hedonic premium on greater accessibility to delivery restaurants. This suggests the advent of convenient home delivery reduced the value of a fully fitted kitchen.

Other attributes of delivery accessible consumption amenities. We also investigate the impact of food delivery services on other attributes of delivery-accessible consumption services, such as cuisine diversity, quality, and price. Our analysis suggests that while food delivery services increase the cuisine diversity and average quality of delivery-accessible restaurants, there is no statistically significant hedonic premium associated with these attributes. However, these results should be interpreted with caution due to potential limitations in the measures used and data constraints. For a detailed discussion of these findings, including the first-stage and 2SLS results, falsification tests, and limitations, please refer to Appendix Section A2.2.

In summary, our exploration of additional impacts suggests that factors such as household size and kitchen conditions play a role in the relationship between FDS and property values.

FDS increased the cuisine types and quality accessible to households and lowered the average price. Moreover, the impact of FDS extends beyond just restaurants and their value, as it also influences the physical form of apartments and household appliances. The reduced value of well-equipped kitchens in the presence of FDS highlights how this technology is reshaping not only consumption patterns but also the design and amenities of residential properties. While the evidence for these channels is not as strong as that for enhanced accessibility, they provide valuable insights into the complex ways in which FDS can influence housing markets, the physical form of apartments and interact with household preferences.

4.2.4 Neighborhood Heterogeneity

Having established the overall impact of deliverable services on property values, we now turn to how valuations vary with demographic and economic characteristics. We split the sample into five sub-samples according to the characteristics of neighborhood quintiles in the initial year (2012). Table 5 presents the results, with Columns 1 to 5 representing quintiles from the lowest to the highest.

We explore the role of demographics in Panels A and B. Panel A focuses on population density, revealing that the valuation for deliverable services is only significantly positive in neighborhoods with the highest population densities (Column 5). This finding suggests that the premium is substantial in large markets with sufficient demand. Moreover, the results indicate that in denser neighborhoods, where space in houses is more expensive, the value of saving kitchen space is higher. Panel B examines the heterogeneity by day-night population difference, calculated using cross-sectional mobile phone pin data. This measure computes the difference between daytime and nighttime populations, with lower values proxying for more residential neighborhoods and higher ones indicating business neighborhoods (Miyauchi et al., 2021, 2022). The results show that the premium is particularly high in purely residential neighborhoods and neighborhoods with significant business characteristics but not in those with the biggest day-night population variations.

Lastly, we examine the role of economic characteristics in Panel C, using nighttime light as a proxy for income: brighter nighttime light indicating higher neighborhood incomes. The results show that the premium on house prices is higher in wealthier neighborhoods, consistent with the idea that demand for FDS and variety is income elastic, making it a more popular choice in affluent areas.

4.2.5 Robustness and Sensitivity

To ensure the reliability of our baseline findings, we conduct two sets of robustness checks. The first set, presented in Appendix Table A5, addresses concerns related to property construction, treatment variable measurement, and potential confounders. We begin by excluding properties built after 2012, our starting year of study, to mitigate the influence of property construction in response to the increasing dispersion of consumption services. The coefficients in Column 2 show a slightly larger magnitude following this adjustment. Next, we investigate whether the results change when we fill in missing values for the number of restaurants accessible through food delivery apps to extend the sample period to include the pre-FDS period (2012-2014).[20] The results in Column 3 show a relatively large deduction compared to the baseline results in Column 1 but remain significantly positive.

To address the potential confounding effect of a property's location relative to a city's sub-center in the context of poly-centric urban structures, we calculate the brightest location for each district in Beijing using nighttime light satellite data and compute each property's distance to the district's sub-center. We include this measure as a new control to capture the potential premium from proximity to a city's sub-center. Additionally, we control for the number of firms and employment at the neighborhood-year level using firm registration data to account for the level of industrialization. The results in Columns 4 and 5 incorporate these potential confounding factors and are found to be similar to our baseline results.

The second set of robustness checks, presented in Appendix Table A6, focuses on alternative measures for the share component of the instrument in the baseline IV regression. Column 1 presents the baseline IV regression outcomes, while the remaining columns utilize the new definitions. We first keep only types of restaurants that also exist in the 2015 deliverable options, such as fast foods,[21] with results shown in Column 2. To further consider the different proportions of each category, we compute the proportion of certain categories among all restaurants accessible through food delivery apps in 2015 and multiply this by the number of that type in the initial year to construct the "weighted" share component. The results in Columns 2 and 3 suggest that using different constructions of instruments does not significantly disturb our findings.

In summary, these two sets of robustness and sensitivity tests confirm the consistency of our baseline findings across changes in sample periods, potential confounders, and alternative measures for the treatment variable and share component, reinforcing the reliability of our results.

5 Conclusion

Cities are about consumption as much as they are about production. The latter, however, has been much more thoroughly studied. Variety was always cited as the main source of agglomeration economies in the consumption of goods: until five years ago London, for example, had not one but two specialist shops selling nothing but buttons. While popular

[20] Recall that our sample period for estimating deliverable amenities is 2015-2017, because the delivery information on DZDP establishments is null before 2015.

[21] This allows us to construct the "selected" share component, defined as the number of delivery-accessible restaurants whose cuisine type existed in the 2015 deliverable options.

history associates the Sears mail order catalogue as the pioneer in the late 19^{th} Century, mail order started a good three decades earlier. Amazon and its international look alikes revolutionized the process with the introduction of ecommerce just 30 years ago. London's shop, the 'Button Queen', now operates from a warehouse in a small town in Wales.

This paper investigates a much more recent phenomenon transforming consumption in cities: home delivery of consumption services – specifically restaurant meals – powered by similar technology to ecommerce. Domino Pizza may have pioneered a technologically unsophisticated home delivery service but platform-based systems – introduced in China very quickly between 2014 and 2016 – suddenly brought meals prepared in almost any restaurant in Beijing directly to people's homes. Unlike durable goods, however, restaurant meals deteriorate quite rapidly meaning the effective range of any restaurant, the diameter of its market area, is still limited.

We utilize a unique combination of over 0.7 million property transaction records and millions of service establishment data collected from a major property listing website and the largest review and rating app in China. This data allows us to estimate the positive and significant impact of walkable consumption services on property prices. We analyze this impact both in terms of their quantity (number of service establishments) and diversity (fractionalization of total consumption services).

The sudden expansion of FDS makes it possible to employ an IV approach to identify the causal effect. Our findings indicate that a one standard deviation increase in restaurants accessible through food delivery apps within a 2-5km radius leads to a 7.1% increase in property values, equivalent to 3,357.03 RMB per unit for an average property. We also explore the valuation of restaurant-deliverable meals across distance bands, further confirming the importance of food delivery services in enhancing property values after the expansion of FDS. We also find more far reaching impacts. Larger households value diversity of deliverable-restaurant meals more highly; the advent of FDS reduces the value of well-equipped kitchens and also increased property prices in those areas less well served by restaurants within walking distance, smoothing the urban rent surface. Not so surprisingly, the value attached to FDS is also larger in more residential, and wealthier neighborhoods.

The technological transformation of access to a wide range of consumer services is changing cities. It may smooth out access to things like top level sports, concerts or restaurant meals but it does not replace them. Sears may have brought the goods in Chicago's shops to Deadwood, S.D. but you still had to go to the Windy City to get the shopping experience. Cities continue to have a monopoly on a range of even home-deliverable restaurant meals, and restaurants, on the 'restaurant-experience'. But this paper demonstrates that FDS are still substantially modifying how cities work and not just the spatial pattern of home prices within them but their physical attributes too.

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Figures and Tables

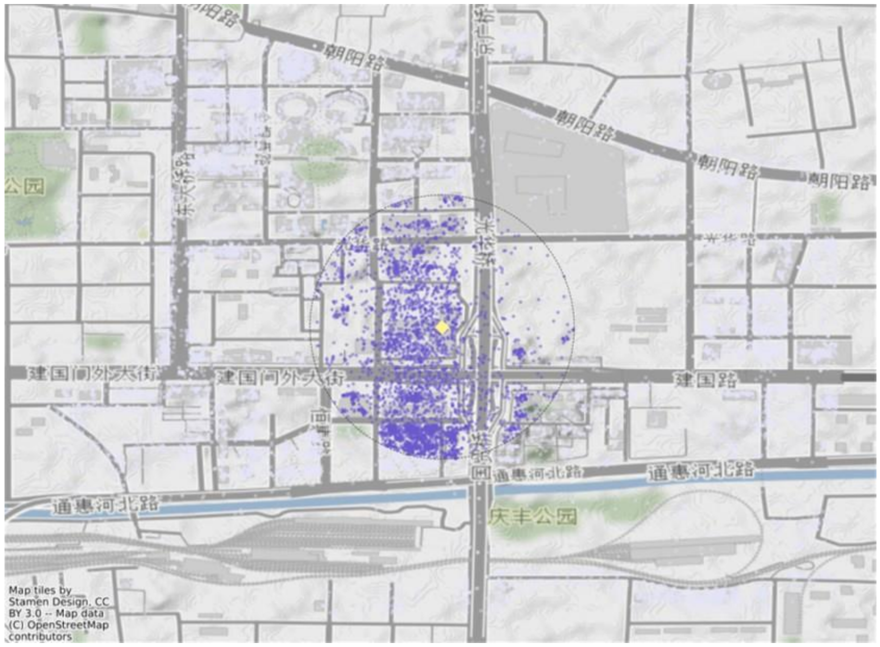
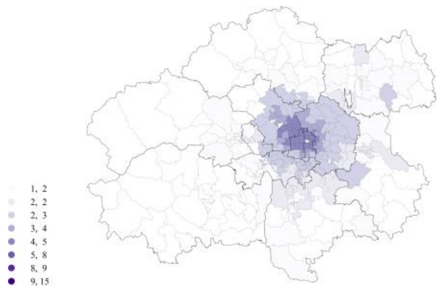
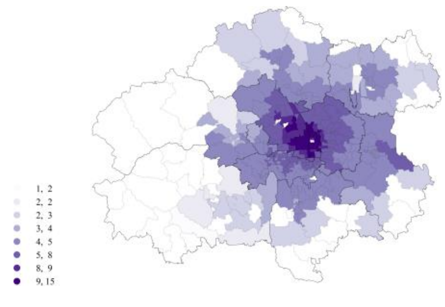


Figure 1: Consumption services near the China World Trade Center, Beijing, 2019

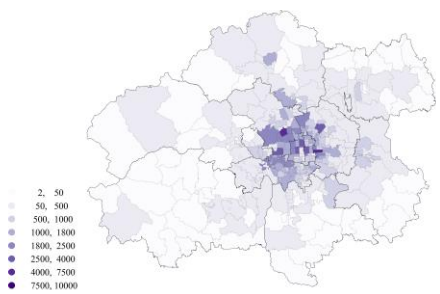
Notes: This figure depicts the spatial distribution of consumption services in the vicinity of the China World Trade Center (*Guomao*) in Chaoyang District, Beijing, using data from *DazhongDianping* (DZDP) for the year 2019. The yellow diamond represents the location of *Guomao*, while the dashed line delineates a 500-meter buffer zone around it. The purple dots indicate the locations of service establishments listed on DZDP within the buffer. These establishments span the following service categories: food and beverage, retail, personal care services, lifestyle and convenience services, entertainment and recreation, home improvement, automotive services, wedding services, childcare services, fitness and wellness, educational services, hospitality, tourism, pet care, and other professional services.



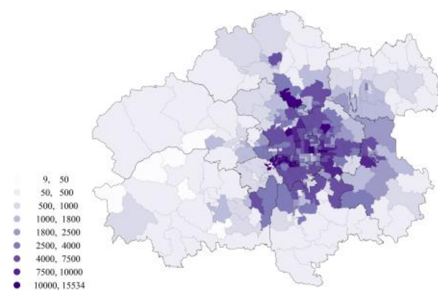
(a) Average transaction price in 2012 (10,000RMB/m^2)



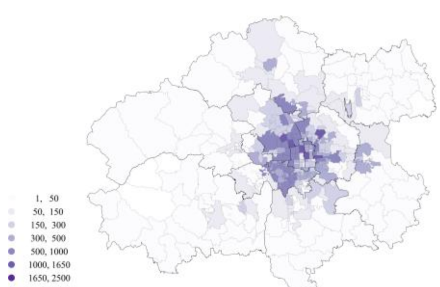
(b) Average transaction price in 2019 (10,000RMB/m^2)



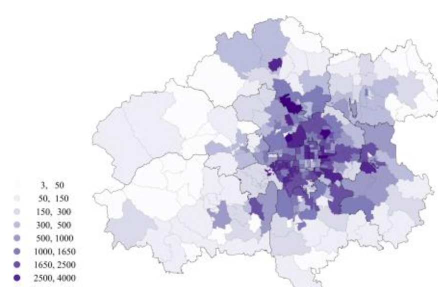
(c) Number of all service establishments in 2012



(d) Number of all service establishments in 2019



(e) Number of restaurants in 2012



(f) Number of restaurants in 2019

Figure 2: Spatial and Temporal Variations in House Prices and Consumption Services across Beijing Neighborhoods

Notes: This set of figures illustrates the spatial and temporal variations in house prices and the distribution of consumption services across neighborhoods in Beijing. The left column depicts the average house transaction price per square meter, the total number of service establishments, and the number of restaurants in 2012, while the right column presents the corresponding data for 2019.

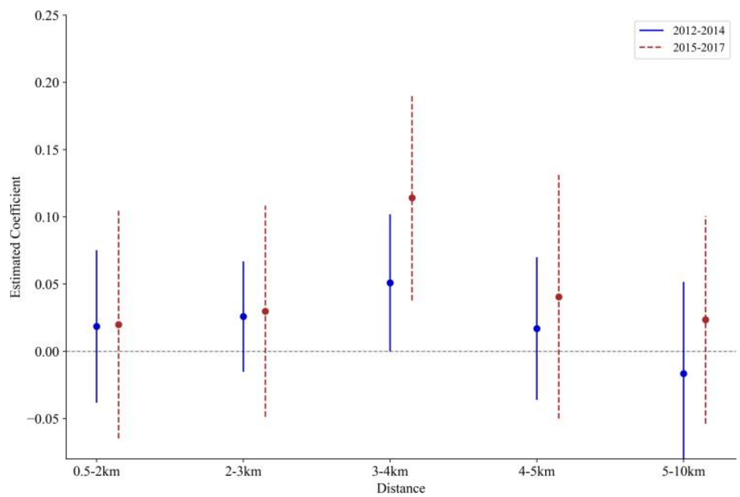


Figure 3: Valuation of Deliverable Consumption Services across Distance Bands

Notes: This figure illustrates the variation in the valuation of deliverable consumption services across different distance bands for pre- and post-FDS periods. The blue solid line represents the coefficients and 99% confidence intervals from a two-way fixed effects (TWFE) specification, which regresses house prices on the standardized number of restaurants within different distance bands for the pre-FDS period (2012-2014). The red dashed line depicts the coefficients and confidence intervals from the IV specification, which estimates the impact of the standardized number of deliverable restaurants within different distance bands on house prices for the post-FDS period (2015-2017). The expansion of food delivery services increases the valuation of restaurants, especially for establishments located beyond walking distance but within the delivery radius.

Table 1: Summary Statistics by Year

Transaction year:	2012		2015		2019	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: Property characteristics						
Total transaction price (10,000 yuan)	198.45	112.99	318.33	211.43	507.46	332.41
Unit transaction price (10,000 yuan per sq.m)	2.49	0.94	3.73	1.51	6.10	2.47
log(unit transaction price)	0.85	0.36	1.24	0.39	1.73	0.38
Floor area (sq.m)	81.68	33.63	86.63	39.74	85.31	43.59
Number of bedrooms	1.97	0.75	2.05	0.78	2.08	0.78
Internal condition (finished or not)	1.02	0.22	3.21	1.02	3.01	1.12
Building age (year)	12.95	8.05	15.11	8.45	18.77	9.33
Floor level	12.82	7.61	13.40	7.83	13.30	7.89
Distance to Tiananmen (kilometer)	13.49	7.48	13.64	7.93	14.16	8.30
Particulate matter 2.5 ($\mu g/m^3$)	93.59	8.61	80.48	5.80	42.01	2.81
Count of subway stations stop within a 500m ring	0.19	0.41	0.28	0.50	0.28	0.52
Count of subway stations within a 500-1000m ring	0.54	0.78	0.79	0.92	0.82	0.98
Count of subway stations within a 1000-1500m ring	0.85	0.97	1.31	1.28	1.35	1.36
Top elementary school (=1 if eligible)	0.02	0.13	0.02	0.14	0.02	0.13
Panel B: Neighborhood characteristics						
Land parcels sold for commercial use	1.27	1.50	0.46	0.75	0.28	0.76
Land parcels sold for residential use	0.63	1.18	0.44	1.06	0.81	2.82
Land parcels sold for public infrastructure use	1.50	2.94	4.48	9.14	0.74	1.61
Nighttime light intensity (neighborhood average)	32.55	10.12	26.35	10.57	31.14	11.95
ln(total population)	11.52	0.77	11.62	0.75	11.75	0.75
Panel C: Surrounding service establishments						
Count of all service establishments within 1km	429.60	546.66	1098.76	931.23	2232.38	2125.13
Fractionalization of all service establishments within 1km	0.73	0.12	0.81	0.05	0.81	0.04
Distance to the nearest restaurant (meter)	276.97	286.65	144.71	150.38	123.67	142.09
Count of restaurants within 1km	161.76	197.55	368.50	320.17	942.65	945.24
Count of delivery-accessible restaurants	/	/	500.09	394.40	/	/
Cuisine types within 1km	0.44	0.30	0.15	0.18	0.22	0.21
Delivery-accessible Cuisine Types	/	/	0.12	0.15	/	/
Quality of restaurants within 1km	0.82	0.53	2.60	0.53	0.06	0.05
Quality of delivery-accessible restaurants	/	/	3.28	0.24	/	/
Price of restaurants within 1km	48.51	37.23	75.99	350.48	376.90	4152.99
Price of delivery-accessible restaurants	/	/	41.67	6.02	/	/
Observations	51010		135094		101757	

Notes: This table presents summary statistics for the key variables used in the baseline regression analysis, focusing on three specific years: 2012 (the first year of the sample period), 2015 (the year of the national food delivery services (FDS) expansion), and 2019 (the last year of the sample period). The variables are organized into three panels. Panel A covers property-level characteristics, including physical attributes and access to local public services. Panel B focuses on neighborhood characteristics that capture the demographic and economic conditions of the local markets. Panel C presents the consumption service variables at the property level, including the quantity and diversity of total service establishments within walking distance, as well as quantity, diversity, quality and price for restaurants within walking and delivery-accessible restaurants within delivery distances. These measures capture the accessibility and variety of local consumption services that may influence property values.

Table 2: Balance of House Price Change before FDS Entry, 2012-2014

Dependent Variable: pre-FDS Δ house price residuals				
	Neighborhood Median		Neighborhood Mean	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Hypothetical Count of Delivery-Accessible Restaurants	-0.005	-0.002	-0.009*	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)
First-Stage F Statistics		1450.511		1551.102
Observations	234	234	234	234

Notes: This table presents evidence that the change in neighborhood house price residuals prior to the entry of FDS is uncorrelated with access to hypothetical deliverable consumption services after FDS expansion. The analysis is conducted in two steps. First, we estimate a TWFE regression of property-level transaction prices on property characteristics, year-month fixed effects, and neighborhood fixed effects for 2012 and 2014. The residuals from this regression capture the variation in house prices unexplained by observable property features or time and location fixed effects. Second, we aggregate these residuals to the neighborhood-year level and calculate the changes in median (Columns 1 and 2) and mean (Columns 3 and 4) residual prices between 2012 and 2014. To measure access to potential deliverable consumption services if FDS were available, we match 2015 (FDS expansion year) delivery-accessible restaurants to properties sold between 2012-2014. The hypothetical count of delivery-accessible restaurants is standardized. Columns 2 and 4 employ a neighborhood-level version of the Bartik instrumental variable (Equation 2). The results show that pre-FDS house price growth is balanced across neighborhoods with varying levels of hypothetical future access to deliverable consumption services, supporting the validity of the identification strategy.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Table 3: Valuing the Quantity and Diversity of Walkable Consumption Services, TWFE

Dependent variable: log of price per square meter (in 10,000 RMB)				
	(1)	(2)	(3)	(4)
Count of All Service Establishments within Walking Distance (Quantity)	-0.004		-0.004	-0.004
	(0.006)		(0.006)	(0.006)
Fractionalization of All Service Establishments within Walking Distance (Diversity)		0.006**	0.006**	0.002
		(0.002)	(0.002)	(0.005)
Interaction of Consumption Service Quantity and Diversity				-0.005
				(0.004)
Observations	762667	762667	762667	762667

Notes: This table presents the TWFE estimates of hedonic premiums associated with the quantity, diversity, and their interaction of walkable consumption services. The analysis follows the Equation 1 specification, which controls for property characteristics, neighborhood-year characteristics, neighborhood fixed effects, and year-month fixed effects. Walking distance is defined as a radius of 1 kilometer from each property. The quantity and diversity measures are standardized to facilitate interpretation and comparison. The interaction term is constructed as the product of the standardized quantity and diversity measures.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the neighborhood level.

Table 4: Valuing Deliverable Consumption Services, IV

	(1)	(2)	(3)
Panel A: First-Stage			
FDS Growth × Potential Count of Delivery-Accessible Restaurants	0.152***	0.055***	
	(0.009)	(0.004)	
FDS in 2015 × Potential Count of Delivery-Accessible Restaurants			0.113***
			(0.008)
Observations	375201	135086	375201
Panel B: 2SLS			
Count of Delivery-Accessible Restaurants	0.071***	0.292***	
	(0.027)	(0.078)	
Count of Delivery-Accessible Restaurants in 2015			0.129***
			(0.037)
First-Stage F Statistics	284.660	209.709	211.224
Observations	375201	135086	375201

Notes: This table presents the first-stage and 2SLS estimates of the hedonic premium of the count of delivery-accessible restaurants, based on Equations 3 and 4. The delivery distance is defined as the 2–5-kilometer radius around each property. Column 1 reports the baseline results. Column 2 focuses on the initial accessibility impact of FDS expansion by limiting the sample to the year of the service's introduction (2015), thereby excluding supply-side competition effects and other longer-term dynamics. Column 3 uses the full sample window but only uses the treatment variation in 2015, as treatment intensity in 2016 and 2017 may be endogenous due to supply-side competition. Restaurant counts are standardized to facilitate interpretation and comparison.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the neighborhood level.

Table 5: Heterogeneity by Initial Accessibility, Household Size, and Internal Condition

Dependent variable: log of price per square meter (in 10,000 RMB)			
	(1)	(2)	(3)
Panel A: Initial Amenity			
Count of Delivery-Accessible Restaurants	0.160*	0.089**	0.063
	(0.089)	(0.042)	(0.042)
First-Stage F Statistics	138.226	417.773	159.502
Observations	126082	124200	124918
Panel B: Number of Bedrooms			
Count of Delivery-Accessible Restaurants	0.054**	0.074***	0.077***
	(0.026)	(0.025)	(0.029)
First-Stage F Statistics	238.827	291.991	287.000
Observations	92031	187502	95650
Panel C: Internal Condition			
Count of Delivery-Accessible Restaurants	0.060**	0.078***	0.069**
	(0.028)	(0.022)	(0.030)
First-Stage F Statistics	310.344	322.039	223.251
Observations	63915	125185	186086

Notes: This table presents the heterogeneity in the hedonic premium for deliverable consumption services across properties with varying initial local conditions and physical attributes. The results are based on 2SLS estimates following Equation 4. The treatment variable is standardized to facilitate interpretation and comparison. Columns 1 through 3 represent subsamples of property characteristics, ranging from the lowest to the highest. Panel A explores heterogeneity by initial accessibility to restaurants within walking distance (1 kilometer) in 2012. Panel B investigates heterogeneity by household size, proxied by the number of bedrooms in each property: up to 1 bedroom, 2 bedrooms, and 3 or more bedrooms. Panel C uses property renovation status as a proxy, categorizing properties into three subsamples: bare shell/unfinished, finished without appliances, and finished with appliances.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Table 6: Heterogeneity by Neighborhood Characteristics

Dependent variable: log of price per square meter (in 10,000 RMB)					
	1st	2nd	3rd	4th	5th
Panel A: Population					
Count of Delivery-Accessible Restaurants	-0.018	-0.041	0.057	0.046	0.175***
	(0.025)	(0.033)	(0.040)	(0.058)	(0.064)
Number of Neighborhoods	48	49	47	48	47
First-Stage F Statistics	29.472	54.899	79.228	174.995	107.275
Observations	37488	53096	61867	97222	114776
Panel B: Day Night Population Difference					
Count of Delivery-Accessible Restaurants	0.281***	0.065	-0.065	0.155***	-0.011
	(0.069)	(0.047)	(0.039)	(0.051)	(0.086)
Number of Neighborhoods	48	48	49	47	47
First-Stage F Statistics	94.972	106.416	49.297	100.691	66.437
Observations	92525	71254	60896	63697	76077
Panel C: Nighttime Light					
Count of Delivery-Accessible Restaurants	0.039	0.103**	0.127*	0.102*	0.182*
	(0.167)	(0.040)	(0.067)	(0.057)	(0.091)
Number of Neighborhoods	48	48	49	47	47
First-Stage F Statistics	55.891	116.054	35.559	78.932	108.647
Observations	57677	96619	69440	87896	52817

Notes: This table presents the heterogeneity in the hedonic premium of deliverable consumption services across different initial neighborhood characteristics. The results are based on 2SLS estimates following Equation 4. The treatment variable is standardized to facilitate interpretation and comparison. Columns 1 through 5 represent quintiles of the neighborhood characteristics, ranging from the lowest to the highest. Panel A explores heterogeneity by market size, proxied by population levels. Panel B investigates heterogeneity by neighborhood attributes, using the day-night population difference as a proxy for the residential or business nature of the neighborhood. A smaller day-night population difference indicates more residential neighborhoods, while a larger difference indicates more business-oriented areas. Panel C examines heterogeneity by degrees of economic development and urbanization, proxied by the average nighttime lights at the neighborhood level.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Appendix

A1 Random Forest

To implement Random Forest, we first run an OLS regression to absorb the year-month fixed effects, neighborhood fixed effects, and dummy variables, including building heights, internal conditions, three rings for subway stations, and the top elementary school dummy. This step helps to control for these factors before applying the Random Forest algorithm. Then, we split the data into training and testing sets and fit the Random Forest algorithm with the standardized number of total establishments (quantity of walkable consumption services), standardized fractionalization (diversity of walkable consumption services) within walking distance, and other standardized time-varying hedonic and neighborhood controls.[22] Next, we construct a prediction dataset with the original values of standardized quantity and diversity, setting all other variables to their median values. Finally, we use the trained Random Forest model to fit the prediction dataset and obtain the predicted house premium. This approach enables us to reveal potential nonlinear effects of the quantity and diversity of consumption services, as well as their interactions, on house prices.

Figure A2 illustrates the predicted house premium in relation to the standardized number of total establishments (quantity) and the standardized fractionalization (diversity) within walking distance, holding all other variables at their median values. The predicted premium is obtained by fitting the price residuals with a Random Forest model that includes standardized quantity, diversity, and other standardized time-varying hedonic and neighborhood controls. The price residuals are derived from an earlier OLS regression that absorbs hedonic dummies and all fixed effects. The Random Forest model consists of 200 decision trees with stable performance.[23]

The figure reveals a nonlinear relationship between the quantity and diversity of consumption services and their impact on house prices. Higher premiums are concentrated around higher diversity levels (moving from left to right), while the pattern for quantity is nonlinear (moving from bottom to top), consistent with the TWFE results in Table 3. Notably, the heatmap suggests that higher house prices are primarily driven by a greater diversity of consumption services rather than the quantity of service establishments. Conditional on the variety of consumption services, an increase in the count of service establishments almost always reduces house prices. This finding suggests that residents value greater variety in consumption services, while the quantity itself may not be utility-enhancing. One possible explanation for this pattern is that increasing the quantity of service establishments without a

[22] These controls include age, number of bedrooms, pollution at the property level, and nighttime light, population, and land use at the neighborhood level.

[23] This Random Forest model uses a random state seed of 68. To address potential sensitivity related to random seeding, we tested other seeds and obtained similar results, as shown in Figure A4 of the Appendix.

corresponding increase in variety may mostly contribute to disamenities such as noise, congestion, and higher rents in a location. The nonlinear relationship revealed by the random forest heatmap highlights the importance of considering both the quantity and diversity of consumption services when assessing their impact on house prices.

Furthermore, the feature importance generated from the Random Forest model, measured by the mean decrease in impurity (Appendix Figure A3), shows that both quantity and diversity are important factors in explaining house prices. In summary, our findings suggest that a higher value of consumption services is largely driven by diversity. The nonparametric Random Forest method helps uncover the underlying nonlinear pattern of people's valuation for consumption services within walking distance while providing results consistent with linear regression, further reinforcing our conclusions.

A2 Restaurants Cuisine Types, Quality, and Price

A2.1 Variable Definitions

Restaurant Quality and Price. As a proxy for quality, we calculate the average rating of all delivery-accessible restaurants for each property in each year. Using ratings as a measure of quality has potential concerns, particularly of self-selection bias, 'fake' reviews and the influence of factors unrelated to the intrinsic quality of the restaurant (Luca and Zervas, 2016).

Similarly, we compute the average delivery-accessible restaurant prices at property-year level. However, this price measure has two notable limitations. First, 74.02% of the restaurants in our sample have missing price information, which affects sample representativeness in the average price of accessible restaurants for any given property/year. Second, the published price information is based on the average per capita expenditure at the restaurant, as reported voluntarily by users. This self-reported nature of the data introduces potential measurement errors and biases.

Despite these limitations, we believe that these measures still provide valuable insights into the overall quality and price levels of restaurants accessible through FDS. We interpret the results with caution in our analysis.

A2.2 Valuing other attributes of delivery-accessible consumption amenities

The advent of FDS not only affects the quantity of delivery-accessible restaurants but also alters other characteristics such as accessible cuisine diversity, quality, and price, through both accessibility and competition channels. We quantify the valuation of these dimensions using the best available data, following the baseline IV specification. Appendix Table A4 presents the first-stage and 2SLS results, while Appendix Table A1 shows the corresponding falsification tests.

The first-stage results in Appendix Table A4 Panel A indicate that FDS increases the cuisine diversity and average quality of delivery-accessible restaurants while reducing their average price, although the latter effect is statistically insignificant. However, the 2SLS estimates suggest that there is no statistically significant hedonic premium associated with these attributes.

We interpret the effect of cuisine types with two potential limitations in mind. First, cuisine type might be too coarse a measure of culinary variety, failing to capture the full extent of differentiated products in the market. Second, there may be limited substitutability between delivery-accessible and dine-in restaurants in terms of cuisine types. Appendix Figure A5 plots the time trends of the share of fast-food restaurants among those offering delivery services versus all restaurants. The figure reveals that delivery-accessible restaurants have a disproportionately higher propensity to specialize in fast food. Consequently, greater cuisine variety within the fast-food category may not yield positive hedonic premiums.

Regarding average quality, residents seem to value it positively, but the effect is not statistically significant. The sign of the price coefficient aligns with the downward-sloping demand curve. However, these two measures suffer from data limitations, as discussed in Section 2.4, and should be interpreted with caution.

Reference

Luca, Michael, and Georgios Zervas. 2016. “Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud.” *Management Science*, 62(12): 3412–3427.

A3 Additional Figures and Tables

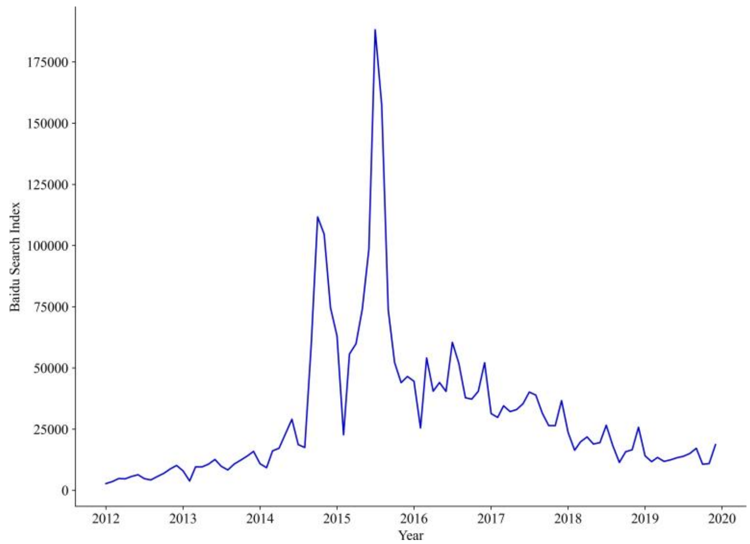


Figure A1: National Trend of the Baidu Search Index for “Ele.me” and “Waimai”

Notes: This figure plots the time trend of the national Baidu Search Index for food delivery service-related keywords: “Waimai” (Chinese for food delivery service) and “Ele.me” (one of China’s two major food delivery platforms). The daily search index data was scraped and aggregated to monthly averages. The figure shows sharp increases in searches in late 2014 and mid-2015, corresponding to the rapid expansion of the food delivery service (FDS) market. After 2016, the number of searches declined, likely due to the widespread adoption of FDS apps on smartphones. The Baidu Search Index serves as a proxy for consumer interest and demand, providing insight into the growth of the FDS market in China.

*The other FDS oligopoly, “Meituan,” is not included because the platform provides other services similar to Groupon, which may confound the search trends specific to food delivery.

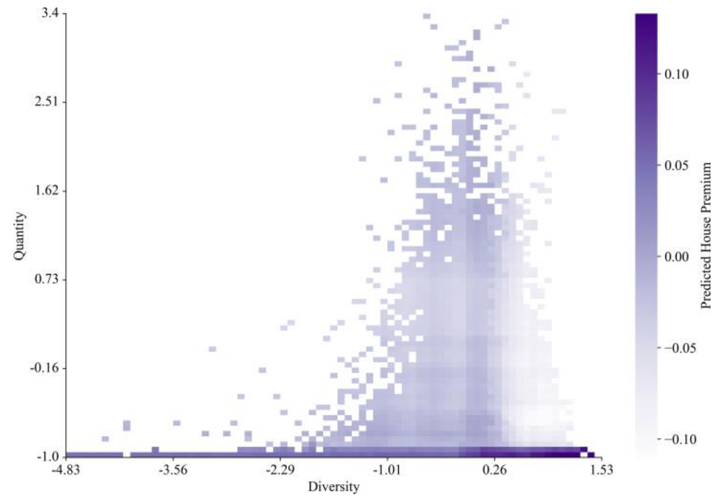


Figure A2: Heatmap of Random Forest Predictions for Residual House Prices

Notes: This figure presents a heatmap of the predicted residual house prices based on a random forest model. The model fits the residual house prices on the quantity (standardized number of total establishments) and diversity (fractionalization) of consumption services within walking distance, conditional on other time-varying hedonic and neighborhood controls. The residual house prices are obtained from a prior OLS regression that absorbs all fixed effects, including binary or categorical hedonic attributes, year-month fixed effects, and neighborhood fixed effects. The heatmap visualizes the variation in predicted residual house prices across different levels of quantity and diversity of consumption services, as well as their interactions. Darker shades indicate higher predicted values. The ranges of quantity and diversity were divided into 200 equal bins, and the predicted residual prices were calculated as the medians within each grid. Grids with fewer than 100 observations (representing 0.01% of the sample) are excluded to enhance visualization. This approach provides insights into the flexible interaction between the quantity and diversity of local consumption services and their impact on house prices, revealing nonlinear patterns not evident in our linear specification.

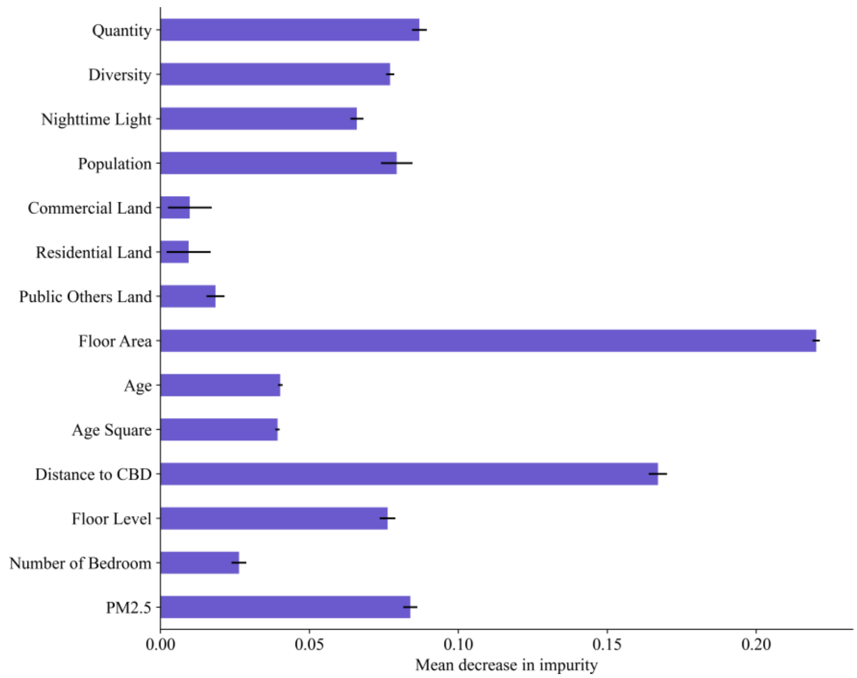
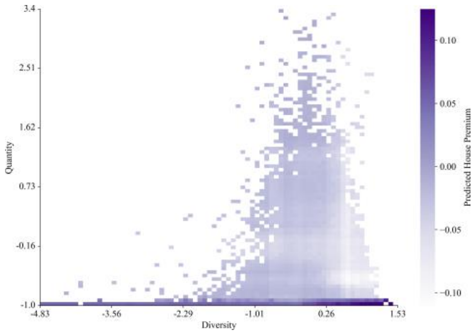
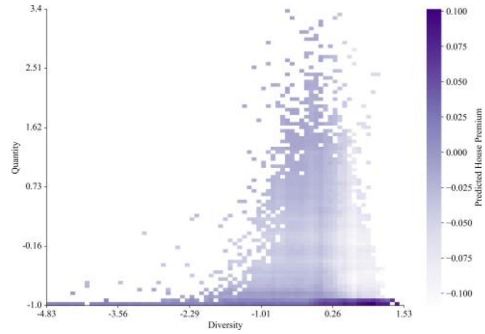


Figure A3: Feature Importance of the Random Forest Model

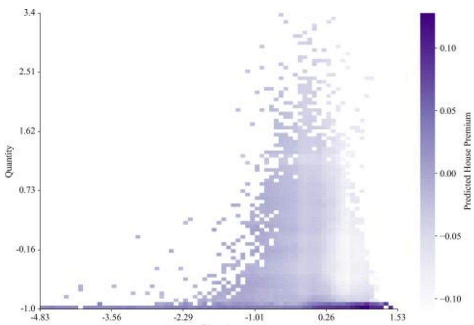
Notes: This figure presents the feature importance derived from the Random Forest model, which measures the relative contribution of each input variable to the model's predictive performance. The feature importance is calculated based on the mean decrease in impurity, quantifying the average reduction in the impurity of the nodes in the decision trees when a particular feature is used for splitting. The length of the purple bars indicates the relative importance of each feature in constructing the Random Forest, with longer bars representing greater importance. The black error bars at the ends of the bars reflect the variability in feature importance across the individual decision trees that comprise the forest. The results highlight that both the quantity and diversity of local consumption services are significant factors in explaining house prices.



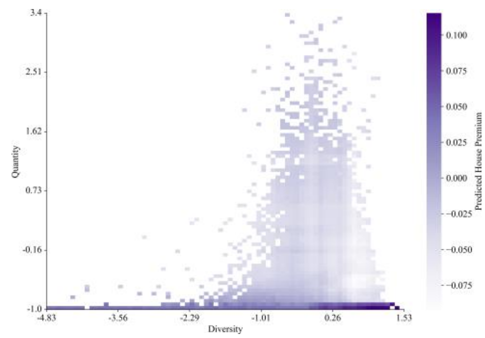
(a) Seed32



(b) Seed 58



(c) Seed 70



(d) Seed 89

Figure A4: Random Forest Model Robustness: Heatmaps using Different Random State Seeds

Notes: This set of figures presents heatmaps of predicted residual house prices generated by the Random Forest model discussed in Section A1. Each heatmap is constructed using the same methodology as in Figure A2, but with different random state seeds. The heatmaps in this set of figures display consistent patterns across different random state seeds.

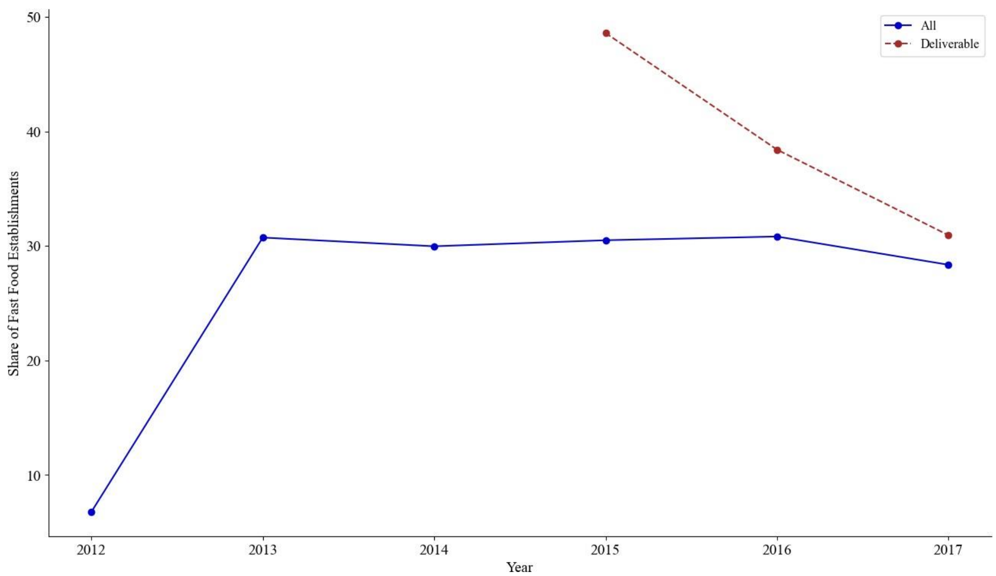


Figure A5: Share of Fast Food Establishments among Deliverable and Total Restaurants

Notes: This figure presents the share of fast food establishments among deliverable and total restaurants within a 2-5 km radius. The blue line represents the share among all restaurants, while the red line shows the share among deliverable options. Fast food establishments are those that self-identify as serving fast food dishes, constituting 46.68% of all categories. The divergence between the two lines in 2015, the year of FDS expansion, suggests that deliverable options have a distinct composition, with fast food accounting for a larger share compared to the overall restaurant market. This finding implies that consumers may value the convenience and speed of delivery more than the diversity of cuisine types available, as fast food establishments are often associated with quick service and standardized menus.

Table A1: Balance of House Price Change before FDS Entry, 2012-2014

Dependent Variable: pre-FDS Δ house price residual				
	Neighborhood Median		Neighborhood Mean	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Cuisine Types				
Hypothetical Delivery-Accessible Cuisine Types	0.011**	-0.013	0.012***	-0.009
	(0.005)	(0.015)	(0.004)	(0.012)
First-Stage F Statistics		13.104		19.519
Observations	234	234	234	234
Panel B: Quality				
Hypothetical Quality of Delivery-Accessible Restaurants	0.014***	0.001	0.015***	-0.001
	(0.002)	(0.007)	(0.003)	(0.008)
First-Stage F Statistics		17.053		16.110
Observations	234	234	234	234
Panel C: Price				
Hypothetical Price of Delivery-Accessible Restaurants	0.012**	0.013	0.012**	0.012
	(0.005)	(0.010)	(0.005)	(0.012)
First-Stage F Statistics		28.848		35.610
Observations	234	234	234	234

Notes: This table demonstrates that the change in neighborhood house price residuals prior to the entry of food delivery services (FDS) is uncorrelated with access to hypothetical deliverable consumption services after FDS expansion. Following the methodology used in Table 2, this analysis focuses on the cuisine types, average quality, and average price of delivery-accessible restaurants. The results show that pre-FDS house price growth remains balanced across neighborhoods with varying levels of future access to deliverable consumption services, thereby supporting the validity of the identification strategy.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Table A2: Robustness Checks using Sub-periods: TWFE Estimates

Dependent variable: log of price per square meter (in 10,000 RMB)				
Sample Periods:	12-19	13-19	14-19	15-19
	(1)	(2)	(3)	(4)
Fractionalization of All Service Establishments within Walking Distance (Diversi	0.006**	0.006	0.007*	0.007*
	(0.002)	(0.004)	(0.004)	(0.004)
Count of All Service Establishments within Walking Distance (Quantity)	-0.004	-0.002	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	762667	711658	641547	580201

Notes: This table replicates the specification in Table 3 Column 3 by limiting the sample period to later years to show consistent and robust results in periods when most vendors would have been listed on DZDP, the data platform used for our consumption services measure. The robustness checks focus on sub-periods when the coverage and accuracy of the DZDP data are expected to be higher, ensuring that the estimated hedonic premiums are not influenced by potential data limitations in earlier years.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the neighborhood level.

Table A3: Valuing Deliverable Consumption Services, OLS and IV

Dependent variable: log of price per square meter (in 10,000 RMB)				
	(1)	(2)	(3)	(4)
Panel A: OLS				
Count of Delivery-Accessible Restaurants	-0.003			
	(0.010)			
Delivery-Accessible Cuisine Types		-0.005		
		(0.008)		
Quality of Delivery-Accessible Restaurants			0.005	
			(0.005)	
Price of Delivery-Accessible Restaurants				-0.001
				(0.002)
Observations	375201	375201	375201	375201
Panel B: 2SLS				
Count of Delivery-Accessible Restaurants	0.071***			
	(0.027)			
Delivery-Accessible Cuisine Types		0.015		
		(0.027)		
Quality of Delivery-Accessible Restaurants			0.049	
			(0.059)	
Price of Delivery-Accessible Restaurants				-0.188
				(0.168)
First-Stage F Statistics	284.660	53.694	14.213	0.992
Observations	375201	375201	375201	375201

Notes: This table presents the TWFE and 2SLS estimates of the hedonic premium of deliverable consumption amenities. Delivery distance is defined as 2-5 kilometers from each property, while walking distance is defined as a radius of 1 kilometer. The measures for restaurant counts, cuisine types, quality, and price of both deliverable and walking-distance consumption services are standardized to facilitate interpretation and comparison. The magnitude of the TWFE results (Panel A) is substantially smaller than that of the 2SLS estimates (Panel B), suggesting the presence of omitted variable bias in the TWFE estimates.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the neighborhood level.

Table A4: Valuing the Quality and Price of Deliverable Consumption Services, IV

	(1)	(2)	(3)
Panel A: First-Stage			
FDS Growth × Potential Delivery-Accessible Cuisine Types	0.107***		
	(0.015)		
FDS Growth × Potential Quality of Delivery-Accessible Restaurants		0.055***	
		(0.015)	
FDS Growth × Potential Price of Delivery-Accessible Restaurants			-0.012
			(0.012)
Observations	375201	375201	375201
Panel B: 2SLS			
Delivery-Accessible Cuisine Types	0.012		
	(0.029)		
Quality of Delivery-Accessible Restaurants		0.049	
		(0.059)	
Price of Delivery-Accessible Restaurants			-0.188
			(0.168)
First-Stage F Statistics	56.178	14.213	0.992
Observations	375201	375201	375201

Notes: This table presents the first-stage and 2SLS estimates of the hedonic premium of the cuisine types, quality, and price of delivery-accessible restaurants, based on Equations 3 and 4. Delivery distance is defined as 2-5 kilometers from each property. To account for the mechanical increase in cuisine types as the number of restaurants grows, we scale the number of cuisine types by the number of restaurants within the same distance range. Quality is measured by the restaurants' average star ratings, while the price is calculated as the average dish prices. All measures—cuisine types, quality, and price—are standardized to facilitate interpretation and comparison. The first-stage results demonstrate the relevance and strength of the instrumental variables used in the analysis, while the 2SLS estimates provide causal evidence on the impact of deliverable consumption services on property values, conditional on the provision of walkable consumption services.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Table A5: Robustness Checks, 2SLS Estimates

Dependent variable: log of price per square meter (in 10,000 RMB)					
	(1)	(2)	(3)	(4)	(5)
Count of Delivery-Accessible Restaurants	0.071***	0.077***	0.052***	0.071***	0.071***
	(0.027)	(0.026)	(0.016)	(0.027)	(0.027)
Restaurants within Walking Distance	0.011	0.013	-0.009	0.011	0.011
	(0.013)	(0.013)	(0.011)	(0.013)	(0.013)
First-Stage F Statistics	284.660	288.317	183.821	283.930	292.709
Observations	375201	365837	557665	375201	375201

Notes: This table presents the robustness of the house premium of deliverable consumption services to address concerns related to property construction, treatment variable definition, and potential confounders. The results are based on 2SLS estimates following Equation 4. Column 1 presents the baseline IV regression outcome for reference. Column 2 excludes the sample with housing units constructed after 2012. Column 3 fills in the deliverable restaurants in 2012-2014 to be 0 to extend the sample period. Column 4 includes the *distance to subcenter* in kilometer measure as an additional control variable. Column 5 includes *number of firms* and *employment* from *firm registration data* as additional controls. Everything else follows from Table 4 Column 1.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

Table A6: Robustness Checks using Alternative IV Share Components: IV Estimates

	(1)	(2)	(3)
Panel A: First-Stage			
FDS Growth × Potential Count of Delivery-Accessible Restaurants	0.152***		
	(0.009)		
FDS Growth × Potential Selected Count of Delivery-Accessible Restaurants		0.134***	
		(0.008)	
FDS Growth × Potential Weighted Count of Delivery-Accessible Restaurants			0.132***
			(0.008)
Observations	375201	375201	375201
Panel B: 2SLS			
Count of Delivery-Accessible Restaurants	0.071***	0.076***	0.070***
	(0.027)	(0.028)	(0.027)
First-Stage F Statistics	284.660	281.660	259.070
Observations	375201	375201	375201

Notes: This table presents the robustness of the house premium of deliverable consumption services using alternative measures of the share component of the instrument. The results are based on the first-stage and 2SLS estimates following Equations 3 and 4. Column 1 presents baseline results for reference. Column 2 uses the number of restaurants in 2012 with categories that exist in 2015's deliverable options, such as fast foods and baked goods, as the share measure. Column 3 uses the number of restaurants in 2012 weighted by the category proportion of category types in 2015 as the share component. All other specifications follow Table 4. The consistent coefficients across columns indicate that the house premium of deliverable consumption services is robust to alternative share measures.

*** p <0.01, ** p <0.05, * p <0.1. Standard errors in parentheses are clustered at the neighborhood level.

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The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE