VALUATION OF THE CHICAGO METROPOLITAN HOUSING MARKET RELATIVE TO CENTRAL BUSINESS DISTRICTS

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Abstract

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In the valuation of the Chicago metropolitan housing market relative to new developed Dual Central Business District, I apply the regular and spatial hedonic model to estimate the MWTP in the targeted groups of homebuyers, high-income millennials. Using the demographic and housing mass appraisal data from the 2010 census tract and the cook county assessor office in 2013 to 2019. In this paper, I provide the market insight into those real estate investors or developers to understand consumer behavior, while seeking higher model performance using the different econometric approach. Also, I derived the causal inference with the difference in difference estimator to analyze the market intervention caused by the commercial real estate market and affecting the surrounding residential housing market. Finally, the Decentralizing CBD market phenomenon can be treated as an urban development policy changes, this paper evaluates the welfare effects that which groups of homebuyers would gain and lose from this Dual CBD policy.

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CHAPTER ONE:
INTRODUCTION & LITERATURE REVIEW

According to Cushman and Wakefield's market report for the third quarter of 2019, the Chicago Metropolitan Area has 1.25 million offices that are used to employ workers in professional business and financial services and information industries. The strong demand in the third quarter of 2019 for Class-A office buildings is stimulated by large technology companies such as Uber, Glassdoor, WeWork that have launched new hubs in Chicago. Especially in the leasing prices of the West Loop and Fulton Market, the new central business district (CBD), has increased at a 35.9% rate. Consequently, it accounts for 57.8% of total CBD leasing.

The total CBD refers to the new CBD and the traditional CBD. The Old CBD is defined by the North Michigan Avenue, River North, East Loop, and Central Loop. Moreover, this new CBD has the lowest vacancy rate in the City with 7.4 % and 11.8% because the facility is more updated for the tech industry's office users. As a result, businesses like Uber and Glassdoor are one of the main purchasers of these office buildings. Consequently, one should expect that these businesses will most likely purchase the buildings by the end of 2020.

As Baker, M., & Rafter quotes from Michael Lirtzman, who is in charge a leasing business at a real estate company, Sterling Bay. In the article regarding "*The Central Business District Decentralized"* and mention "McDonald's was a case in point to that, where they really wanted to change their culture and recruit a younger employee base." As the time progressed, office space sprawl outward to the West Loop and River North, which the CBD is no longer confined in the Loop. A natural question arises, what are the amenities that entice the business to expand into these districts? Many believe work life balance is a heavy influencer to why these corporations are locating in the West Loop and Fulton Market. Also, increases demand in working wanting to live closer to work is another influence.

I consistently follow insight from industry leaders on why this business behaves in this manner and the real estate market response. Therefore, I analyze the above decentralizing CBD market phenomenon (i.e. a city with two distinct CBDs). Specifically, I examine how dual CBDs affects the residential housing demand in the surrounding housing market in the last five years. The second aspect of this thesis is to discover how much high educational millennial home buyers would gain from such a decentralizing CBD also call employment sprawl by researching specific homebuyer groups.

Even though there are many studies that have used pollution and location data to measure the impact of environmental amenities on housing prices, theses type of studies measures the value of proximity for a particular service or site. Dubin (1992) found the existence of distance decay, while the hedonic model consisted of travel time to the CBD variable especially in a monocentric city. After that travel time to the workplace has been used as a measure for a convenient location for many real estate hedonic studies whether in a non-spatial hedonic represented by Bajari and Kahn 2008 or spatial hedonic model by Anselin, L., Lozano-Gracia, N. 2008.

There is no research that uses the travel time to work to explain the decentralizing CBD market phenomenon. One similar paper evaluates the welfare effects for the anti-sprawl policies by using travel time variables without considering spatial effects. They estimate "how much suburban homebuyers would lose compared with how much urban home buyers would gain from such an employment sprawl reversal" (Bajari and Kahn 2008, p. 3).

However, in this thesis, travel time to work with two different CBD locations, the West Loop and North Michigan Avenue are used. I calculate the travel times by using Google Map application programming interface (API). To clearly map out the travel time for each group homebuyer, I examine the decentralizing CBD policy that affected two groups of homebuyers segmented by education attainment against the housing preference. Using a hedonic model to estimate their marginal willingness to pay for each housing attribute (e.g. lot size, age, square feet) and demographic attributes (such as commute time to work, income, and education attainment).

Hedonic price modeling model measures consumer behavior by considering the supply and demand simultaneously in the equilibrium equation (Rosen 1974). Under the assumption of homebuyers are utility maximizers, the utility function consisted of housing attributes, price, and numeraire, and subject to the budget constraint. For the marketing interest, the desired result generated from the first-order condition of the housing hedonic function is marginal willingness to pay. Cropper (1988) suggested that the semi-log functional form has better performance, it was used in this study as a functional form.

In addition, the welfare effect will be an additional discussion in this paper by applying the classical compensation criterion as known as cost and benefit analysis. It is often desirable to know when a market phenomenon or policy will improve social welfare (Varian HR, 1992). For example, dual CBD may provide economic benefits for the surrounding community's residents from a local blooming business activity, then some particular housing with desirable characteristics may have received higher market value. Here is unanimously to assert everyone's house value will elevate along with its better proximity to the new CBD. The reason is that a particular property which deserves a higher value must meet the desirable housing attribute that a particular group of homebuyers are interested in. Intuitively, most of the workforce who want to live closer to the campus in the new CBD are STEM professionals. Therefore, educational attainment can be a segmentation to distinguish the high skilled workforce and other groups of workforces. Then this paper will try to find out which group of workforces will benefit from this decentralizing CBD.

Regarding the estimation framework in econometrics, one parametric approach is to assume constant covariance in the disturbance term, the other is a non-parametric approach with random coefficient in error term has a heterogeneity problem and their marginal willingness to pay differs across the consumers. Using the local linear regression with a kernel matrix is one of the solutions to estimate implicit prices for each individual consumer accounting for the heterogeneity problem presented in a non-parametric approach (Bajari and Kahn 2008). However, the fully nonparametric approach is difficult to apply in this case because of the intrinsic dimension of housing data and an additional spatial dimension (Baranzini 2008).

"Higher income households may be willing to pay more for housing (per unit of housing services) to maintain neighborhood homogeneity'' (Goodman et al., 2003, p.123). Based on this hypothesis I can impose the fixed effect for the homebuyer group segmented by educational attainment that makes the coefficient to a group-specific constant term in the regression model. Then, with this solution that can helps to understand the heterogeneous homebuyers on housing preference.

Housing submarket and market segmentation have been debated many times in real estate economics literature. Currently, submarkets are being determined by researchers' base on the characteristics of housing, census units, and neighborhoods (Bourassa et al.,1999). However, geographical submarkets have been proved for its better prediction accuracy of real estate prices (Bourassa et al., 2003).

Spatial econometrics is a recently developed econometric subset that has been widely applied in plenty of empirical real estate hedonic price studies. An advantage of the spatial econometric subset is they capture the unobserved neighborhood effects - heterogeneity, and market interaction (Anselin, 2006). Following these two steps, I will discuss how I deal with spatial dependence. This is the reason I incorporated spatial econometric subsets in a regular hedonic model to improve the model performance and accuracy on demand estimation.

First, the spatial interaction effect is the focus of this thesis by using a spatial lag model, which I will discuss in the next section model specification. Second, instead of resorting to the spatial error by applying the spatial error model to deal with the unobserved neighborhood effects, spatial fixed effects will be used. Market segmentation for heterogeneity can be classified as non-spatial and spatial, which I discuss the non-spatial sub-market approach in the previous paragraph, and here will discuss the spatial aspect. “The spatial heterogeneity is existing when there has market barriers or another type of market imperfection across space” (Anselin and Lozano-Gracia, 2009, p.1239).

Regarding the submarket and spatial heterogeneity, most empirical studies defined by a metropolitan area without considering it as a submarket. Therefore, by holding the coefficients of housing attributes constant, then each attribute in this single market is assumed to have its own marginal price (Anselin & Rey, 2014).

However, heterogeneity is still existing in housing because of spatial immobility of housing. The neighborhood, regional attributes, variety of land, structural, and proximity are the most common influencer to the housing price, and there are much research have accounted for homebuyer characteristic, which easing the marginal price of housing to different across the household profile (Kestens et al., 2006).

According to Kestens in 2006, the income and the educational attainment of the households have been detected by a spatial structure, and a spatial heterogeneity from the Lagrange Multiplier and Moran Test with significant value at the 0.05 confidence level, while they used geographically weighted regression model.

For example, the housing transaction in downtown Chicago and not in downtown can be considered the spatial submarket (spatial regime), and to see does the spatial structure exist from each homebuyer profile. However, due to most of the housing transaction in downtown are condo, which is a lack of information on physical housing attributes. Therefore, in this paper, I am not able to impose the spatial regime by imposing spatial fixed effects that constraint the spatial spillover effect across the boundary between the downtown and non-downtown.

CHAPTER TWO: METHODOLOGY

DATA:

In this chapter, I discuss the data that I analyze. The source of the data is the Cook County Housing Assessor's Office and the 2010 Census. The variable names and descriptions are presented in Table 1. Descriptive statistics are presented in Table 2.

Table 1: VARIABLE NAMES AND DESCRIPTIONS

Variable	Description
Property_Class	The property class for single-use market and condo will not be include because of a lack of housing physical attributes information.
Apartment	Number of apartments in the building
Sale_Year	Year of sale from 2013 to 2019Price is set to
Sale_Price	start from 300k, which is a median housing sales price Chicago in 2019.
Room	Number of rooms in the building.
Bedroom	Number of bedrooms in the building.
Full Baths	Number of full bathrooms. If this value is missing, the value is set to 1.
Central_Air	Central air conditioner; 1 = yes, 2 = no

Fireplaces	Number of fireplaces.
Age	Age of the property. If missing, set to 10
Age_Squared	Square of age
Land_SF	Square feet of the lot
Lot_Size_Squared Building_SF	$Square\_feet\_of\_the\_land^2$
Blding_SF_Squared	Building square feet, building
O’Hare_Noise	Within one mile of O'Hare Airport
Floodplain	Properties on a floodplain
Longitude	Spatial location measure
Latitude	Spatial location measure
Edu_Attainment	Percent % bachelor's degree or higher
Median_income	Median household income (dollars)
AGE_CT	AGE - 35 to 44 years
White	RACE – White
Commute_jll	Travel Time (minutes); Using the location of JLL Corporation (NYSE: JLL) in Michigan Ave district represents as a travel destination for travel time calculation to old CBD.
Commute_McDonald	The travel origin is calculated from the center of each census tract with Google Map API Travel Time (minutes); Using the location of McDonald corporation (NYSE: MCD) in

	Fulton Market district represents as a travel destination for travel time calculation to New CBD. The travel origin is calculated from the center of each census tract with Google Map API

Table 2: DESCRIPTIVE STATISTICS

	mean	std	min	max
Land_Square_Feet	9439.89	20048.61	245.00	2980767.00
Rooms	7.15	1.54	2.00	25.00
Bedrooms	3.58	0.84	1.00	12.00
Garage_1_Size	2.72	1.35	0.00	15.00
Building_Square_Feet	2107.95	823.37	400.00	13144.00
Sale_Price	482566.57	167211.94	300001.00	999999.00
Full_Baths	1.87	0.73	1.00	42.00
Age	55.78	34.03	1.00	172.00
Age_Squared	4270.01	4361.83	1.00	29584.00
Lot_Size_Squared	491053143.43	36015658405.49	60025.00	8884970000000.00
Improvement_Size_Squared	5121377.00	4479017.67	160000.00	172764736.00
com_mcdonald	27.76	8.98	3.43	48.42
com_jll	29.02	9.03	0.85	50.07
EDUCATIONAL_ATTAINMENT	50.11	18.82	0.00	95.00
Median_household_income	85537.45	32869.31	10217.00	233409.00
AGE_CT	12.49	8.23	1.70	56.10
WHITE	78.49	17.09	0.00	99.50

MODEL SPECIFICATION

Before using spatial effect into the hedonic model, I begin with the simple hedonic model with OLS, the model specification is in model 1. For i=1…n with 76129 of a housing transactions, and j=1…J, where there are two different submarkets; segmented by educational attainment. More specifically, each regime has its own intercept and coefficient, and it is equivalent to run two separate OLS. The assumption for heteroskedasticity that I mentioned in the introduction can be expressed as $Var[\varepsilon ij] = \sigma^2 j$ for each submarket.

(1) $yij = \propto j + X'ij\beta j + \varepsilon ij$

I construct a spatial lag model with spatial regimes. Instead of embedding spatial variance and covariance matrices as a distance decay function to measure the same variable at two different locations, also called “spatial ordering” proposed from (Kelejain and Robinson 1992). I apply a spatial lag (spatial dependence) model to discover the interaction effects from their linear correlation of one variable at one location and another location. As the neighbor for each individual housing transaction is hard to predict where the spatial effects materialize, the spatial lag (WY) variable is the weighted average of neighboring observations (Anselin, 2003).

The reduced form explains the notion for a simultaneous spatial process model that is only modeling the neighbor housing attribute (X) solely without neighbors' housing price (Anselin, L., Lozano-Gracia, N. 2008). This model follows Anselin and Lozano-Gracia (2008).

(2) Model 1: $Y = \rho WY + X\beta + u$

(3) Reduced form: $Y = (I - \rho W)^{-1}X\beta + (I - \rho W)^{-1}$u

(4) Spatial multiplier: $(I - \rho W)^{-1} = I + \rho W + (\rho W)^{2} + \ldots \ldots$

Where Y is the Vector of housing sale price, X is the Matrix of housing attribute and demographics, and W= nXn spatial weight matrix, U= error term in an identical normal distribution, and ρ is the spatial autoregressive coefficient.

The spatial multiplier reflects the notion of spatial indirect effect and distance decay; one individual housing attribute depends on the neighbors' housing attributes, and the spatial effect will lessen as the distance increases (Kim et al. 2003). This will apply to policy analysis through how the less travel time to work captures the value of the property.

The travel time to CBD is measured from the center point of the census tract as the origin. The travel time is not only affected by the residents at the center of the census tract but also affects the neighborhood surrounding through the spillover effect. As I mentioned in the Introduction, I impose a fixed effect with non-spatial approaches that makes the coefficient to be a group-specific constant term in the regression model for each submarket. This paper has price segmentation, single-family property use segmentation, and education attainment segmentation for low and high for each census tract.

CHAPTER THREE: ANALYSIS

ESTIMATION

First, I create a Rook's spatial weight matrix that defines neighbors by "the existence of a common edge between two housing unit" (Anselin & Rey, 2014, p.36). The matrix is all row standardization. On average, it contains six neighbors to minimize neighbors to 18 maximize neighbors.

Table 3. Diagnostics for Spatial Dependence

TEST	VALUE	PROB
Moran's I (error)	61.9200	0.00000
Lagrange Multiplier (lag)	2775.2992	0.00000
Robust LM (lag)	3.5505	0.05953
Lagrange Multiplier (error)	3806.3866	0.00000
Robust LM (error)	1034.6379	0.00000
Lagrange Multiplier	3809.9371	0.00000

Second, after tested the existence of spatial lag (spatial structure) from the Lagrange multiplier test. I use Spatial Two-Stage Least Square estimation with instrumental variables.

This approach has the advantage of dealing with endogeneity in spatially lag dependent variable WY and heteroscedasticity.

The endogeneity of spatial hedonic exists in the reduced form because there is a correlation between spatially lag dependent variable WY and error term, then the ordinary least squares (OLS) estimator is no longer consistent. Therefore, the instrumental variable Q has been introduced to correct the endogenous variable WY, the first and second orders of spatially lagged explanatory use as instrument variable are generated from the idea of the conditional expectation of WY given X,

(5) $E[Wy|X] = W(\sum_{p=0}^{\infty} \rho^p W^p)X\beta.$

Therefore, the instrumental variable Q consisted of exogenous and spatially lagged variables (Anselin and Rey 2014).

(6) $Q = [X, W(\sum_{p=0}^{\infty} \rho^p W^p)X\beta].$

The following model best corrects the endogeneity issue, and the spatial two-stage least squares estimator is defined below the model adjustment (Anselin and Rey 2014).

(7) Model adjustment: $Y = Q(\rho\,\beta\,\acute{})\,\acute{} + u$

(8) Estimator: $\theta 2sls = [Z'Q(Q'Q)^{-1}Q\,\acute{}\,Z]^{-1}Z\,\acute{}\,Q(Q\,\acute{}\,Q)^{-1}Q\,\acute{}\,y$

RESULTS:

After initiating an OLS linear regression with education attainment segmentation, I noticed the following results:

TABLE 4 REGRESSION RESULTS

Variable	Pool Regression	Low	High	Median
Const	12.4239*	12.7871*	11.6426*	12.3931*
Land_Square_Feet	7.674e-07*	9.082e-07*	2.062e-07	2.323e-06*
Rooms	0.0045*	-0.0040*	0.0131*	0.0048*
Bedrooms	0.0049*	-0.0002	0.0013	0.0057*
Central_air	0.0030	-0.0117*	0.0303*	0.0066*

Fireplaces	0.0328*	0.0270*	0.0432*	0.0266*
Garage_1_Size	0.0058*	0.0050*	0.0126*	0.0046*
Building_Square_Feet	0.0002*	9.077e-05*	0.0004*	0.0002*
Full_Baths	0.0379*	0.0427*	0.0411*	0.0283*
Age	-0.0038*	-0.0043*	-0.0033*	-0.0042 *
O’Hare_Noise	-0.0144*	0.0072	1.294e-15*	-0.0403*
Floodplain	-0.0035	0.0071	0.0079	-0.0236*
Age_Squared	3.477e-05*	3.44e-05*	3.228e-05*	3.602e-05*
Lot_Size_Squared	-2.892e-13*	-3.372e-13*	-1.394e-12*	-6.683e-12*
Improvement_Size_Squared	-1.235e-08*	2.615e-09 *	-4.054e-08*	-1.113e-08*
Com_mcdonald	-0.0023*	0.0030*	0.0147*	-0.0028*
Com_jll	-0.0105*	-0.0138*	-0.0205*	-0.0114 *
Educational_attainment	0.0054*	0.0034*	0.0076*	0.0063*
Median_household_income	4.704e-07*	-1.609e-07	2.861e-07*	-7.341e-07*
Age_inCT	0.0020*	0.0034*	0.0035*	0.0035*
White	0.0020*	0.0011*	0.0035*	0.0035*
R-Squared	0.541	0.378	0.481	0.491

Then I transitioned to a Spatial 2 Stage Least Square and I unearthed different results from my OLS:

TABLE 5 SPATIAL TWO STAGE LEAST SQUARES

	Pool Regression	Median Census tract
Const	10.5282089 *	11.6327943*
Land_Square_Feet	0.0016468 *	0.0000021*
Rooms	0.0047412*	0.0048937*
Bedrooms	0.0044866*	0.0056701*
Central_air	0.0055108	0.0072275*
Fireplaces	0.0282023*	0.0252069 *
Garage_1_Size	0.0056223*	0.0046285*
Building_Square_Feet	0.0002005*	0.0002082*
Full_Baths	0.0372580 *	0.0283766*
Age	-0.0033303 *	-0.0040323 *
O'Hare_Noise	-0.0125280*	-0.0379729*
Floodplain	-0.0047552	-0.0228356*
Age_Squared	0.0000306 *	0.0000344*
Lot_Size_Squared	-0.0000000*	-0.0000000*
Improvement_Size_Squared	0.0000306*	-0.0000000 *
Com_mcdonald	-0.0042054*	-0.0037637*
Com_jll	-0.0071918*	-0.0097891*
Educational_attainment	0.0044737*	0.0059289*
Median_household_income	0.0000003 *	-0.0000007*
Age_inCT	0.0016468*	0.0032695*

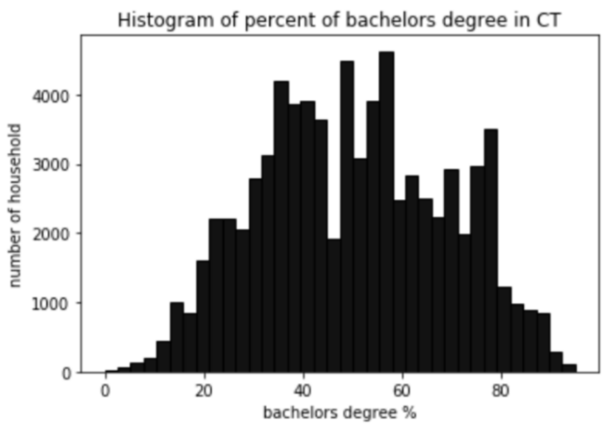
White	0.0017999*	0.0032648*
W_Sale_Price	0.1493923*	0.0601542*
R-Squared	0.58	0.5093
Anselin-Kelejian Test	1269.883	920.821

Regarding the price segmentation for the housing market. Although the $100,000 starting price for each market segmentation has better R square performance, this paper used the $300,000 starting price as the housing market segmentation due to the homebuyer that we target are high-income earners. Instead of estimating seven different OLS regressions for each demographic, I let the housing price determine our target group of homebuyers-high income.

From Figure 1, I realize the $100,000 starting price contains lower education attainment census tracts in Cook County. Therefore, I set the price at $300,000 to capture the higher education attainment census blocks. In addition, in Figure 2, the dot represents the coordinate and distribution of each housing transaction in three levels of education attainment Census Tract in Cook County. The high education attainment is set to the first quantile – these 466 tracts only have 0% to 35% of the population that holds a bachelor's degree or higher, the lower educational attainment is set to 3rd quantile- these 158 tracts contains 64.9% to 100% population with a college degree. The population in the median education attainment community with a college degree is between 35.7% and 64.9% and covered 295 tracts.

FIGURE 1 PRICE SEGMENTATION

300k vs 100k



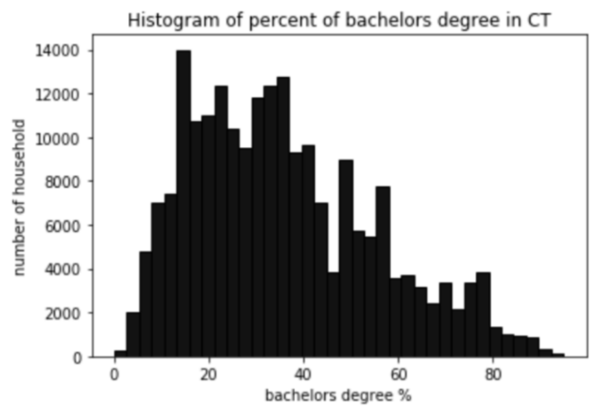
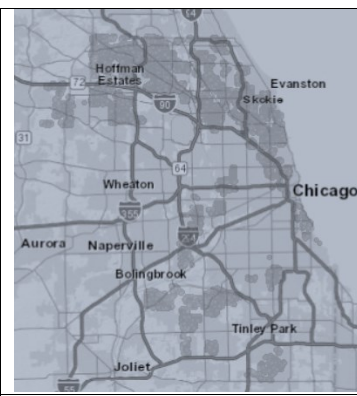


FIGURE 2 DISTRIBUTION OF EDUCATION ATTAINMENT LEVEL



High education attainment CT	Low education attainment CT	Median education attainment CT

CHAPTER FOUR: CONCLUSIONS

The results of housing physical attributes and demographic attributes are matched with the results that have been proved from the previous literature. For instance, we expect housing price is positively correlative with the number of room and garage size, etc. and is negatively correlative with house age in those housing physical attributes.

In addition, considering the demographic attributes that draw the community residents' profile, travel time is be expected to negatively correlate with housing prices due to the notion of convenient location that increases one minute of travel time on work will decrease one unit of the price that one homebuyer valued.

The high educational attainment homebuyer can represent high-income millennials this group of homebuyers which is the main group of consumers that benefits from the decentralizing CBD, due to these two dimensions are correlated. Even though this study did not estimate another regression based on income as a submarket of homebuyer profile, but with this information, it is enough to observe the community's resident's income by observed three different levels of education attainment census tract. Comparing the result different from the spatial and non-spatial hedonic model, the sign of the correlation is identical in both pool regression and submarket which is what we expect. Instead of a focus on correlation sign that only provides little meaning on demand estimation, the marginal willingness to pay will be the main interest and will be discussed next.

The motivation to incorporate spatial econometrics in the hedonic model is not only to improve the model performance and accuracy but also to conduct the policy analysis to interpret welfare on direct effect (value is derived from the non-spatial hedonic model) and spatial multiplier effect by evaluating their marginal willingness to pay. In the non-spatial semi-log hedonic model, the MWTP calculated as prices times the coefficient of each attribute by taking the derivative with respect to each attribute. In contrast, in the spatial semi-log hedonic model, the MWTP is calculated with an extra term which multiplies by one over one minus the coefficient of spatial autoregressive (Anselin, Lozano-Gracia, 2008).

Beginning with the welfare evaluation from direct effect. Based on our calculation with a 300k housing price, on average the homebuyer is willing to pay $1350 for extra one rooms, and the high education homebuyer willingness to pay higher with $3930 in the traditional hedonic model. Comparing how the difference in how much a high and low education resident values the age of the house, a homebuyer holds a bachelor degree or higher are less desired to live in the new house, they are only willing to pay $ 990 for one year newer house than others groups homebuyer's want to pay more with $1290. The regression includes age and age square that came from the quadratic form that I generated. The results have a negative effect on age and a positive effect of age squared. This represents that as the house gets older the effect of age is lessened. In other words, when the housing age is reaches a certain age, the consumer will no longer value it as they did in the past. Such as the homebuyer without an educational degree may be willing to pay one year house newer for $1290 for 10 years, but if the house is in the 11th year, the homebuyer will less likely to pay the $1290 as they valued it in the past. Furthermore, to understand how the different educational homebuyer willingness to pay on their community composition, then we have a surprising discovery that the high education homebuyer willingness to pay $1050 for white neighbors than the other groups only want to pay $330.

According to Small and Steimetz (2012), before calculating the marginal WTP with a spatial multiplier effect, the researcher has to ensure the spatial multiplier effect is caused from certain residential amenities such as air quality; here we use travel time to workplace, then I further conduct the marginal welfare effects for decentralizing CBD policy analysis. As we mention in the model specification, the less travel time is not only affected by the residents at the center of the census tract but also affects the neighborhood surrounding through the spillover effect.

Therefore, the following marginal WTP will be calculated with a spatial multiplier effect and comparing to the direct effect. First of all, in the direct effect, the average homebuyer is willing to pay $3,150 for old CBD-Michigan Ave to avoid travel time than pay $690 to the new CBD- Fulton Market. However, once the spatial multiplier effect has been accounted for, they are willing to pay $1,483 for their Fulton market than $2,536 for Michigan Ave. There is significant mitigation that people valued their house with a convenient location to those two workplaces from $2,460 to $1,053. We can conclude that the housing demand for a convenient location with less travel time to new CBD has grown as the new CBD developed in these five years.

Table 6: OLS Regression Result for Uni-CBD and Dual CBD

	Variable	Pool	Low	High	Median
Dual CBD/ Decentralizing CBD	Com_mcdonald	-0.0023*	0.0030*	0.0147*	-0.0028*
	Com_jll	-0.0105*	-0.0138*	-0.0205*	-0.0114 *
Uni CBD	Com_cbd	-0.0127	-0.0105	-0.0055	-0.0105

	Variable	Pool	Low	High	Median
Dual CBD/ Decentralizing CBD	Com_mcdonald	-690	900	4410	840
	Com_jll	3150	4140	6150	3420
Uni CBD	Com_cbd	-3810	-3150	-1650	-3150

*Uni CBD is calculated as the center point of four sub-region of traditional CBD; North Michigan Ave, River North, East Loop, and Central Loop.

Following Varian HR’s textbook in welfare analysis theory in 1993 by considering two allocations of dual CBD and Uni-CBD. The allocation of dual CBD can be defined as Pareto Dominated by a Uni-CBD if homebuyers prefer a dual CBD to a Uni-CBD. In this case, some people prefer dual CBD and some people prefer single CBD. From Table 6, for the high educational people, they are willing to pay about $6150 and $4410 for dual CBD in Fulton Market and Michigan Ave district than Uni-CBD. However, the low educational people are willing to pay more about $4140 for proximity to Michigan Ave. Although they do not satisfy one of zone classified in our new CBD which makes sense because most companies are located in the New CBD are technology companies those workforces are more likely to be STEM professional, but they have higher satisfaction for the other zone of this Dual CBD policy than previous Uni-CBD. Therefore, in my welfare effect analysis suggests that the Dual CBD policy would generate a larger welfare gain. This implies that the Dual CBD policy increases the utility of most homeowners or residents.

CAUSAL INFERENCE

Businesses are interested to know the different responses from different groups of consumers when the new policy or new marketing instrument was implemented and further derived the business insights, which is called causal inference in economics or A/B testing in marketing. This paper will discuss what if the Dual CBD affects the homebuyer by partitioning the housing transaction before and after McDonald's announced they would move their headquarters to the Fulton market. This can capture a more heterogeneous homebuyer by identifying the characteristic of the consumer having the intense response for the intervention and further analyzing the effect of the decentralizing CBD. I propose that the house have shorter travel time to new CBD would increase its housing value, therefore I imposed a difference in difference model.

$$Sales_{price} = \beta 0 + \delta 0 year2017 + \beta 1 NCBD + \delta 1\ 2017 * NCBD + \beta 2 Xi + \varepsilon i$$

The intercept $\beta 0$ is the average price that a house that does not have good proximity to the new CBD before 2016 (13.0352). The coefficient $\delta 0$ captures all house values changes during the time (June 2016) when McDonald is announced their headquarter move to Fulton Market. The coefficient of $\beta 1$ measures the effect of better proximity to the new CBD.

$$\delta^{\wedge} = (\$after\ 2016, NCBD - \$after2016, FCBD) - (\$before2016, NCBD - \$before2016, FCBD\ ) = 0.0270$$

Finally, the estimate of the policy effect of the decentralizing CBD on the value of a house is 0.0270 (MTWP=$9450), which is called difference in difference estimator or interaction effect in the model. A positive sign for policy effect is this paper seeking, but the result for the indicator variable is not this paper want, and it can be explained in the following. A negative relationship for the year variable $\delta 0$ in the model can be explained through a cause by an unbalance data set and price segmentation, in which the 350k to 1 million housing market may not follow the growth path of the overall real estate market in Chicago since 2016.

Table 7: Difference in Difference Regression Result

Independent Variable	(1)	(2)
Constant	13.0352	11.8356
Year2016	-0.0351	-0.0070
NCBD	0.0695	0.1571
2016*NCBD	0.0270	-0.0048

Other Controls	NO	Full Set (housing attributes and demographic include)
R-Squared	0.016	0.546

*NCBD defined as better proximity to new CBD by sorted the properties which are less than 21.16 minutes travel time; FCBD is otherwise.

REFERENCES

Anselin, L., & Lozano-Gracia, N. (2009). Spatial hedonic models. In Palgrave Handbook of Econometrics: Volume 2: Applied Econometrics (pp. 1213-1250). Palgrave Macmillan. doi:10.1057/9780230244405_26

Anselin L. Spatial Externalities, Spatial Multipliers, And Spatial Econometrics. International Regional Science Review. 2003;26(2):154-155. doi:10.1177/0160017602250972

Anselin, L., Lozano-Gracia, N. Errors in variables and spatial effects in hedonic house price models of ambient air quality. Empirical Economics 34, 5–34 (2008). doi:10.1007/s00181-007-0152-3

Anselin, L., & Rey, S. (2014). Modern spatial econometrics in practice: A guide to geoda, geodaspace and pysal. Chicago, IL: GeoDa Press LLC.

Baranzini, Andrea, Ramirez, José, Schaerer, Caroline, Thalmann, Philippe. Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation. New York, NY: Springer New York; 2008:1-278. doi:10.1007/978-0-387-76815-1

Bourassa S, Hamelink F, Hoesli M, Macgregor B. Defining housing submarkets. *Journal Of Housing Economics*. 1999;8(2):160-183. doi:10.1006/jhec.1999.0246

Bourassa SC, Hoesli M, Peng VS. Do housing submarkets really matter? Journal of Housing Economics. 2003;12(1):12-28. doi:10.1016/S1051-1377(03)00003-2

Bajari P, Kahn ME, Baranzini A, Ramirez J, Schaerer C, Thalmann P. Estimating Hedonic Models of Consumer Demand with an Application to Urban Sprawl. In: Hedonic

Methods in Housing Markets: Pricing Environmental Amenities and Segregation. New York, NY: Springer New York; 2008:129-155. doi:10.1007/978-0-387-76815-1_7

Baker, M., & Rafter, D. (2018, April 17). The central business district, decentralized. Retrieved from https://rejournals.com/the-central-business-district-decentralized

Cropper ML, Deck LB, McConnell KE. On the Choice of Functional Form for Hedonic Price Functions. The Review of Economics and Statistics. 1988;70(4):668-675. doi:10.2307/1935831

Cook County Assessor's Office Data & Modeling Department. (2020). Cook County Assessor's Residential Sales Data. Retrieved from https://datacatalog.cookcountyil.gov/Property-Taxation/Cook-County-Assessor-s-Residential-Sales-Data/5pge-nu6u

Cushman and Wakefield. (2019). MARKETBEAT Chicago CBD Office Q3 2019. Retrieved from https://cushmanwakefield.com › marketbeat-pdfs › q3

Dubin RA. Spatial autocorrelation and neighborhood quality. Regional Science and Urban Economics. 1992;22(3):433-452. doi:10.1016/0166-0462(92)90038-3

Goodman AC, Thibodeau TG. Housing market segmentation and hedonic prediction accuracy. *Journal of Housing Economics*. 2003;12(3):181-201. doi:10.1016/S1051-1377(03)00031-7

Kelejian HH, Robinson DP. Spatial autocorrelation: A new computationally simple test with an application to per capita county police expenditures. Regional Science and Urban Economics. 1992;22(3):317-331. doi:10.1016/0166-0462(92)90032-V

Kestens Y, Thériault M, Des Rosiers F. Heterogeneity in hedonic modelling of house prices: looking at buyers' household profiles. *Journal of Geographical Systems*. 2006;8(1):61-96. doi:10.1007/s10109-005-0011-8

Kim C, Phipps T, Anselin L. Measuring the benefits of air quality improvement: A spatial hedonic approach. American Journal of Agricultural Economics. 1998;80(5):1183-1183.

Rosen S. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. Journal of Political Economy. 1974;82(1):34-55. doi:10.1086/260169

Small KA, Steimetz SSC. spatial hedonics and the willingness to pay for residential amenities*. Journal of Regional Science. 2012;52(4):635-647. doi:10.1111/j.1467-9787.2012.00774.x

Varian HR. Microeconomic Analysis. 3nd ed. New York: W.W. Norton; 1992.