Driverless Cars, Virtual Offices and Their Effects on Local Government Property Tax Revenues

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Introduction

Innovations in self-driving cars and virtual offices (historically referred to as telecommuting) has the potential to greatly change some of the revenue streams local government have come to rely on. Telecommuting has been shown to reduce vehicle miles traveled (Choo, Mokhtarian, & Salomon 2005). Both technologies can affect commuting patterns. Changed commuting patterns could affect property values, through the well-studied urban economic monocentric city model. The property tax is an important source of funding for local governments and schools. In Georgia, some local governments may face political pressure to keep millage rates down even in the face of falling property values. While school systems, may find themselves up against the state constitutional cap on millage rates. Thus, these technologies could have a meaningful effect on local government revenues.

There have already been estimates of the potential impact on local government revenues of self-driving cars, including declining fee and ticket revenue as well as declining gas tax collections. Governing magazine (2018) estimated that for the top 25 most populous cities these streams of auto related revenue accounted for $5 billion in fiscal year 2016. Telecommuting also can reduce this revenue, through similar channels. There have also been studies on the effects of telecommuting on suburbanization (Sridhar & Sridhar 2003). Others have studied the effect that driverless cars will have on commercial real-estate (Henderson & Spencer 2016).

Driverless cars and telecommuting have the potential to decouple the traditional relationship found in urban economics, which holds that property closer to the central business district will be more valuable than that farther away due to lower commuting costs. This decoupling could have important implications for local governments and school systems that rely on the property tax.

This paper studies the impact that commuting times have on property values using a rich panel data set with over 1 million single-family home sales from the metro Atlanta region. This data is merged with Census Journey to Work data at the census tract level as well as relevant school characteristics to create a model that allows us to estimate the affect that changes in commuting times can have on property values.

Our research contributes to the literature by utilizing several newly available data sources for travel time and combining them with a vast database on home sales and property characteristics for Georgia. Estimating the value homebuyers place on distance to work and commute times is difficult due to data limitations as well as the endogeneity of congestion measures. To overcome these obstacles, we use

various techniques including, instrumental variables, exogenous changes to travel times, and a matching approach to generate a control group. Our results indicate that residents of Atlanta value shorter commute times when purchasing their home even after controlling for the other factors affecting home prices.

The literature on estimating the value of travel time and distance to work is briefly discussed next. The following section reviews the sources of data. The estimation methods are discussed next, followed by some concluding thoughts.

Literature Review

There is a large literature that estimates the willingness to pay for shorter travel times. There is also a substantial a literature on transportation access on property values. In this research, we estimate the value changes in commute times, due to traffic congestion, have on property values. The use of actual commute times is important, as using proxies for commute times such as distance to the CBD has been found to give results that can be inconsistent with economic theory (Sherry 1999). An accurate estimate of the value homebuyers place on commute times has important implications for local governments as the property fair market value (FMV) is an element used to determine property tax levy's. Higher property values will raise more revenue for local governments at a lower millage rate. If shorter commute times have a large effect on property values, the decoupling of commuting costs by advances in either telecommuting or autonomous vehicles could have an impact on the FMV of homes and thus alter the property tax millage rate necessary to raise needed local government revenue. We briefly review the literature next.

One strand of the travel time literature has estimated the amount that commuters are willing to pay to reduce their travel time to work. This literature takes advantage of the use of congestion pricing on toll roads first used in California in the 1990s. Various studies using this congestion pricing data as well as survey research find that commuters are willing to pay roughly $20-$30 to reduce travel time by one hour (see Lam and Small (2001) and Brownstone et al. (2003)).

Another strand of the literature examines how transportation infrastructure effects home prices through the concept of capitalization. This literature generally uses hedonic modeling to estimate these effects (see Bartholomew and Ewing (2011) for a review of the hedonic pricing literature). The capitalization of commute times into property values is based on basic urban economic theory. In the standard urban model, employment is concentrated in the Central Business District (CBD) Within this framework,

increases in rents and housing prices are related to decreases in commuting costs. This decrease in commuting costs is due to either greater access to effective transportation options, or merely being closer to the CBD. Capitalization occurs when the reduced commuting costs allow households to spend more on housing and, in turn, bid up the rents or prices of homes located in areas with low commuting costs. This relationship is what creates the land value/density gradient. (A thorough review of the literature and theory on studies of land value/density gradients can be found in Anas, Arnott and Small (1998)).

However, in a study done by Kilpatrick et al. (2007), it was shown that mere proximity to a transit corridor is not enough to improve property values. The properties must also have sufficient access to allow residents to benefit from the presence of the corridor. Additional evidence regarding the relationship between accessibility to transportation options and home prices and rents are shown in the studies below.

The Sedway Group (1999) finds housing prices decline as distance increased from Bay Area Rapid Transit (BART) stations. These values declined with distance, starting at $74 per foot within the first quarter of a mile of a BART station and dropping to $30 per foot for those houses greater than a quarter of a mile away. Baum-Snow and Kahn (2001), using data from five large US cities, Boston, Atlanta, Chicago, Portland, and Washington DC finds that moving from three miles to one mile away from a transit station creates a housing premium of $4,972. They also find rents rose by $19 per month, for the same distance. Garrett (2004), in a study of the Metrolink light rail system in St. Louis, finds an increase of $140 in home prices per every 10 feet closer to a Metrolink station.

The effect that changes in commute times due to congestion have on property values is not as well studied. Commute times are determined generally by two components, distance to work and congestion along the route. Homebuyers can observe both of these determining factors before deciding to purchase a home. Estimating the effects that these two components have on home prices is problematic for researchers, for different reasons. The distance measurement of commute time is generally from a neighborhood rather than an individual home, and likely does not vary over time. Thus, any effect it has on home prices will be washed out in the standard fixed effects modeling approach, used to control for unobserved neighborhood characteristics. The second determinant of commute time, congestion, could be endogenous in certain high demand neighborhoods, again making the standard fixed effects approach problematic. To overcome these obstacles, we use various techniques including, instrumental variables, exogenous changes to travel times, and a matching approach to generate a control group.

Data

To implement our estimation strategy, this research combines several data sources. The sources and procedures used to create the variables of interest are briefly described next. Our dependent variable, home sales price, came from Data Quick. These data were used to identify the location, date and price for more than 200 thousand arms-length residential homes sales. These data include home characteristics such as: number of bedrooms and bathrooms, square feet, condition, and the date of any recent major renovation. Sales data include the years of 2005-2013 and include location component that is matched to other locational data using Geographical Information Systems (GIS).

To link home sales to school quality, we use shapefiles provided by the various school districts of the Atlanta metro area to tag these sales to their zoned elementary school. We use the percentage of tests on which students exceeded expectations on the Criterion-Referenced Competency Tests (CRCT) from the zoned traditional public elementary school.[1] The CRCT was the only standardized test administered at all elementary schools in Georgia over the entire study period. Elementary schools were chosen because their attendance zones are significantly smaller than middle and high school zones and are a narrower indicator of local school quality.

To create our variable on commuting times and distances, we use several different census data sets. First, the Longitudinal-Employer Household Dynamics Program LEHD Origin-Destination Employment Statistics data is used to estimate the straight-line distance that employees travel to work.[2] We calculate a weighted average distance between each home block group and the work block groups. The weights are determined by the number of workers in the home block group that make the trip to each corresponding work block group. Tract level average commute to work times are from the American Community Survey five-year samples for the years of 2009-2013 and the decennial census of 2000. We also used the census for tract level demographic and income data.

Other measures of congestion use average annual car and truck traffic data from Georgia Department of

[1] We obtained the historical attendance maps for as many school districts as possible to ensure that test scores were accurately matched to transactions historically. Districts for which we were able to obtain historical attendance zones include the city of Atlanta, Fulton County, Cobb County, Gwinnett County and DeKalb County.

[2] LEHD Origin-Destination Employment Statistics (LODES) Data
U.S. Census Bureau. LEHD Origin-Destination Employment Statistics Data (2002-2015. Washington, DC: U.S. Census Bureau, Longitudinal-Employer Household Dynamics Program [distributor], accessed on {CURRENT DATE} at https://lehd.ces.census.gov/data/#lodes. LODES 7.3 [version]

Transportation (GADOT) from its traffic stations. These permanent traffic measurement stations count the number of cars and large trucks that pass. Details regarding major traffic projects completed and the subsequent reduced travel times are from the GADOT annual reports.

See Table 1 of summary stats

Methods: Hedonic Price Model

The hedonic price model is widely used for analysis of this type (see Bartholomew and Ewing 2011). It explains the sales price of a home as a function of observed home characteristics, school quality, distance from work and travel time to work. T represents a travel to work variable and is indexed over block groups and years. **X** represents a vector of home characteristics including square feet, number of bedroom rooms, number of bathrooms, lot size, garage and fireplace status, condition indicators, and indicator for recent renovation. TS represents the CRCT test score at the zoned elementary school in the year prior to the home's sale. MY are set of the month year indicators.

$$E1: Ln\left(P_{hmy}\right) = \beta_1 T_{bt} + \boldsymbol{\beta X}_{hy} + \beta TS_{ts} + \delta MY + \varepsilon$$

Our first key variable of interest in this model is the weighted average straight-line distance from home to work where the distances have been weighted by the number of jobs in the work-home combination. It is statistically significant at the one percent level in this model and indicates that one extra mile traveled to work predicts a 1.4 percent decline in home price (see Table 1, column 1). At the average homes sale amount 1.4 percent represents in $1,869 dollars in sales price. Similarly, average travel time to work in minutes is statistically significant at the one percent level and predicts an 0.9 percent decline in home price for one more minute of travel time to work (see Table 1, column 2) or $1,202 at the mean sales price. When both are included in the model we find similar results (see Table 1, column 3). These are consistent with the predictions of the monocentric city model as homeowner's value shorter commutes, controlling for school quality.

$$E2: First\ stage\ \acute{T}_{bt} = \beta_1 TT_{st} + \boldsymbol{\beta X}_{hy} + \beta TS_{ts} + \delta MY + \varphi BG + \varepsilon$$

$$E3: Second\ stage: Ln(P_{hmy}) = \beta_1 \acute{T}_{bt} + \boldsymbol{\beta X}_{hy} + \beta TS_{ts} + \delta MY + \varphi BG + \varepsilon$$

These models do not account for the possible bias from unobserved neighborhood characteristics. The second specification, shown by E2 and E3, adds block group fixed effects (BG) to control for unobservables. Under this specification, the model relies on the marginal variations across time in the independent variables within neighborhoods, to estimate the effects on the dependent variable. These across time variations in travel time to work, are also a function of changes in local demand for homes and are potentially endogenous. To control for this endogeneity, this specification uses two stage least squares, where average annual large truck traffic (TT) in E2, instruments for travel time to work and is assumed to be correlated with commute times but independent from changes in local demand for housing.

See Map 1

To execute this instrumental variables (IV) approach, we tagged each home sale to the major corridor that a homeowner living there would have to access to travel to work in the Atlanta city center. Traffic measuring stations on these metro Atlanta major highways counted the number of large trucks using these corridors. This instrument has a t-statistic of 12.39 in our first stage regression indicating that it is strongly correlated with commute times. The F-statistic if over 4,000 and the R-squared is 0.507 is our first stage as well indicating that we are modeling commute time in our first stage with confidence.

However, after controlling for neighborhood effects and potential endogeneity the statistical relationship between distance to work and travel time to work wanes (see Table 1, column 4). The coefficient estimate on commute time to work becomes a statistically insignificant 0.021 after including neighborhood fixed effects and instrumenting for commute time using daily truck traffic.

This is suggestive evidence that utilizing neighborhood fixed effects is too restrictive to isolate the value that home buyers have for shorter commutes.[3] Upon purchasing a home, buyers have an expectation of their travel time to work. The factors that determine this expectation, such as transportation infrastructure, transit options and distance to employment, likely do not vary much over time within a given neighborhood, thus they disappear in models that control for neighborhood unobservables through the fixed effects approach.

[3] It is also possible that home buyers in the Atlanta area do not value shorter commute times, but this would be contrary to the considerable evidence to the contrary, including studies done using data from the city of Atlanta (Bowes and Ihlanfeldt 2001)

Effect of New Transportation Infrastructure

In our next specification we make use of new transportation Infrastructure that was completed during our study period. In October 2008 a $155 million project in Gwinnett county was completed that added 14 miles of high occupancy vehicle (HOV) lanes to interstate 85 to the north east of the city as well as nearby state route 316. It added two new flyover bridges and expanded the existing collector distributer system. According to the GADOT this "massive project brought significant improvement to the area" as it increased speeds and shortened rush hour by one hour. According to GADOT data a key segment of I-85 took 28 minutes to travel before the improvement and 17 minutes after and a typical commute to the city center was reduced by 15 minutes.[4]

We make use of this exogenous 15-minute change to commute times to estimate its effect on home values associated with this corridor. All homes likely utilizing this corridor into the city for work are designated as treated home sales before and after the project was completed. The control group excludes homes that are on this corridor but inside of the I-285 perimeter, as they do not benefit directly from the project and may also have other unobservable neighborhood characteristics that differ from those outside of I-285.

To create a control group of home sales, we use Mahalanobis nearest neighbor matching based on home characteristics, elementary school test scores, and straight-line distance to work to create representative groups of homes sales for comparison. Sales were exactly matched to homes that sold in the same month and year, to control for any seasonal variations and broader economic fluctuations. The control sales all come from other parts of the city all outside of I-285 and on a similar type of interstate corridor.

We run the model before and after the treatment has occurred, with the difference in the two coefficients being the estimate of the effect the treatment has on home prices. Running the model before implementation allows to control for any difference in the treatment areas home values that are fixed over time. Homes associated with treatment area sold for 11.5 percent more than the matched comparison sales in the control area before the project completed.

We then run the model after the project was completed and find that homes in the treatment area sold for 14.7 percent more than the matched sales in the control area. The difference between before and after is a statistically significant 3.3 percent. At the mean, this 3.3 percent represents $4,406 of sales value. Our baseline models predicted a 0.8-0.9 percent decrease on the sales price of a home for a one-minute commute. This model finds a 3.3 percent increase in the sales price of homes compared to the comparison

[4] Many small projects are completed every year on Georgia's roads. No projects of this scale were completed from 2008-2013.

sales from an approximately 15-minute reduction in commute time. Due to the location of the project it is unlikely that all home sales had a full 15-minute reduction to their expected commute, so a direct comparison across the different model specifications is difficult.

Nearest Neighbor Matching for Difference-in-Difference and Average Treatment Effects

To try and better understand how commute times and congestion effect a broader swath of properties in the Atlanta area, we next try to leverage changes to commute times from a broader set of exogenous events, not related to demand for local housing as a treatment and compare the price of homes to a matched group of homes. Our strategy relies on the measurement of car and truck traffic growth on highways outside of the I-285.[5] Looking at annual average of daily traffic for the years between 2008 and 2013 we identify two major corridors into the city where congestion was being driven by growing traffic from outside the perimeter but growth from traffic entering from the corridor inside the perimeter was flat or declining. These were I-75 to the northwest of the city and I-85 to the south west of the city and the homes there are defined as our treated sales in our first average model. We also found two corridors where growth in average annual traffic was flat inside and outside of the I-285 perimeter and the homes sold here are defined as our control sales.

See Map/figure 2

To control for endogeneity, yet not eliminate important variation in our independent variables, we next use a matching approach similar to that used in Patrick and Mothorpe (2016) to create treatment and control neighborhoods. Again we use Mahalanobis one-to-one nearest-neighbor covariate matching we match treatment block groups to their closest potential control block group based on their 2009 values of average test scores, average home square footage, average numbers of bedrooms, average home prices, average travel time to work, demographic characteristics, and median annual earnings. After matching we focus our analysis on only the sales that occurred in the treated block groups and their matched control block groups from 2005- 2013.

The difference in difference model E4, is our hedonic price model (E1) with three new indicator variables. The first is an indicator for a sale being located in a treatment block group (T) and indexes over block groups but does not change over time within a block group. This controls for any effect of being in the treated area. Then we add an indicator for after 2009, the beginning of our treatment period, which is

[5] These are: I-85 to the north east, I-20 to the east, I-75 to the south east, I-85 to the south west, I-20 to the west, I-75 to the northwest and state route 400 to the north.

indexed over time only and does not vary across sales within years This controls for any effect of being after the treatment period regardless of location. The interaction of the two indicator variables (TxA) is the difference in difference estimator and is our variable of interest.

$$E4: Ln(P_{hmy}) = \beta_1 T_b + \beta_2 A_y + \beta_3 T_b x A_y + \boldsymbol{\beta X}_{hy} + \beta TS_{ts} + \delta MY + \varepsilon$$

Our difference in difference estimates are not significant (see Table 2, labeled dd). However, we do have the expected sign on the coefficient for the northside corridors. Our southside corridor specification may suffer from data limitations involving fast growing Fayette County. Fayette County does not make its school attendance zones available in a GIS format, thus home sales in the county could not be matched to school quality and are excluded from our matching protocol. This may create bias in our sample of home sales used as potential treatments. It is also possible that these results may be due to a weak level of treatment. The model was specified to have congestion, driven from outside the perimeter highway of I-285 as the only difference between the control and the treatment groups. The change in average daily traffic over this period between the treatment and control groups may not be substantial enough for a measurable effect.

Conclusion

Both autonomous vehicles and advances in technology that facilitate working remotely are on the rise, potentially altering the link between home prices and commuting costs. If the link between commute times and home prices were to weaken or even disappear many communities in metro areas could see changes to the value of their tax digests. This research uses extensive data on home sales as well as commute times and distances to estimate the value home buyers place on both distance to work and the time it takes to get there. Starting with a naive hedonic price model and controlling for school quality we find that home buyers do value both shorter distances to work as well as shorter commute times, as predicted my the urban economics monocentric city model. Using the average home price in the model and the coefficient values, this model estimates that homebuyers are willing to pay $1,869 for one less mile of distance to work and $1,202 to reduce commute times by 1 minute. However, as was discussed earlier, it seems likely that these estimates may be biased due to unobserved neighborhood effects and endogenous growth in congestion. Our initial attempt to control for these factors uses an IV specification with neighborhood fixed effects. We find no statistically significant effect from this model. As was previously discussed, the fixed effects approach eliminates the variation across neighborhoods necessary to estimate the changes in distance and commute times.

We next turn to a section of I-85 that GADOT improved significantly and use this as a treatment event for homes sales nearby. We match these treatment sales to other sales along the similar interstate corridors around Atlanta that did not receive similar improvements. We find that homebuyers are willing to pay roughly 3.3 percent more for homes that received the treatment, the estimated 15 minute improved commute time, compared to those homes that did not. Using the average home price in this sample of sales yields an estimate of $4,406 premium for treated homes.

Finally, in an attempt to test this relationship on a broader set of homes throughout the metro Atlanta area, we utilize the difference in difference model that relies on variation in congestion from outside the city I-285 perimeter compared to those areas inside the city that did not experience similar growth in traffic from beyond the I-285 perimeter. This model finds inconclusive effects. The northside corridor sample of homes has a coefficient with the expected sign but was not statistically significant. While this suggests that homebuyers again value shorter commute times, the insignificant point value does not allow us to estimate the value of this preference.

The estimates for the effect of the treatment on the southern corridor, are not statistically significant nor is the sign of the expected value. As was discussed in this section this may be due to some data limitations in coding home sales to school quality, potentially creating a biased sample of sales. More work needs to be done here.

In conclusion, this study generally finds that home prices do reflect changes in commute times. The size of these effects suggest that places where the negative commute effect on home prices is high, could have their property appreciate faster than expected. However, places benefitting from the premium to live closer to work with the associated shorter commute times, could see their digests appreciate slower than expected or even decline, with potential implications for policy makers trying to fund local public services.

Table 1. Summary Statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Average Minutes to Work - ACS	208572	28.57	9.52	2.00	52.20
Average S.L. Distance to Work - LODES	208587	18.27	7.44	4.45	82.10
Percent Exceeds of CRCT - DOE	208587	0.29	0.17	0.03	0.80
Data from Data Quick*					
Log Sales Price	208587	11.80	0.99	4.61	19.20
Square Feet	208587	2027.00	1109.31	0.00	73102.00
Lot Size in Square Feet	208587	32,216	476,920	0.00	130,592,880
Number of Bedrooms	208587	2.90	1.42	0.00	99.00
Number of Bathrooms	208587	2.40	1.20	0.00	40.00
Basement Finished Square Feet	208587	80.08	330.98	0.00	9413.00
Garage Indicator	208587	0.57	0.50	0.00	1.00
Fireplace Indicator	208587	0.62	0.48	0.00	1.00
Below Average Condition Indicator	208587	0.03	0.16	0.00	1.00
Above Average Condition Indicator	208587	0.19	0.39	0.00	1.00
Recent Renovation Indicator	208587	0.75	0.43	0.00	1.00

*For a small number of properties the tax digest portion of the data lists zeros for certain homes characteristics where positive number are expected. This explains minimum values as zero in these summary stats. Dropping these observations makes no difference in these preliminary findings.

Figure 1. Truck Traffic Map

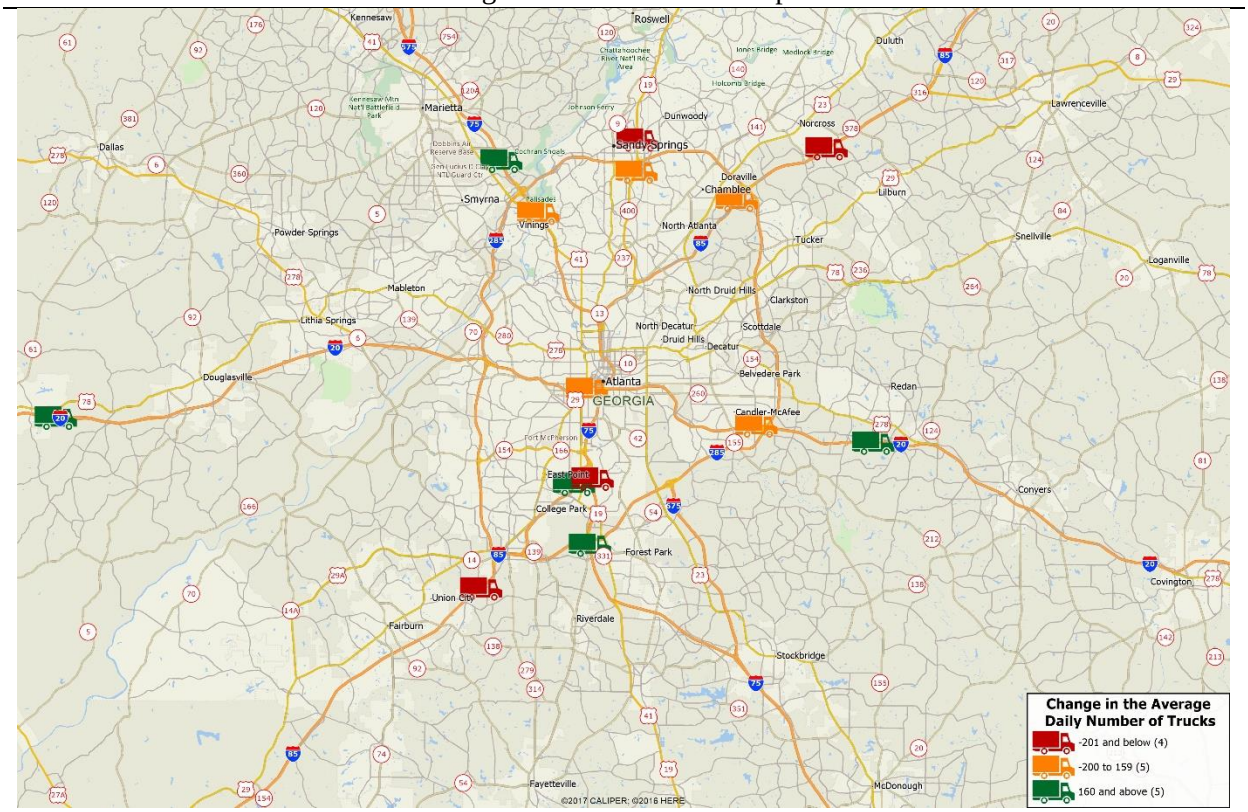

Table 2. Hedonic Price Model Result

VARIABLES	(1) Log of Sales Price	(2) Log of Sales Price	(3) Log of Sales Price	(4) Log of Sales Price -IV
Mean Miles to Work	-0.0142***		-0.0133***	0.0213
	(0.00207)		(0.00197)	(0.0459)
Mean Travel Time to Work		-0.00907***	-0.0083***	
		(0.00142)	(0.00132)	
Elementary Test Scores	1.795***	1.772***	1.716***	0.915***
	(0.110)	(0.110)	(0.106)	(0.150)
Finished Square Feet	0.000277***	0.000277***	0.000275***	0.000193***
	(2.86e-05)	(2.86e-05)	(2.86e-05)	(2.55e-05)
Finished Basement Square Feet	5.90e-05**	4.01e-05	6.73e-05***	8.81e-05***
	(2.29e-05)	(2.47e-05)	(2.48e-05)	(1.28e-05)
Bedrooms	-0.0173*	0.000745	-0.0162*	0.0103
	(0.00921)	(0.00966)	(0.00920)	(0.00752)
Bathrooms	0.109***	0.103***	0.108***	0.106***
	(0.0190)	(0.0191)	(0.0191)	(0.0164)
Lot Size	5.69e-09	-1.68e-09	5.84e-09	1.11e-08
	(1.06e-08)	(1.03e-08)	(1.06e-08)	(1.12e-08)
Garage Dummy	0.114***	0.108***	0.128***	0.139***
	(0.0210)	(0.0210)	(0.0204)	(0.0131)
Fireplace Dummy	-0.0106	-0.00600	-0.0108	0.0105
	(0.0221)	(0.0210)	(0.0212)	(0.0136)
Below Average Condition Dummy	-0.0848*	-0.0703	-0.0819*	-0.120***
	(0.0453)	(0.0431)	(0.0431)	(0.0243)
Above Average Condition Dummy	0.104***	0.108***	0.104***	0.0844***
	(0.0287)	(0.0291)	(0.0268)	(0.0130)
Recent Renovation	0.0816***	0.114***	0.0877***	0.0529***
	(0.0227)	(0.0226)	(0.0220)	(0.0180)
Month Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*
Block Group Fixed Effects	*No*	*No*	*No*	*Yes*
Number of Trucks IV	*No*	*No*	*No*	*Yes*
Constant	10.99***	10.98***	11.22***	10.48***
	(0.0714)	(0.0652)	(0.0834)	(1.540)
Observations	208,587	208,572	208,572	208,572
R-squared	0.477	0.475	0.483	0.588

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Average Treatment Effects from I-85 Project			
VARIABLES	Before Log of Sales Price	After Log of Sales Price	Difference
r1vs0.treatment	0.115***	0.147***	.0327***
	(0.00943)	(0.00833)	T-Stat
			2.6002
Observations	105,259	103,328	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 2. Block Groups by Major Corridor

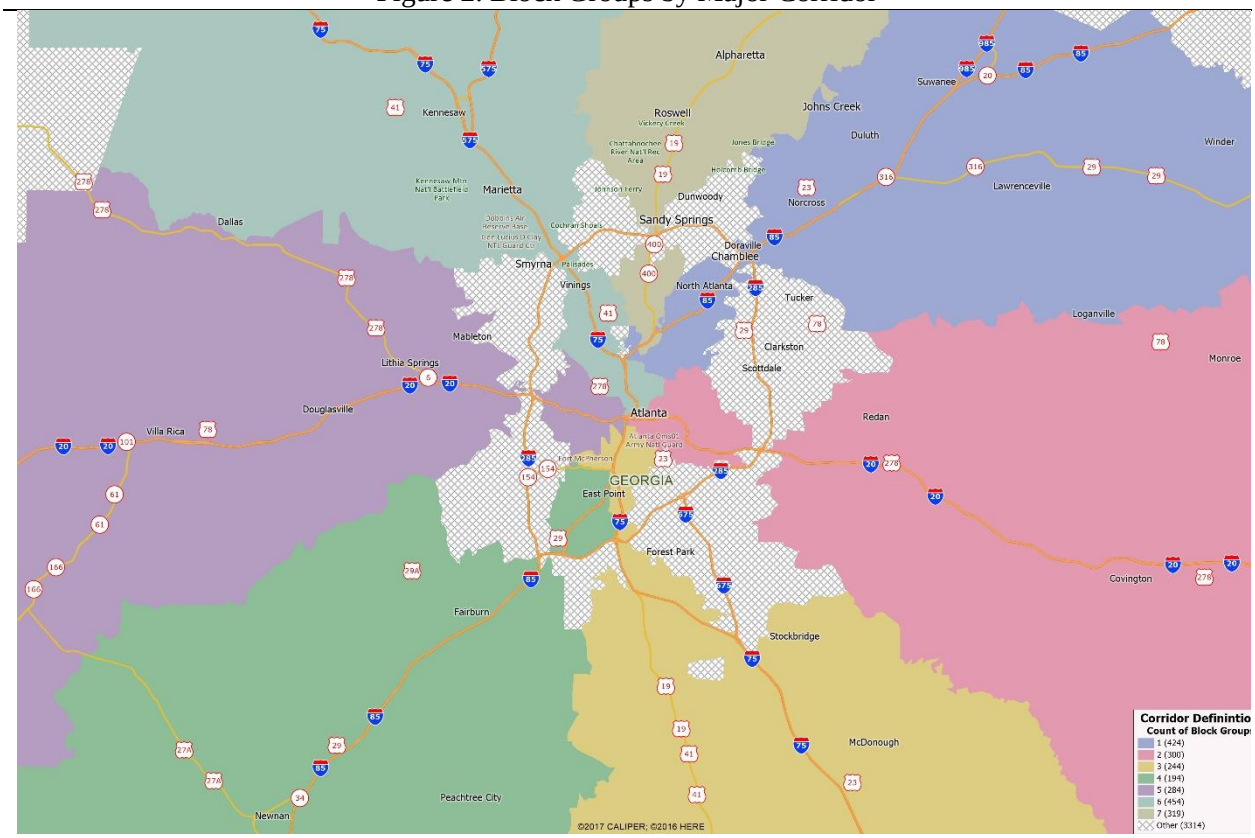

Table 4. Difference in Difference Within Matched Block Groups		
	North	South
VARIABLES	lnprice	lnprice
treatment	-0.315**	0.225**
	(0.136)	(0.0800)
after	0.0153	-1.515***
	(0.209)	(0.206)
dd	-0.221	0.246
	(0.178)	(0.172)
Elementary Test Scores	1.994***	1.089
	(0.372)	(0.709)
Finished Square Feet	0.000135***	0.000445***
	(3.33e-05)	(5.34e-05)
Finished Basement Square Feet	-0.000122	-0.00165***
	(8.74e-05)	(0.000358)
Bedrooms	0.0113	-0.0645***
	(0.0261)	(0.0193)
Bathrooms	0.109***	0.133***
	(0.0285)	(0.0267)
Lot Size	7.62e-07	3.80e-06
	(4.92e-07)	(3.79e-06)
Garage Dummy	0.108**	0.0485**
	(0.0474)	(0.0202)
Fireplace Dummy	0.305***	0.0560
	(0.0820)	(0.0474)
BAC Dummy	0.123	-0.0172
	(0.0955)	(0.0870)
AAC Dummy	0.0418	0.0916
	(0.0651)	(0.0567)
Renovation	0.0711	-0.0520
	(0.0594)	(0.0378)
Month Year Fixed Effects	*Yes*	*Yes*
Constant	11.10***	10.62***
	(0.199)	(0.123)
Observations	5,481	4,273
R-squared	0.569	0.408

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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