Using Appraisal Data to Estimate a New BRT Line's Effect on Property Values in San Antonio

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INTRODUCTION

Context

As with many American cities, the history of mass transportation in San Antonio during the 20th century is a history of the successive conversion of the same streetcar lines to different modes of transportation (Texas Transportation Museum n.d.). Mule- and horse-driven streetcars gave way to electric streetcars, and as early as the 1920s these began to be converted to bus service, whose coverage has sprawled with the city and its highways in the century since (Hendricks 2017). San Antonio is referenced by multiple authors as the first American city to begin and complete the conversion of its streetcar network to bus service, in 1933 (Hendricks 2017; Texas Transportation Museum n.d.; Viña 2011; Caine 2017, pp. 6-7). The completion of this conversion saw the creation of a public agency whose descendant, VIA Metropolitan Transit (hereafter "VIA"), still manages the city's mass transportation system.

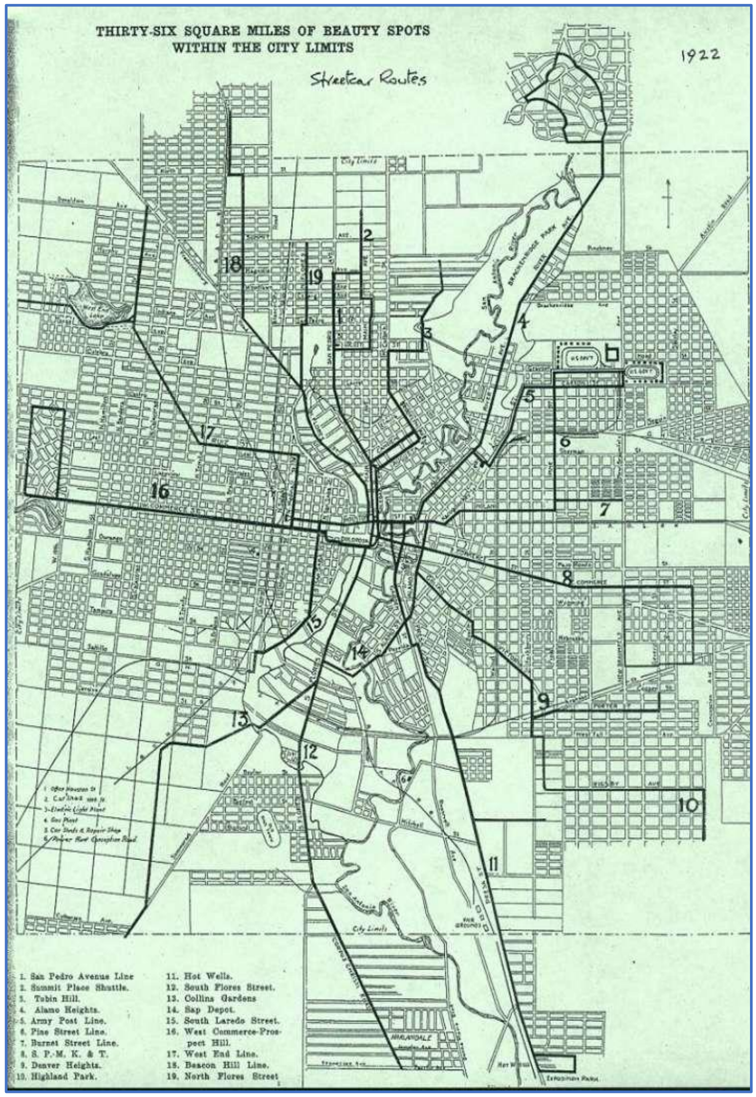

Figure 1: Map of San Antonio Streetcar Lines in 1922

More recently, the city government and regional planning authority have made efforts to encourage infill development and use of transportation modes other than the car. The city's most recent comprehensive plan, published in 2016, envisions the densification of the region's transportation corridors as well as of the "regional centers" those corridors run between (MIG 2017, p. 10). One such effort is VIA's Prímo bus service, which is distinguished from non-Prímo routes by its higher frequency and its use of several newly-renovated bus terminals (see image, left). VIA currently operates two of these routes as Route 100 and Route 101, and the agency has announced plans to begin service in 2019 on two more, as Route 102 and Route 103 (Prímo Service n.d.). This paper focuses on the first of these routes, VIA Route 100, which began operations in late 2012 (Riley 2012).

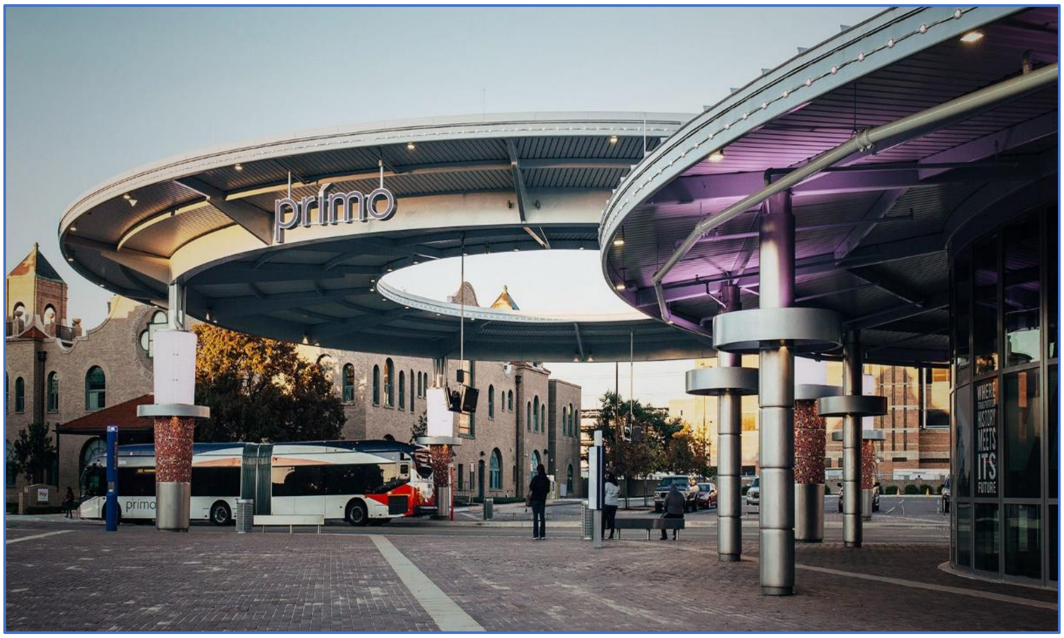

Figure 2: New VIA Bus Terminal

As will be the case for the upcoming routes 102 and 103, Route 100 connects several major employment centers and runs along one of the city's major corridors. The route was conceived and continues to be described as a connection between San Antonio's downtown and the South Texas Medical Center, site of several hospitals and of one campus of the city's University of Texas branch. Between these two centers, Route 100 mirrors a converted streetcar route by running along Fredericksburg road, whose abutting neighborhoods contain multiple historic districts and parks.[1] Figure 3, below, depicts the entirety of the route:

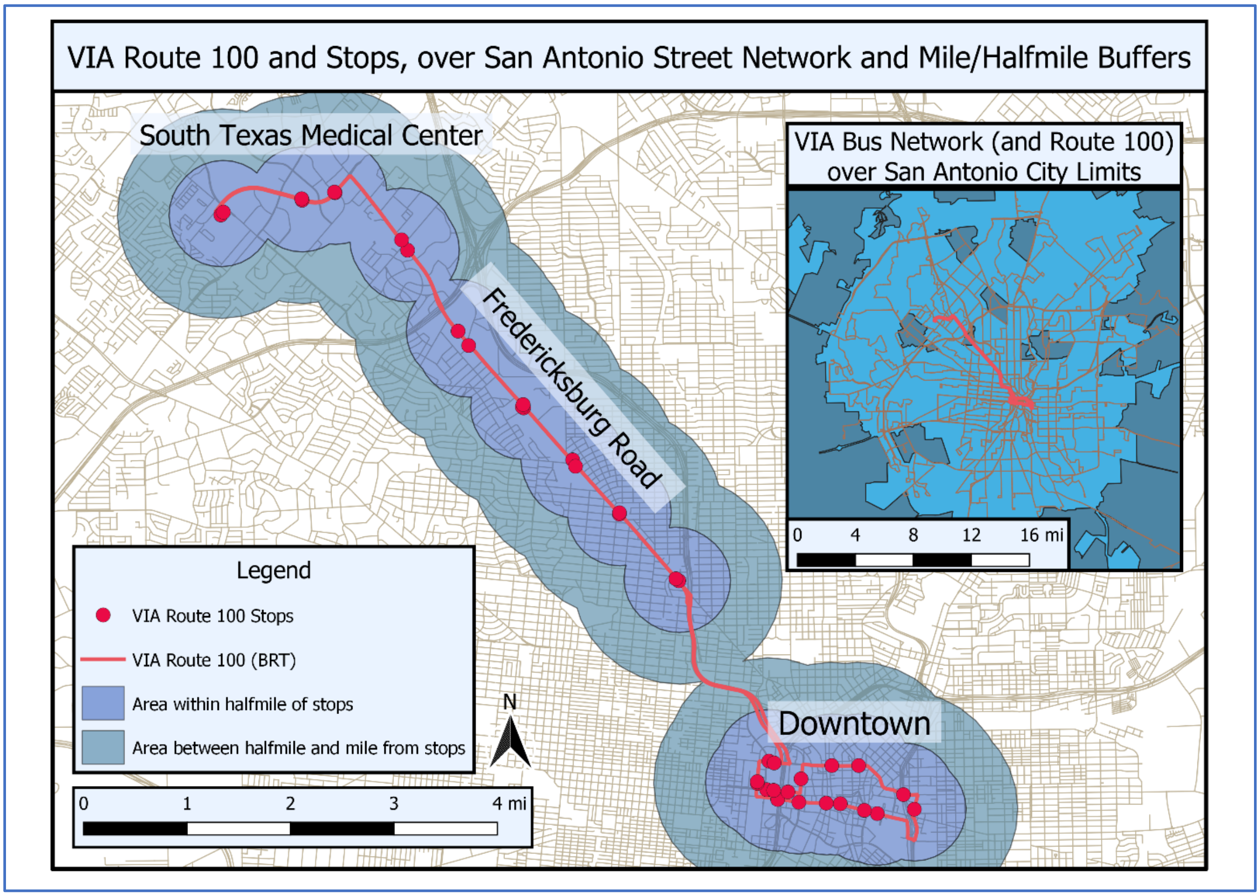

Figure 3: VIA Route 100 and Stops over VIA Bus Network

Prímo service has been designed with a variety of other features that would be expected to increase accessibility along its route. Probably most notable is the service's designation as BRT, which in practice means that Prímo routes run at significantly higher frequencies that a typical, fairly low-frequency VIA route (*Prímo 100 Schedule* n.d.). Weekdays feature 10 minute frequencies between peak hours of 9am and 6pm, with 15-30 minute frequencies for most of the rest of the day. Leaving VIA's depot in the outbound direction (away from downtown), the first bus departs at 4:15am, and the last departs at 12:30am the next day. Saturdays and Sundays, the

[1] See Figure 1 for a map featuring this route, among others.

route operates a roughly similar schedule with longer headways throughout the day—the daytime 10 minute frequencies become 15 minute frequencies, and other hours' 15-30 minute frequencies become 30-40 minute frequencies.

The service lacks certain features of BRT systems that have been the focus of international study, like Bogotá's paradigmatic TransMilenio system (Transportation Research Board n.d., p. 2). In particular, Prímo service is not separated from private car traffic, and does not attempt or plan to attempt frequencies lower than 10 minutes. Still, assuming the scheduled frequencies are met, Prímo offers clear improvement over more typical VIA routes, which offer 20-30 minute weekday frequencies and longer weekend frequencies. Overall, the service offered by VIA's Prímo Route 100 represents potentially a more significant corridor-specific improvement in mass transit accessibility than has been seen in San Antonio since the early 20th century. As suggested by the brief literature review below, such an improvement could reasonably be expected to have particular, predictable effects on land use in the neighborhoods nearest to the route.

Study Aims and Literature Review

The connection between transportation and land use has been studied in a variety of contexts, allowing researchers to develop a finer understanding of how individuals decide where to live and work, as well as where firms decide to locate. The literature on the rail accessibility "premium," for example, is diverse and goes back decades (Bowes and Ihlandfeldt 2001; Pagliara and Papa 2011; Bohman and Nilsson 2016). By 2016, this relationship had been studied thoroughly enough that one paper on the subject noted it was offering to retell "[a]n old tale" (Zhong and Li 2016). Overall, the effect is what might be expected: despite variation due to market segment, land use, and other factors, a property's increased proximity to a rail transit station is fairly reliably associated with increased value for that property.

A similar effect would be expected from improvements in bus service, which typically do not represent nearly the level of expense of an increased rail transit service but nevertheless promise to better connect the areas the service runs through. Studies of this hypothesis are less numerous than studies of the rail premium effect, and the literature is on the whole a more recent one. In addition, the effects it finds are more ambiguous, varying in size and direction due to factors like the market segment a property occupies and the timeframe of the study (Perk and Catalá 2009; Wang et al 2015; Jun 2012; Munoz-Raskin 2010).

A more recent study deserves additional focus, because it serves both as a representative example of the literature on bus routes' effect on property values and as a model for part of this paper's methodology. Perk and Catalá (2017) study the effect of several new BRT routes in Eugene, OR on the sales values of nearby properties. Notably, the authors call Eugene's EmX system a "full-featured rail-like" system, similar to Cleveland's HealthLine (Perk and Catalá 2017, p. 7). The authors construct one hedonic regression model for each of three points in time: before the introduction of BRT service, several years after the introduction of BRT service in the late 2000s, and again several years later to allow the model to be run with the most recent data. The authors then calculate the network distance to the nearest BRT station of each property within 3 miles of the BRT station, and combine this distance as a variable in a regression that included typical variables for a hedonic model—square footage, school district, median income, etc. Overall, Perk and Catalá find that decreasing distance had a significant and positive effect on sales value. Depending on the year, their model predicts an increase in sales prices of between

$823 and $1,128 for every 100 meters closer a property is to a BRT station (Perk and Catalá 2017, p. 24).

Both theory and empirical literature suggest that if a new, higher-frequency bus line improves accessibility for the areas it runs through, it will also lead the economic value (and property values) of those areas to increase. It is hard to believe frequency improvements as significant as VIA Prímo's would have little detectable effect on the value of nearby properties. However, the system also lacks many of the "rail-like" characteristics that some studies suggest cause more reliable increases in property values, and even studies of fully-featured systems like TransMilenio have produced conflicting estimates of the effect of BRT systems on property values. To further test the prediction that the increased accessibility provided by a BRT system will be associated with increased property values, this paper examines the land values of properties within a mile of bus stops served by San Antonio's Prímo stops.

Data

Data sources

Seemingly every study of BRT's impacts on property values has used some type of data on actual sales. This paper, in contrast, uses appraisal data as collected by the Bexar County Appraisal District (BCAD), which assesses all properties in San Antonio and nearby municipalities for the purposes of property tax collection. This data was chosen in part for the practical reason that it was most easily available, but it was also hoped that using a tax assessor's data would lead to insights that data on actual sales might not. BCAD provided its GIS datasets for the years 2006, 2012, and 2018. The appraisal district's GIS data contain basic geographic information, as well as a subset of the information that appraisers collect for particular properties.

Stop and route information for VIA Route 100 were sourced from VIA's GTFS feed, which was accessed through Transitland's collection of transit operator GTFS feeds.[2] This information included stop and route locations, allowing the distance to each stop to be calculated for inclusion in a regression model.

All other datasets were obtained either from the City of San Antonio (COSA)'s spatial data portal or from the EPA's Smart Location Database. The former provided information on relevant amenities like historic districts and parks. The latter was used as a source of data on neighborhood and accessibility characteristics whose influence on property values would need to be accounted for in a hedonic regression.

Data processing

From VIA's GTFS data, all stops served by VIA's Route 100 were extracted. Several stops were removed by hand to reflect the route as currently depicted on Google Maps, which is the navigation service VIA encourages its riders to use for trip planning. VIA's GTFS feed includes stops served by what seems to be a planned but unused service pattern, involving inbound and outbound travel through downtown on two parallel streets a block apart from each other (Villarreal 2012).[3] Although their inclusion did not significantly affect the selection of properties for analysis, stops associated with this unused service pattern were nevertheless removed.

To select properties for analysis, GIS software was used to construct circular buffers of a mile and a half-mile in radius, measured from each VIA Route 100 stop. The mile buffer was

[2] See the following link for VIA's feed registry: https://transit.land/feed-registry/operators/o-9v1z-viametropolitantransit.
[3] The linked article features a map displaying this service pattern through downtown: https://therivardreport.com/via-primo-service-improvement-or-disruption/.

used to select all properties within a mile of any stop. This subset of properties was then used for the removal of outliers and oddly-valued records, as described below.

Once the appropriate property subsets were constructed, the datasets required significant cleaning before they could be reliably used for calculations and regression analysis. A list of the manipulations conducted is provided in Appendix A.

Next, the variable of interest was calculated: land value per acre. Because most of these calculations produced extremely large values, these values were then converted to units of square feet to allow easier interpretation. Outliers were excluded at 3 standard deviations' difference from the mean. For 2006, this entailed excluding 502 properties, for 2012, 8 properties, and for 2018, 528 properties. Each year's GIS dataset originally contained roughly 30,000 property records. The much smaller number of outliers for 2012 seems to be due to a small number of extremely high-value properties being split and recombined for no reason that was apparent from the dataset alone. As might be expected, excluding outliers beyond 3 standard deviations in 2006 and 2018 largely excluded properties in the densest parts of San Antonio's downtown, and the hard-to-explain idiosyncrasies that those properties display in 2012 suggests that excluding them in 2006 and 2018 allows drawing somewhat more reliable conclusions.

Finally, for each year, the mile and half-mile buffers were used to select all properties within a half-mile of any VIA Route 100 stop and all properties between a half-mile and a mile from any VIA Route 100 stop. These subsets were used to compare mean land values, as described below.

Methodology

Comparison of means

In order to determine whether properties within a half-mile of any VIA Route 100 stop appreciated more quickly than properties between a half-mile and a mile away from any VIA Route 100 stop, mean land values were calculated for each property subset. The differences between these means were then compared by calculating percentage differences and by running t-tests with each pair of means. This combination of procedures allows two questions to be tentatively answered. Do properties less than a mile and more than a mile from VIA Route 100 stops have different mean values, and did the properties given the VIA Route 100 "treatment" starting in 2012 increase in value more or less quickly than properties not given the "treatment"?

Regression

In addition to a comparison of means, an ordinary least squares regression model was fit, so that the effect of a variety of variables could be estimated and controlled for. As explained in Perk and Catalá, a typical hedonic regression model of property values takes as predictors four vectors of variables, which account for the distance of parcels to places of interest, the characteristics of individual parcels, locational amenities, and neighborhood characteristics (Perk and Catalá 2017, pp. 12-13).

This paper's regression model did not include building characteristics that are typically included in hedonic models of property values, like number of bedrooms, presence of a fireplace, and year of construction. A very small number of these variables were present in BCAD's GIS datasets, and those that were were inconsistently recorded. Focusing on land value rather than the combination of land and improvement value may have somewhat mitigated this weakness, but this nonetheless represents a major departure from most other models that have been used to estimate BRT systems' impacts on property values.

A summary of the predictor variables used can be found in the chart below. Although the model includes fewer variables than would be ideal, there are at least two to represent each of the above-listed categories of vectors:

VARIABLES AND SOURCES		
Variable Name	**Variable Description**	**Source**
LandValPerLandSqFt	Variable indicating land value per land area (in square feet)	BCAD GIS dataset
MinDistToStops	Variable indicating distance to closest VIA Route 100 stop (in meters)	BCAD GIS dataset and VIA GTFS feed
HistoricZone	Categorical variable indicating property's presence in a Historic District	COSA data portal
MinDistToHistoricSite	Variable indicating distance to closest historic site boundary (in meters)	COSA data portal
MinDistToPark	Variable indicating distance to closest park boundary (in meters)	COSA data portal
ResDensity	EPA dataset's variable 'D1A'—gross residential density, as housing units per acre	EPA Smart Location Database (from 2010 Census)
JobDensity	EPA dataset's variable 'D1C'—gross employment density, as jobs per acre	EPA Smart Location Database (from 2010 Census)
RoadDensity	EPA dataset's variable 'D3a'—total road network density	EPA Smart Location Database (from 2010 Census)
Jobs45MinDrive	EPA dataset's variable 'D5ar'—jobs within 45 minutes' travel by car	EPA Smart Location Database

In summary, predictor variables included those that attempt to account for the effect under investigation (MinDistToStops), several that attempt to account for major amenities (HistoricZone; MinDistToHistoricSite; MinDistToPark), and several that account for neighborhood and accessibility characteristics of each parcel's location (ResDensity; JobDensity; RoadDensity; Jobs45MinDrive).

For variables involving distance, straight-line distances were calculated from the centroids of all parcels to either the closest point or the closest edge in a layer of interest. For example, MinDistToPark reflects the result of calculating the distance of each parcel's centroid to its closest park boundary. Although network distance would better approximate the actual route between a given parcel and a given stop, it was judged that there were no significant geographic features that would cause parcels' network distance to be different enough from their straight-line distance that the direction of the relationship between distance and land value would be strongly affected.

RESULTS

Comparison of Means

COMPARISON OF MEANS			
Extent	**Mean Land Value (2006)**	**Mean Land Value (2018)**	**Percent Change**
Half-mile from any VIA Route 100 stop	\$3.45 per sq ft	\$7.06 per sq ft	+105%
Between a half-mile and a mile from any VIA Route 100 stop	\$2.33 per sq ft	\$6.19 per sq ft	+166%
Percent difference (half-mile vs. mile/half-mile)	+33%	+12%	
Difference of means test statistic	33.96	9.84	
Difference of means p-value	$4.68e^{-248}$	$8.17e^{-23}$	

As reflected in the chart above, the comparison of means suggests several relevant conclusions. In both 2006 and 2018 (before and after the beginning of Prímo service), properties within a half-mile of Route 100 stops had a higher mean value than properties between a half-mile and a mile from Route 100 stops, with a high degree of confidence. This is as expected, because of the closely related factors of the accessibility premium of major corridors and the concentration of highly-valued properties around those corridors.

However, the comparison also shows a clear reduction between 2006 and 2018 in the difference between the two groups' means. The test statistic for the difference of means shrinks by several times between the two years, and the group of properties further away from VIA 100 stops increased in mean value by roughly 50% more than the group of properties closer to the stops. This is exactly the opposite of the change that would be expected if the introduction of Prímo service led to an increased accessibility premium for properties closer to its stops.

This change can be more effectively visualized with a box plot, as below:

Figure 4: Box Plot of Land Value (outliers beyond 1.5 * IQR hidden)

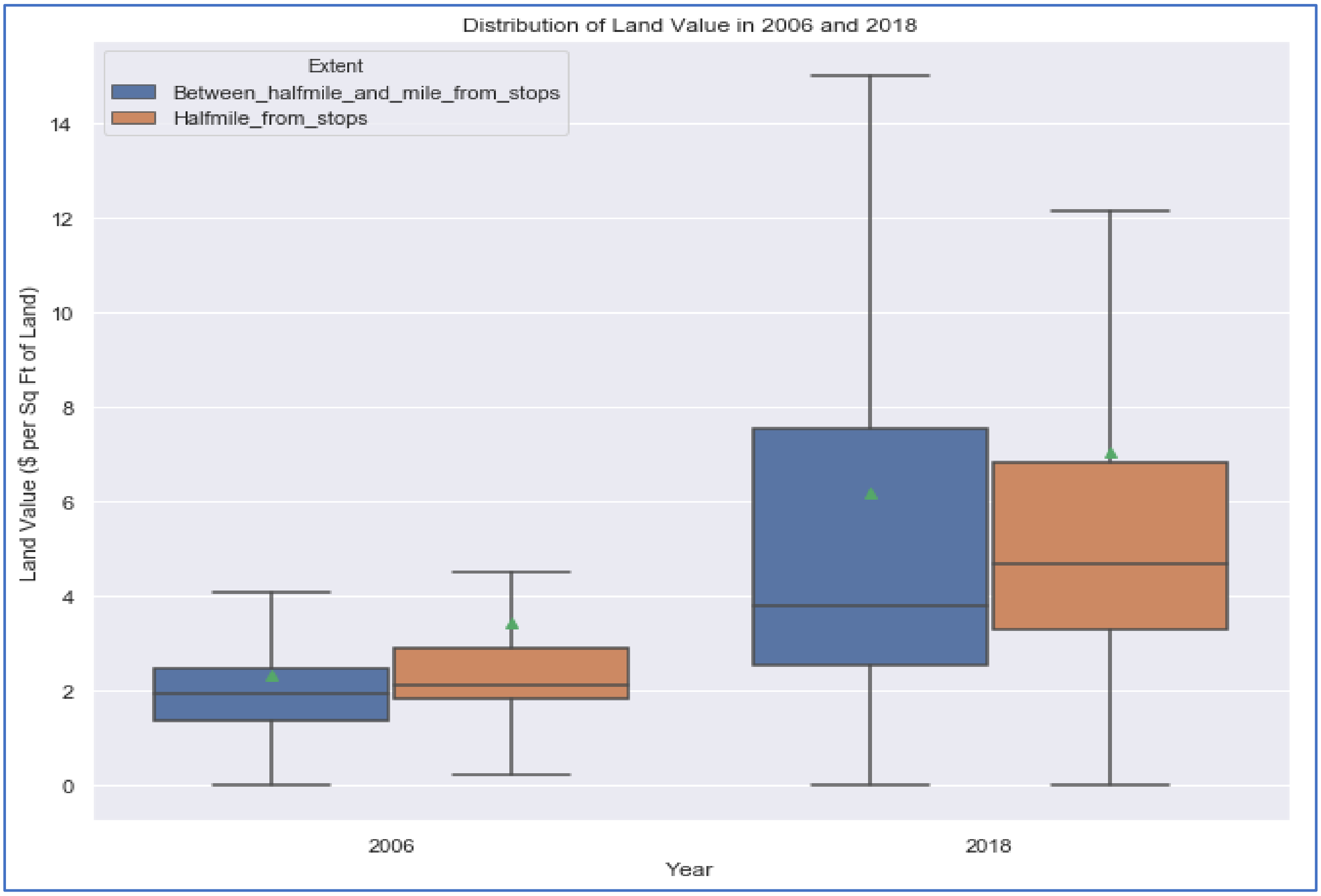

Figure 4: Box Plot of Land Value in 2006 and 2018

As discussed above, the mean values (represented by the green triangles) of the two groups clearly converge, even though the properties within a half-mile of Route 100 stops have a larger mean value in both years. More interestingly, the box plot also helps visualize the large increase in the inter-quartile range of each group of properties. Small and roughly equivalent in 2006, each group's IQR has expanded by several times by 2018, and the IQR of properties beyond a half-mile now fully overlaps the IQR of properties within a half-mile. Although both distributions are extremely right-skewed, this change suggests that the relative increase in the mean values of properties beyond a half-mile from Route 100 stops could be due to an increase in value by a large number of properties in the upper half of that group's distribution. This interpretation is supported by an ugly (but useful) box plot displaying the values beyond 1.5 * IQR:

Figure 5: Box Plot of Land Values in 2006 and 2018 (showing outliers beyond 1.5 * IQR)

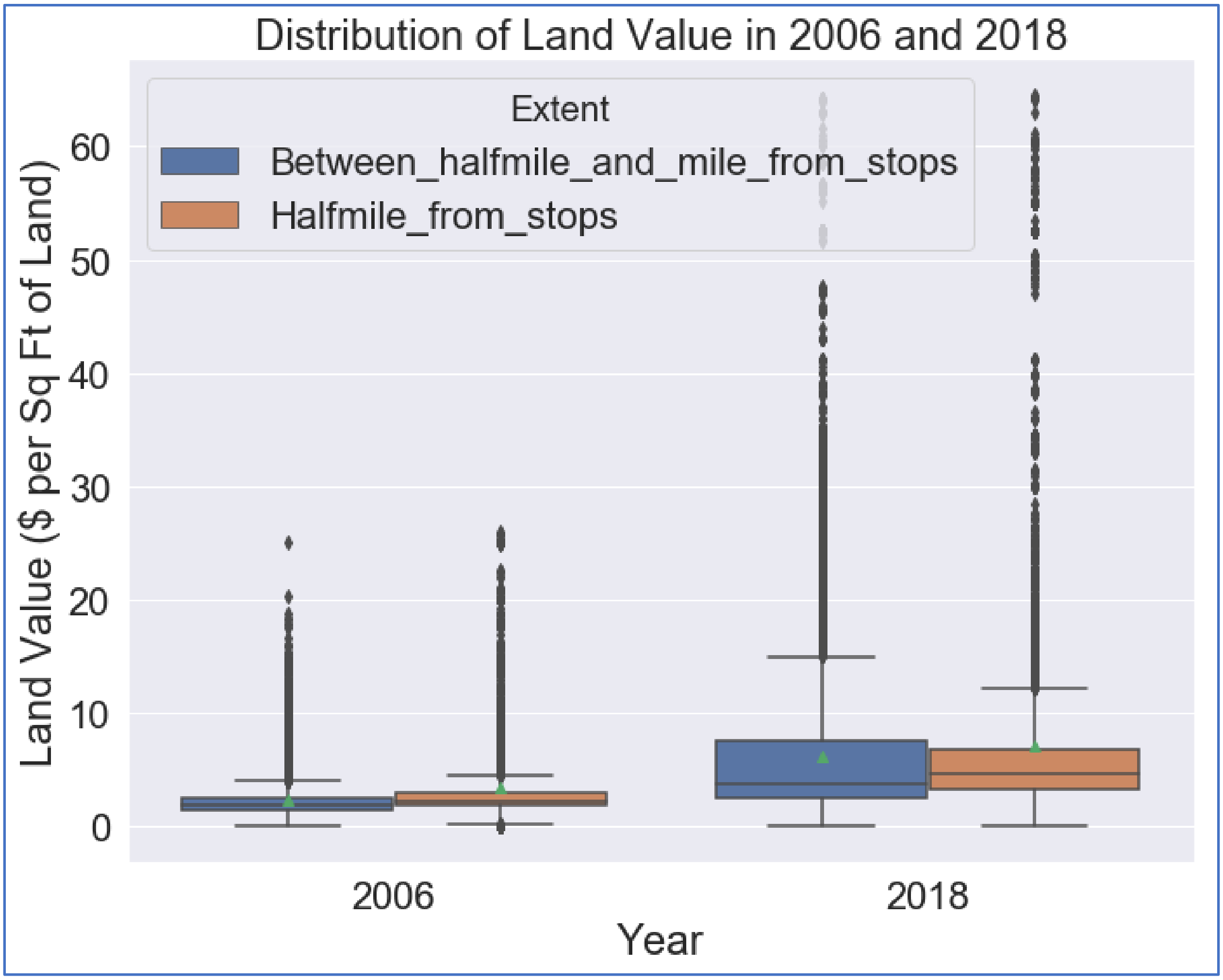

*Figure 5: Box Plot of Land Values in 2006 and 2018, Including Values > (1.5*IQR)*

Regression

Variable Name	Coefficient *(Standard Error)*	t Statistic	p-value (* indicates α = 0.05)
	REGRESSION RESULTS (2018)		
Intercept	7.7716 *(0.583)*	13.323	0.000*
MinDistToStops	**-0.0002** ***(8e^{-05})***	**-2.786**	**0.005***
HistoricZone	3.3574 *(0.104)*	32.324	0.000*
MinDistToHistoricSite	-0.0020 *(6e^{-05})*	-29.559	0.000*
MinDistToPark	0.0022 *(9e^{-05})*	23.275	0.000*
ResDensity	0.0068 *(0.020)*	0.349	0.727
JobDensity	0.2810 *(0.003)*	111.055	0.000*
RoadDensity	0.1453 *(0.006)*	24.575	0.000*
Jobs45MinDrive	-4e^{-05} *(3e^{-06})*	-13.374	0.000*
R-squared	**Observations**	**F-statistic**	
0.420	28,588	2584 (p=0.00)	

The results of the regression also suggest some contradictory conclusions. As in Perk and Catalá (2017) and a number of other studies, the regression produces a model with a negatively-valued coefficient for the term representing a parcel's distance to its nearest bus stop. That is, parcels that are closer to bus stops are predicted to have higher land values, by virtue of being closer to a bus stop. The model suggests this estimated effect is right on the line of statistical significance at the 95% level, and the size of the effect is moderate. For every meter closer to a bus stop, the model predicts an increase in value of $0.00007 per square foot, or an increase of 7 cents per square foot for every 100 meters closer. In other words, if a 1-acre property (43,560 sq. ft.) is 100 meters closer to a bus stop than another 1-acre property, the closer property is predicted to have a total appraised land value roughly $3,000 greater. A more typically-sized residential lot of

8,000 square feet would be expected to have a land value roughly $560 greater for every 100 meters closer to a Prímo stop. The estimated premium seems very roughly on the order of the premium estimated by Perk and Catalá, who as noted in the literature review above estimate an increase in sales price of between $823 and $1,128 for every 100 meters closer to a BRT stop.

All of the other predictor variables produce estimates with a higher (virtually 100%) degree of confidence, other than residential density. Compared to the other distance-related variables, the effect of the BRT stops seems fairly small in comparison. An unexpected result is that increasing distance to parks is associated with increasing land values. An entirely expected result is the effect of distance to historic sites and presence in a historic zone, the latter of which far outweighs the effect of any other predictor. The same hypothetical 8,000 square foot lot would be expected to see an increase in land value of $26,880 in a historic district.

Similarly, job and road density are both predicted to increase property values with a high degree of confidence. Interestingly, the EPA measure of jobs within a 45 minute drive shows a very small effect relative to the measure of job density, which is the predictor with the second-highest estimated effect after historic zone presence. By effectively suggesting that jobs closer to a parcel contribute to its value much more than jobs further away, this might be interpreted as a vindication of the same vein of theory that predicts an accessibility premium from BRT stops.

The model's R^2 value suggests that the model explains a fairly large amount of the observed variance (42%), though as explained below this should value should be treated with caution due to apparent heteroscedasticity.

Discussion

Checking regression assumptions

Multicollinearity

VARIANCE INFLATION FACTORS	
Variable	**VIF**
MinDistToStops	1.09
HistoricZone	1.20
MinDistToHistoricSite	2.92
MinDistToPark	2.75
ResDensity	1.21
JobDensity	1.23
RoadDensity	1.42
Jobs45MinDrive	1.43

The variance inflation factor (VIF) is a measure of how much a predictor variable's variance is increased by its relationship to other predictor variables. A higher VIF suggests a stronger correlation between a given predictor variable and at least one of the other predictor variables. VIFs that are traditionally thought of as being large (i.e. VIF > 5) indicate a high degree of correlation between two or more of the predictor variables, which could cause a regression model's estimates to vary due to relationships among the predictor variables, rather than due to a relationship between the predicted variable and the predictors.

As can be seen in the chart above, none of the variables display very worrying VIFs, other than perhaps distance to historic sites and distance to parks. These both have fairly large VIFs (2.92 and 2.75, respectively), which could indicate their correlation with each other. Overall, though, multicollinearity was not judged to be present to a significant degree, so no variable were excluded on this basis.

Homoscedasticity

Another fundamental assumption of regression is that the errors of a linear model exhibit equal variance for each value of an independent variable. The figure below of fitted values plotted versus residuals shows that this assumption is clearly violated in this case, for reasons that will be suggested below.

Figure 6: Scatterplot of Fitted Values versus Residuals

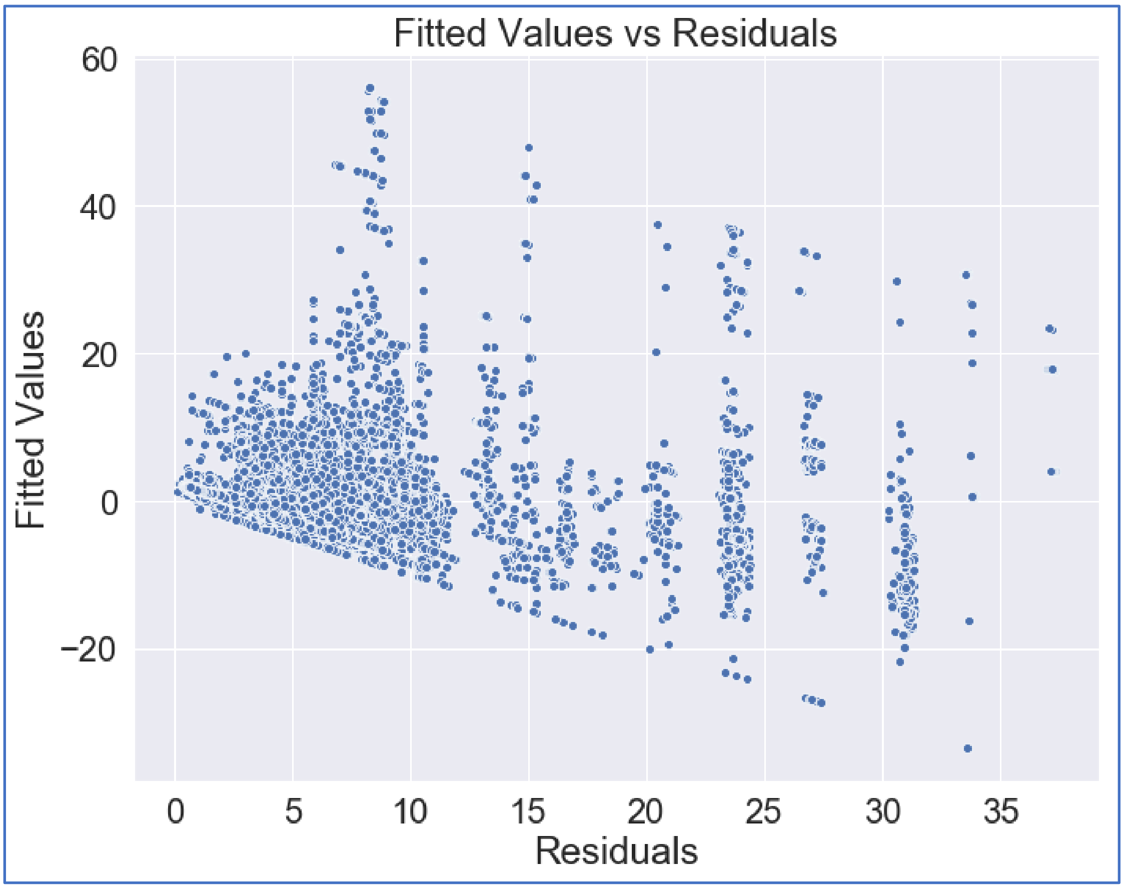

Figure 6: Fitted Values vs. Residuals

The residuals show a "banded" pattern, in which a wide range of fitted values are often associated with roughly the same residual value, and vice versa. This seems to be due to a large numbers of properties having a land value that matches at least one other. Specifically, 2/3 of the roughly 30,000 records in the 2018 dataset have a land value that matches the land value of at least one other property. An example is provided in the map below. In the figure, two groups of properties are displayed, the total land value for each of which has been appraised as one of two values: $17,970 or $18,520. Overall, this group of properties numbers roughly 200. For each of these properties, the per-area value estimated by the model might vary significantly, but the estimated value would also vary consistently with the distance-based variables included in the models. This could produce distinct clusters of properties that have roughly similar fitted values but very different residual values, depending on which side of the boundary between these clusters a property happens to fall. A similar effect could be caused by historic district presence, the major predictor and also one that is very sensitive to boundaries.

Figure 7: Map of Identically-valued Parcels along Route 100

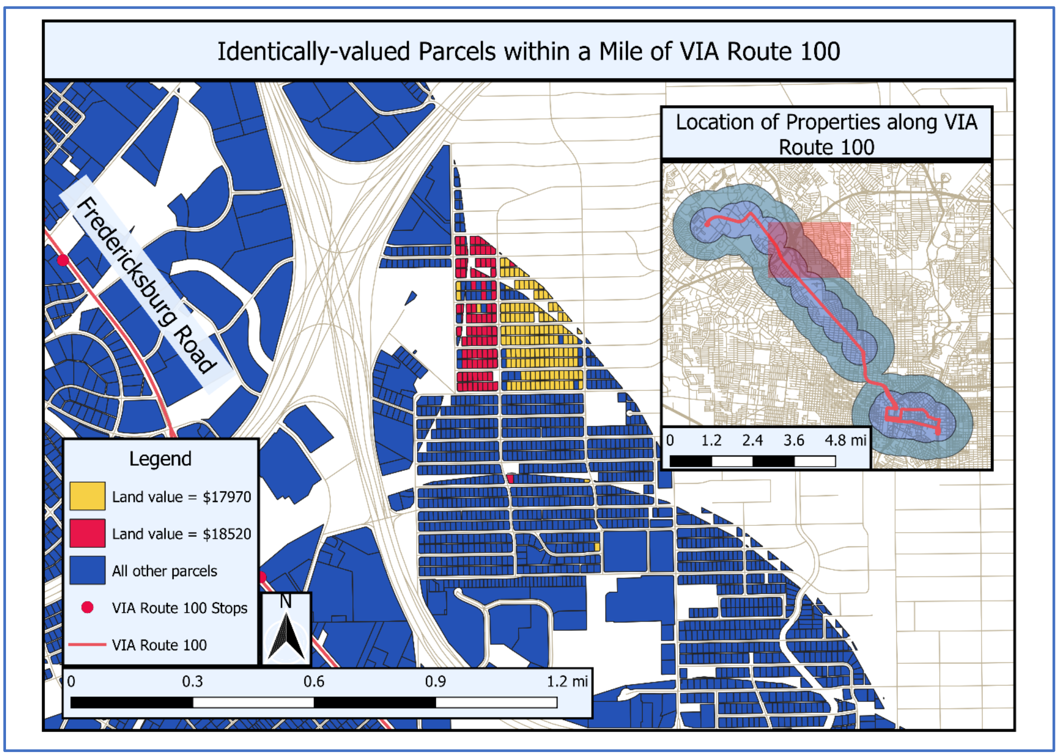

Figure 7: Identically-valued Parcels

CONCLUSION

Overall, this paper produces two major findings, which are somewhat contradictory. A comparison of mean land values suggests that properties closer to VIA Route 100 stops increased in value much more slowly than properties further from VIA Route 100 stops, between 2006 and 2018. On the other hand, the linear regression model suggests that decreasing distance to Route 100 stops can be reliably predicted to increase a parcel's land value by a moderate amount, after holding other factors constant. A potential explanation is that the subset of properties between a half-mile and a mile from Route 100 stops experienced some effect that properties within a half-mile did not, but it is difficult to speculate what that effect might be. In any case, the results lend support to the idea that higher-frequency bus service, even if not "rail-like" BRT, is associated with an increase in land values.

Moreover, this paper's methodology allows the accessibility premium to be tied specifically to land value, in ways that methodologies relying on sales price cannot. Conceivably, appraisal data could be used to answer further questions about the differential impact of accessibility on land value versus improvement value.

Using appraisal data for this purpose also presents some challenges. In part this paper might be best understood as a study of Bexar County appraisers' opinions of how changes in bus service affect the value of land that is nearer to the altered service. The overwhelming effect of historic zones might be an indicator of this. Of all the factors included in the regression, presence in a historic zone is by far the easiest for an appraiser to determine—it seems unlikely that Bexar County's appraisers consider distance to parks or distance to transportation in a fine-grained way, but historic districts offer a binary signal that can be easily factored into appraisals. On the other hand, this also suggests the notable conclusion that appraisers seem to factor accessibility into their estimates of land value.

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Figures

Figure 1:

A 1922 map of San Antonio streetcar routes shows the system at its peak, 1922, image. Howell, Mike, “Historical Streetcars: Take a look back at SA’s trademark transportation.” Available from: https://www.mysanantonio.com/news/local/slideshow/Historical-streetcars-67262/photo-4978960.php. [9 December 2018].

Figure 2:

Bus terminal image featured on VIA Metropolitan Transit webpage, n.d., image. Available from: https://www.viainfo.net/primo-service/. [9 December 2018].

Figure 3:

Author creation.

Figure 4:

Author creation.

Figure 5:

Author creation.

Figure 6:

Author creation.

Figure 7:

Author creation.

APPENDIX A:

A list of data manipulations performed for this analysis is below:

- Some properties were recorded with zero value—these were entirely removed;
- For each year, properties with land values (per unit area) more than 3 standard deviations away from the mean land value (per unit area) were considered outliers and removed;
- Certain fields contained duplicated information, including land values and what looked to be unique property ID numbers. These were judged to be duplicated records, and they were removed;
- Significant numbers of properties were recorded with negatively-valued ID fields—as with the zero-valued land value fields, this seems to be due to the assessor's needing to assign a value shapes that are not in practice valued by the assessor but that nevertheless appear in their dataset, like a segment of river or road. These records were removed.