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End of the line: The impact of new suburban rail stations on housing prices

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Abstract: This study leverages the staggered opening of new Metro stations in a suburb of Washington, DC to estimate the impact of proximity to public rail transit on housing prices. Both hedonic and repeat sales models indicate that housing prices increase as distance increases, suggesting that living near public transportation in Prince George's County is primarily viewed as a disamenity. For properties at one mile from the nearest station, the preferred repeat sales model estimates a marginal price increase of 4.6 percent for a one-mile increase in distance. I argue that the suburban environment may be key in explaining the results. In the suburbs, a greater share of the population relies on automobiles, and rail stations are typically equipped with large parking lots. The suburban environment allows households the opportunity to both benefit from public transportation access and mitigate the negative externalities associated with living right next to the station.

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1 Introduction

Public transportation is a ubiquitous part of urban environments. Benefits of public transportation are wide-ranging, such as reducing traffic congestion, improving air quality, and expanding access to jobs (Baum-Snow & Kahn, 2000; Bhatta & Drennan, 2003). Additionally, reducing barriers to public transportation can help reduce the gap between higher income households who can afford private modes of transportation and lower income households who rely on public transportation to access jobs (Baum-Snow & Kahn, 2000). However, investments in public transportation are not without controversy. Many cities continue to grapple with declines in public transit usage and persistent concerns regarding the impact of transit-oriented development on proximate neighborhoods and residents (Baum-Snow & Kahn, 2000; Manville & Cummins, 2015; Padeiro et al., 2019).

As government continues to invest in public transportation, researchers have attempted to quantify the relationship between proximity to public transportation and housing prices. Whether proximity to public transportation is an amenity or disamenity is theoretically ambiguous. For example, housing prices may be higher near stations as households may be willing to pay more to be closer and take advantage of accessibility benefits. On the other hand, housing prices may be lower near stations as households may be willing to pay more to avoid nuisances associated with station areas. Hedonic regressions that control for housing and locational characteristics have been widely used to estimate the relationship

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between proximity and housing prices. However, the threat of omitted variable bias is high unless the model has an extensive set of controls. One strategy to reduce bias is to take advantage of panel data and use a repeat sales model where the hedonic model is transformed into a fixed effects regression. This approach makes a stronger case for causality by controlling for all time-invariant characteristics of each property and thus its neighborhood, but it requires an exogenous shock to public transit proximity to be feasible.

Although there is a well-established literature that uses the hedonic framework to estimate the capitalization effects of proximity to public transportation, only a few studies produce both estimators (Billings, 2011; Kim & Lahr, 2014; McMillen & McDonald, 2004). I employ both hedonic and repeat sales models to quantify the relationship between proximity and housing prices. Using a panel of sales transactions data from 1998 – 2007, I exploit the potentially exogenous staggered opening of six stations in Prince George's County to estimate the net effect of proximity to the Washington Metropolitan Area Transit Authority's (WMATA) Metrorail system ("Metro") stations on housing prices in Prince George's County, Maryland.

This study makes the following contributions to the literature. First, the study directly focuses on a suburb. As cities expand, a growing share of investments has been directed towards connecting central business districts to suburban communities. Examining suburban neighborhoods fills a contextual gap in the field as the literature predominantly focuses on central city neighborhoods. It is premature to assume that findings from central cities can be generalized to the suburbs. Residents who sort into the suburbs have different preferences for public transportation, responding to differences in the built environment, public transportation culture, and amenities relative to cities. Second, I estimate models with an unrestricted continuous distance measure, which may be better suited for the suburban context. The majority of the studies investigating the relationship between proximity to rail in central cities examine small study areas, typically not exceeding three miles from the stations (Billings, 2011). Walkability to the station is a key justification for examining small study areas, which may be less appropriate in more car-centric suburbs.

Both the hedonic and repeat sales models estimate that housing prices increase as distance increases, suggesting that living near public transportation in the suburbs is primarily viewed as a disamenity and the marginal household is willing to pay more to be incrementally farther from the station. The main findings are robust to alternative distance specifications and sample selection. For properties at one mile from the nearest station, the preferred repeat sales model estimates a marginal price increase of 4.6 percent for a one-mile increase in distance. Proximate properties experience the largest marginal price increases and effects get smaller as distance increases. This suggests that the negative externalities from the station may be dominating the positive externalities for properties within close proximity. Additionally, plotting the marginal effects demonstrates that I estimate statistically significant marginal price increases beyond walkable distances. The main findings contrast with the majority of studies that find a premium for properties located near rail stations in central city neighborhoods. I argue that the suburban environment may be key in explaining this difference. In the suburbs, a greater share of the population relies on automobiles, and it is not surprising for commuters to be driving five to 10 miles to utilize rail stations with large parking lots. The suburban environment allows accessibility benefits to extend beyond walkable distances. By choosing to live within driving distances of the station, households can still obtain accessibility benefits while mitigating nuisance elements from the station.

The paper is structured as follows. I will begin with the theoretical foundation of bidding and sorting that underlies the use of hedonics to value amenities and review of the recent literature. I then provide a more detailed description of the Metro and study area and describe the study sample. The next section will introduce the empirical strategy, followed by the results of the empirical analysis and robustness checks. I conclude with a discussion of the main findings and areas of future research.

2 Conceptual framework and literature review

Differences in housing prices based on variations in access to public transportation are tied to the theory of bidding and sorting. Each household type has a bid function that indicates how much the household is willing to pay for housing at a given location (Alonso, 1964; von Thünen, 1826). The winner at a specific location is the household type with the highest bid, leading to the sorting of heterogenous households across different locations with different levels of amenities. Rosen's (1974) seminal paper formally connected the theory of bidding and sorting to hedonic regressions by showing that the resulting hedonic price function is the envelope of the underlying bid functions and further reinforced the use of hedonics in measuring the impact of amenities on housing prices.

Many empirical studies have used the hedonic framework to investigate the relationship between proximity to rail and housing prices. Findings are mixed, but the majority point to a degree of positive capitalization. It is not surprising that the field has not reached a consensus given that multiple mechanisms drive the relationship. Bowes and Ihlanfeldt (2001) identified several factors that could potentially affect whether public transportation is viewed as an amenity or disamenity. On the positive side, they hypothesized that public transportation could bring accessibility and economic development benefits. Households may be willing to pay more for housing near stations to reduce commuting cost and improve access to other amenities. Public transportation stations can also serve as anchors that spur neighborhood revitalization. On the negative end, public transportation could bring nuisances into the neighborhood. Living close to a station is associated with more noise, traffic congestion, pollution, and even crime. Therefore, households may be willing to pay more to live farther away from rail stations to avoid these negative externalities. The majority of empirical studies estimate the net effect of proximity but are unable to identify which factor(s) drives the effect. Even when researchers have been able to disentangle the mechanisms, the strength of each mechanism can also differ depending on the setting (Bowes & Ihlanfeldt, 2001).

Several comprehensive literature reviews and meta-analyses, including Debrezion et al. (2007), Mohammad et al. (2013), and Hamidi et al. (2016), have highlighted the mixed findings. For example, Debrezion et al. (2007) found that in studies that used a continuous measure of distance, property values for single-family homes increased by an average of 2.4 percent for every 250 meters closer to the station, with estimates ranging from -3.1 percent to 13.4 percent. These reviews point to variations in methodological approach, measurement of proximity, and local context to explain the mixed findings.

Overall, heterogenous findings and challenges of external validity have motivated researchers to apply the hedonic framework to estimate the effect of proximity to rail stations on housing price across new settings. Table 1 identifies a sample of recent empirical studies (published after 2010) investigating the relationship between proximity to rail and housing prices in the United States. The table highlights that consensus on findings remains elusive despite the growing use of the repeat sales method. Historically, studies have focused on central cities with prominent transportation networks and ridership, but recent research has extended the field by studying non-traditional urban areas with less robust transportation systems, such as Charlotte (Billings, 2011; Yan et al., 2012) and Minneapolis (Cao & Lou, 2018; Pilgram & West, 2018). Additionally, Table 1 underscores that suburban stations have not been a focus of previous studies. Many authors excluded suburban stations due to data limitations (Pilgram & West, 2018; Yu et al., 2017). Studies that included suburban stations did not focus on the suburban context but rather included the suburban stations as part of the broader system.

In terms of the Washington, DC area, earlier studies, including Damm et al. (1980), Grass (1992), and Benjamin and Sirmans (1996), found that prices were higher for properties near the Metro in DC, but these studies used limited datasets and focused on a small number of neighborhoods. In a more recent study, Zolnik (2020) broadly studied the entire Metro system and found that housing prices were two percent higher near Metro stations.

Table 1. Summary of previous literature estimating the effect of proximity to rail stations on housing prices

Author (Year)	Study Geography	System/Line	Study Area	Repeat Sales	Amenity or Disamenity
Billings (2011)	Charlotte, NC	LYNX, Blue Line	Entire line connecting downtown Charlotte to county line, included a mixed of stations inside the central city and suburban stations.	Yes	Amenity
Yan, Delmelle, and Duncan (2012)	Charlotte, NC	LYNX, Blue Line	Entire line connecting downtown Charlotte to county line, included a mixed of stations inside the central city and suburban stations.	No	Disamenity
Golub, Guha-thakurta, and Sol-lapuram (2012)	Phoenix, AZ	Valley Metro Rail	Entire line connecting three cities (i.e., Phoenix, Tempe, and Mesa) from Northern Phoenix neighbor-hoods to downtown Mesa.	No	Amenity
Chatman, Tulach, and Kim (2012)	Southern NJ	New Jersey Tran-sit, River Line	Entire line connecting Camden and Trenton, NJ. Stations area mostly in small towns.	Yes	Disamenity
Pan (2013)	Houston, TX	Harris County MetroRAIL, Main Street Line	Entire line connecting Downtown Houston to Fannin station (near Astrodome). All stations are inside the central city.	No	Disamenity for proximate properties
Kim and Lahr (2014)	Southern NJ	New Jersey Transit, Hudson-Bergen Light Rail	Limited studies to four stations lo-cated across the line. The entire line connects densely populated commu-nities in Hudson County: Bayonne, Jersey City, Hoboken, Weehawken, Union City, and North Bergen.	Yes	Amenity
Zhong and Li (2016)	Los Angeles, CA	Los Angeles County Metro Rail	Limited study to stations inside the city boundary.	No	Disamenity
Yu, Zhang, and Pang (2017)	Austin, TX	Capital MetroRail	Limited study to stations inside the city boundary.	No	Amenity
Wagner, Komarek and Martin (2017)	Norfolk, VA	Hampton Roads Transit, The Tide	Entire line in Norfolk, VA.	No	Disamenity
Camins-Esakov and Vandergift (2018)	Bayonne, NJ	New Jersey Transit, Hudson-Bergen Light Rail	Examined a single station extension in Bayonne, NJ.	Yes	Neutral
Cao and Lou (2018)	Minneapolis, MN	Metro Transit. Green Line	Limited study to stations located in St. Paul. Line connects downtown Minneapolis to downtown St. Paul.	No	Amenity
Pilgram and West (2018)	Minneapolis, MN	Metro Transit, Blue Line	Limited study to stations inside the city boundary. Line connects Minne-apolis to Mall of America (suburb).	Yes	Amenity
Ransom (2018)	Seattle, WA	Sound Transit, Central Link	Limited study to stations located in Rainer Valley, included a mixed of stations inside the central city and suburban stations.	No	Neutral

3 Study area

3.1 WMATA Metro

In 1968, the WMATA approved a 100+ mile rail transit system plan to serve the Washington, DC area. The Red Line opened in 1976 with five stations, followed by Blue and Orange in 1977 and Yellow in 1983.[1] The last planned line, Green, opened in 1991 with three stations.

I will specifically exploit two rail expansions in Prince George's County during the 2000s. First, 6.5 miles were added to the Green Line and opened in January 2001, connecting Anacostia to Branch Avenue. The original plan was finally completed with this expansion and remained fairly intact, with the exception of a small realignment agreed upon in 1984 (Lynton, 1984; Vesey, 1982). Second, 3.2 miles were added to the Blue Line, the first ever expansion outside of the 1968 plan, and opened in December 2004, connecting Addison Road to Largo Town Center. Although not part of the original plan, the Blue Line expansion had been a part of decades-long discussions regarding the future of the Metro. These two expansions would "basically complete the Prince George's line" for the foreseeable future (Ginsberg, 2004). Figure 1 displays the WMATA Metro system in 2005, after the Blue Line expansion.

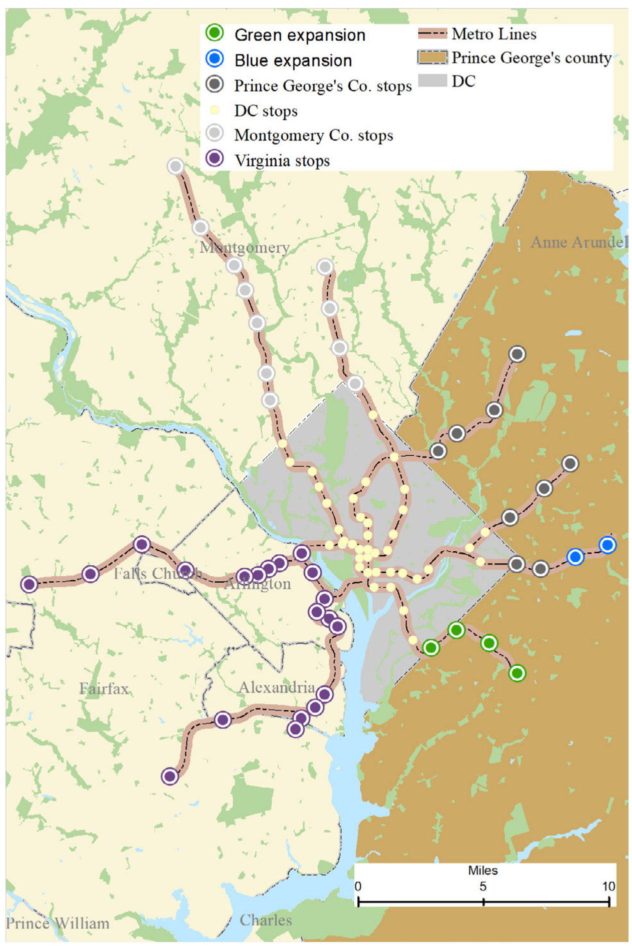

Figure 1. WMATA Metro system, 2005

Note: Shapefile for Metro stations and lines are from National Capital Region Transportation Planning Board (https://rtdc-mwcog.opendata.arcgis.com/).

[1] For the 1976 WMATA system map, please see: https://www.transitmap.net/wmata-1976-pamphlet/.

3.2 Station areas

All of the new stations in the study area are island platforms with associated Park and Ride facilities. Figure 2 zooms into the last station of the Green (left) and Blue (right) Lines expansions and highlights the size of the station areas and large supply of parking spaces. Residential zoning begins about 0.5 mile outside of the transit stop. Previous studies that examined the impact of new stations on housing prices tended to limit treatment areas within walkable distances to the stations (Debrezion et al., 2007). However, these figures highlight that this distance restriction may not be applicable in suburban stations where stations encompass large areas and are more accessible to vehicles. Furthermore, previous research on Park and Rides has suggested that Park and Ride facilities have the potential to increase transit usage (Zhao et al., 2019), redefine catchment areas (Horner & Grubesic, 2001), and attract suburban riders who are willing to travel longer relative to central city riders (Nelson et al., 1997). The Maryland-National Capital Park and Planning Commission (2014) analyzed WMATA parking origins survey data for the southern Green Line stations and found that more than two-thirds of Branch Avenue parking customers were driving more than five miles, providing evidence that private vehicles are an important mode of access in Prince George's County.

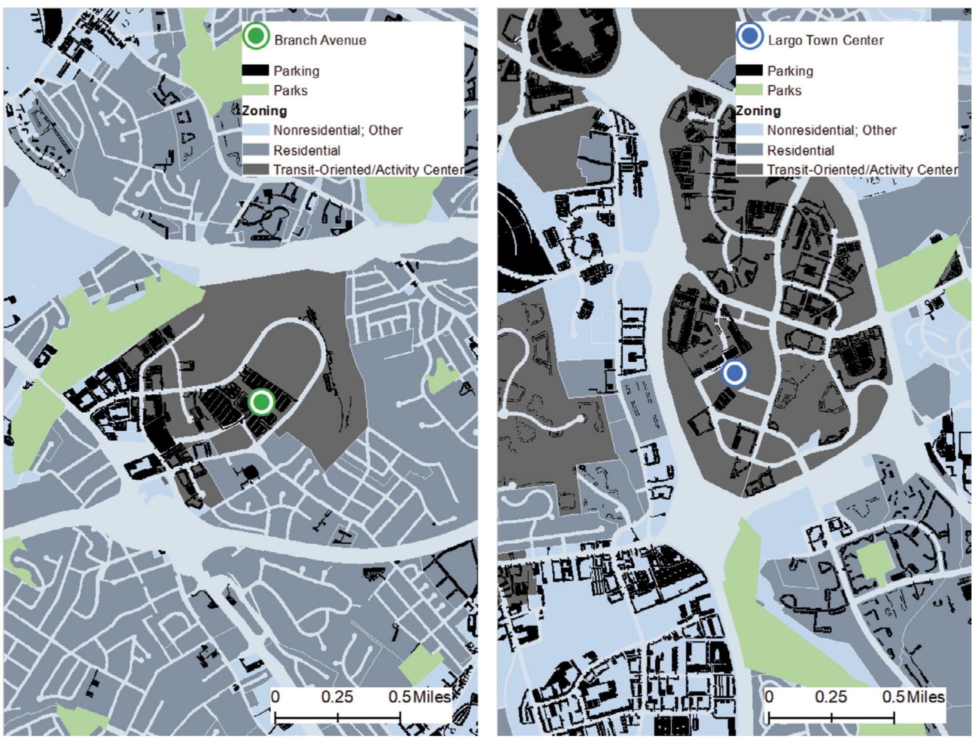

Figure 2. Station areas

Note: The left panel zooms into zoning surrounding Branch Avenue, the last station of the Green Line. The right panel zooms into zoning surrounding Largo Town Center, the last station of the Blue Line. Shapefile for metro stations is from National Capital Region Transportation Planning Board (https://rtdc-mwcog.opendata.arcgis.com/). Shapefile for zoning information is from Prince George's County Planning Department (https://gisdata.pgplanning.org/opendata/).

3.3 Prince George's County

Prince George's County is an eastern suburb of Washington, DC where some of the richest Black neighborhoods in the United States are located (2015). During the 1970s and 80s, Black professionals from DC turned to Prince George's County in search of the American Dream. The in-migration of Blacks led to racial tensions and a large share of Whites started fleeing the county during the 1980s (Cashin, 2001; Greene, 1999). In 1980, non-Hispanic Whites accounted for 60 percent of the county population. By 1990, Prince George's County was a majority-minority county, with non-Hispanic Whites only accounting for 40 percent of the population (Maryland Department of Planning, 2014).

The in-migration of Black professionals and out-migration of Whites transformed the county into a "Black middle-class mecca" (Texeira, 1999). According to the 2010 American Community Survey (2019a, 2019b), the county median household income for Blacks was $70,288, while the statewide median was $54,549. However, even with a relatively affluent population, the county continues to face barriers to development compared to neighboring predominantly White counties, such as higher crime rates, difficulties in attracting quality retail, and failing schools, which some have linked to the racial makeup of the county (Cashin, 2001; Texeira, 1999).

Figure 3 shows the spatial distribution of the population of Prince George's County, with the left panel showing the share of Blacks at the tract level and the right panel showing the Black median household income at the tract level. The majority of the tracts have at least 25 percent Blacks, with the highest Black concentration located near the expansion lines. The tracts with the lowest Black concentration are primarily along the county lines bordering other Maryland counties. For the most part, the lower income tracts are located along the DC border. Figure 3 highlights that the Metro lines in Prince George's County were built in neighborhoods with relatively higher share of Blacks and lower income households.

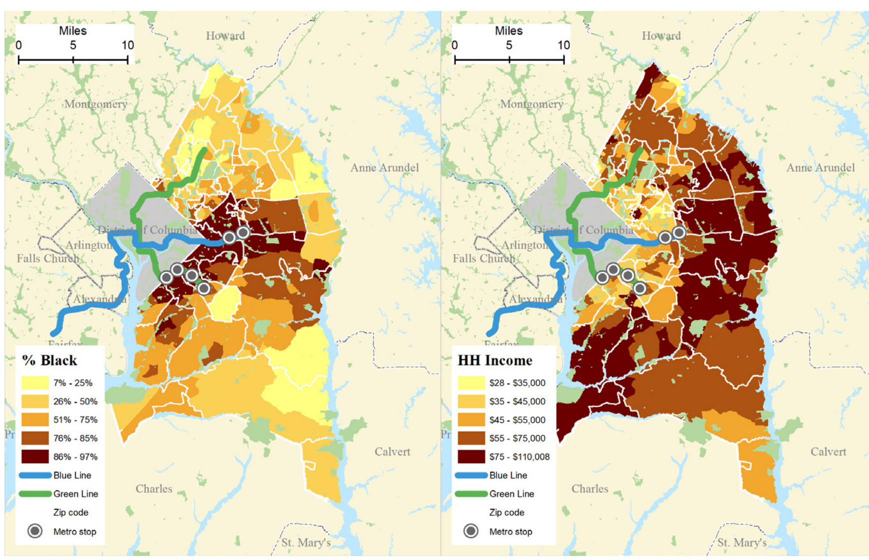

Figure 3. Demographics of Prince George's County by census tract, 2000

Note: The left panel provides information on the share of Black population at the census tract level. The right panel provides information on median household income for Blacks at the census tract level. Demographic data are from the US Census Bureau, Census 2000 Summary File 1. Shapefile for Metro stations and lines are from the National Capital Region Transportation Planning Board (https://rtdc-mwcog.opendata.arcgis.com/).

4 Data

The primary data for this study is property sales transactions in Prince George's County between 1998-2007 from the Maryland Real Property Assessments obtained through Maryland's Open Data Portal. Maryland Real Property Assessments combines statewide property records from the State Department of Assessments and Taxation and parcel information from the Maryland Department of Planning. Each property record included information on sales transactions, housing characteristics, and locations. The dataset included 150,547 sales transactions between 1998-2007, but I further restricted the study sample to include only private sales of single-family, residential properties. I also obtained data on Park and Ride lots from Commuter Connections, which included geographic coordinates and parking spaces for the Washington, DC metro area and WMATA shapefiles from the DC Office of the Chief Technology Officer through Open Data DC. I used ArcGIS to estimate Euclidean distance between each property and the nearest station and rail line during the sales year.

The full sample included 65,979 sales transactions of 57,495 unique properties after the data cleaning, while the repeat sales sample was further restricted to 16,511 sales transactions of 8,027 unique properties that sold more than once during the study period. About 60 percent of my sample is within five miles of the nearest station, which roughly estimates to a 10 to 15 minute drive to the nearest station. Therefore, the average house at about four miles would still be within a 15-minute travel time that previous studies have considered reasonable, albeit they assumed walkable distance. Overall, nearly all properties in my sample are located within a 20 to 25 minute driving distance to the nearest station.

As expected, there is a significant drop in observations between the full and repeat sales samples. The repeat sales model makes a stronger causal argument relative to the hedonic model as it includes house fixed effects, but the smaller sample size can lead to reduced precision and introduces additional concerns regarding external validity. To generalize to the broader sales population, properties that sold more than once during the study period must not be systematically different from properties that only sold once.

Table 2 presents summary statistics for the full and repeat sales samples, highlighting the similarities in housing characteristics between the two samples. In each sample, the majority of the properties were about 30 years old, 1800 square feet, in below average condition, and priced at about $250,000. The average sales price in both samples increased tremendously, nearly 100 percent, during the time period. Given the similarities between the two samples, I argue that the repeat sales sample is a good representation of overall sales transactions in Prince George's County and the risk of sample selection bias is low.[2]

[2] I conducted a more formal test and applied Equation 1 to the repeat sales sample in addition to the full sample. The estimated marginal effects were similar, further building the case that the results from the repeat sales sample are generalizable to the broader sales population. See Appendix Table A1 for results.

Table 2. Descriptive statistics of full and repeat sales samples

Baseline characteristics	Full sample	Repeat sales sample
Number of sales transactions	65,979	16,511
Average sales price	$253,000	$248,000
1998	$178,000	$172,000
1999	$180,000	$176,000
2000	$185,000	$181,000
2001	$191,000	$187,000
2002	$203,000	$199,000
2003	$229,000	$223,000
2004	$259,000	$251,000
2005	$317,000	$311,000
2006	$362,000	$347,000
2007	$353,000	$332,000
Housing characteristics		
Age (years)	29	30
Structural area (sq. ft)	1,921	1,826
Basement	74%	71%
Below average	66%	68%
Split level	18%	16%
Average distance to nearest Metro	4.3	4.4
Percent of sales by distance		
Less than 5 miles	58%	57%
Between 5 and 10 miles	39%	41%
Greater than 10 miles	3%	2%

Note: Dollars adjusted to 2000 dollars. Percent of sales by distance may not add up to 100 percent due to rounding.

5 Empirical strategy

Drawing on previous literature, I utilize the hedonic framework to estimate the relationship between proximity to rail and housing prices. Ideally, to estimate a causal relationship between proximity to rail and housing prices, I would observe the price of the same house with and without station access. In the absence of random assignment of proximity to rail stations to properties, I exploit the opening of new stations which potentially produced an exogenous change in distance. However, even with the potentially exogenous shock, many housing and locational characteristics can covary with both proximity and housing prices, which can lead to biased estimates. I present several ways in my models to address endogeneity concerns stemming from unobservables that covary between proximity and housing prices.

I apply the following baseline hedonic model to the full sample:

$$ln(P_{i,t}) = \beta_0 + \beta_1 D_{i,t} + \beta_2 D^2_{i,t} + \beta_3 \boldsymbol{X} + \beta_4 Parking_s + \gamma_n + \delta_t + \gamma_n T + \epsilon_{i,t} \quad (1)$$

With the hedonic model, the identification strategy assumes that conditional on covariates, houses far from the station would serve as an appropriate counterfactual for houses near the station. The dependent variable, $ln(P_{i,t})$, is the natural logarithm of sales price for transaction i in sales year-quarter t. The primary explanatory variable of interest, proximity to public transportation, is represented by a quadratic specification of distance (miles) to the nearest station, $D_{i,t}$. Given the characteristics of the station areas and suburban context of Prince George's County, I choose to model distance as a continuous variable. X represents a vector of housing characteristics, including age of the home, age squared, basement, area, condition, and split level. Parking is the number of all-day parking spaces within one mile of the nearest station s to account for the fact that many suburban riders drive to the stations.[3] ZIP code fixed effects, γ_n, mitigate concerns that houses near the stations are systematically different from houses far away from the stations by accounting for factors common to all properties within the same ZIP code. With the ZIP code fixed effects, the model only compares houses within the same ZIP code. Time fixed effects, δ_t, are represented by sales year-quarter dummies and control for unobservable characteristics that are constant across properties but vary over time. The time fixed effects control for the general upward trend that housing prices in Prince George's County experienced during this period.[4] Lacking time-varying neighborhood characteristics at the sub-county level, I include ZIP code-specific linear time trends, $\gamma_n T$. Specifically, the linear time trends control for unobservable linear changes common to all properties within a ZIP code over time, such as neighborhood revitalization efforts that steadily enhance the quality of the neighborhood.[5] Standard errors are clustered at the ZIP code level.

Although the various controls and fixed effects in the baseline hedonic model accounts for a wide range of housing and locational characteristics to reduce the threat of omitted variable bias, I transform the standard hedonic model and apply the following fixed effects regression model to the repeat sales sample for my preferred specification:

$$ln(P_{i,t}) = \beta_0 + \beta_1 D_{i,t} + \beta_2 D^2_{i,t} + \beta_3 Parking_s + \alpha_i + \delta_t + \gamma_n T + \epsilon_{i,t} \tag{2}$$

The main advantage of the repeat sales model is that it includes house fixed effects, α_i. With the house fixed effects, the identification strategy compares the same house over time, where the house is sold before and after the expansion and a change in distance is produced by the opening of new stations. Distance will decline for houses that are affected by the new stations and remain unchanged for houses that are not affected; therefore, the estimated effects will be identified by houses that experience a change in distance over time. The housing characteristics and ZIP code fixed effects drop out, while parking, time fixed effects, and ZIP code-specific linear time trends remain.

Overall, the repeat sales specification presents a stronger counterfactual as it is more conceivable that a house at an earlier date is comparable to the same house at a later date with or without the new stations as opposed to comparing houses located near stations to those that are farther away.[6] A stronger strategy to address the concern of omitted variable bias would be to supplement the repeat sales model with a difference-in-differences design. Billings (2011) was able to apply this strategy in Charlotte and used a proposed, unselected corridor as the comparison group; however, the planning and implementation of the expansions I study do not provide the opportunity for a comparison corridor. Therefore, a key assumption in my identification strategy is that the introduction of the new stations in Prince George's County is plausibly exogenous. Although the exogeneity of the new stations is not fully testable, especially with the lack of traditional treatment and comparison groups, the fact that the station locations were identified in 1968 and finalized in the 1980s should ease concerns that recent trends in

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[3] As a robustness check, I also ran models with parking defined by the total number of spaces within 2.5 miles of the station and number of commuter lots within 1 and 2.5 miles. Results were consistent across models.

[4] See Appendix Figures A1 and A2 for graphs of the average sales price by distance from 1998-2007.

[5] As a robustness check to provide confidence that the models are allowing predominantly Black neighborhoods to trend differently than predominantly White neighborhoods, I also ran models that grouped Census tracts based on the share of Black residents and controlled for a racial-composition-specific linear trend instead of a ZIP code-specific linear trend. Results are consistent and available in Appendix Table A2.

[6] I assume that housing characteristics are unchanged between sales due to data limitations. This is an assumption commonly made in repeat sales models. I feel that this is a credible assumption in this study given the ten-year study period and the average length of time between sales is 3.5 years.

housing prices drove the location selection of the expansion lines. In addition to the selection of the new stations, I am also concerned about housing prices responding in anticipation of the new stations, which I address in the robustness checks.

6 Results

Table 3 presents the results of the main findings.[7] Both the hedonic and repeat sales models estimate positive coefficients on distance, suggesting that housing prices increase as distance to the nearest station increases, and a negative squared term, indicating that housing prices are increasing at a decreasing rate. The hedonic model estimates that for properties at one mile from the nearest station, a one-mile increase in distance to the nearest station leads to a marginal price increase of 2.4 percent.[8] Among the housing characteristics, structural area, whether the house has a basement, is a split level, and in below average conditions were statistically significant. Not surprisingly, having a larger home, basement, and being a split-level increased housing prices, while being in below average condition decreased housing prices. The repeat sales model suggests that the hedonic model understates the effects. For properties at one mile from the nearest station, the repeat sales model estimates that a one-mile increase in distance to the nearest station leads to a marginal price increase of 4.6 percent.

Table 3. Main regression results

Variables	(1) Hedonic		(2) Repeat Sales	
	Estimate	*SE*	Estimate	*SE*
Intercept	8.940***	0.128	11.800***	0.037
Distance				
Distance	0.028***	0.007	0.050***	0.011
Distance squared	-0.002**	0.001	-0.002*	0.001
Housing Characteristics				
Age	-0.001	0.001		
Age squared	-0.000	0.000		
Structural area (ln)	0.411***	0.019		
Basement	0.161***	0.010		
Below average	-0.109***	0.017		
Split level	0.060***	0.012		
Parking				
Parking	0.000	0.000	0.000	0.000
Fixed Effects				
Housing			X	
ZIP code	X			
Time	X		X	
ZIP code linear time trend	X		X	
Observations	57,912		16,511	

Note: The dependent variable is the natural logarithm of sales price, adjusted to 2000 dollars.
*Statistical significance level at *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

[7] See Appendix Table A2 for an alternative specification where sales price (dependent variable) and structural area are not logged.

[8] Since I use a quadratic model and include linear and quadratic terms for distance, I calculate the marginal price effect by taking the partial derivative of sales price with respect to distance at one mile. For the hedonic model, $\partial/\partial D(\beta_0 + \beta_1 D_{i,t}) + \beta_2 D^2_{i,t} + \beta_3 Parking_s + \alpha_i + \delta_t + \gamma_n T + \epsilon_{i,t}) = \beta_1 + 2\beta_2 D_{i,t} = .028 - 2(.002)(1) = .024$.

Another way to illustrate the effect is by evaluating the effect size for the average property. In both samples, the average distance is about four miles. The predicted sales price at four miles is $254,127 in the full sample and $236,779 in the repeat sales sample. The hedonic model estimates a marginal effect of 1.4 percent at four miles, which suggests that the marginal household is willing to pay about $3,558 to live one mile farther. The repeat sales model estimates a marginal effect of 3.5 percent at four miles, which suggests that the marginal household is willing to pay about $8,287 to live one mile farther. This further highlights that the hedonic model underestimates how much residents are willing to pay to be incrementally farther from the station.

Figure 4 plots the hedonic price (i.e., predicted sales price) and implicit price functions (i.e., marginal effects) for both the hedonic (red) and repeat sales (blue) models.[9] Each circle represents the point estimate at a specific distance and the whiskers represent the associated 95 percent confidence interval. Although, I do not restrict the models, I restrict the figures to 10 miles since nearly 100 percent of my sample is located within 10 miles of the nearest station. The hedonic price functions demonstrate the non-linear positive relationship between distance and sales price, graphically illustrating that sales prices are increasing at a decreasing rate as distance increases. For both models, the predicted sales prices rapidly increase at lower distances then eventually level off.

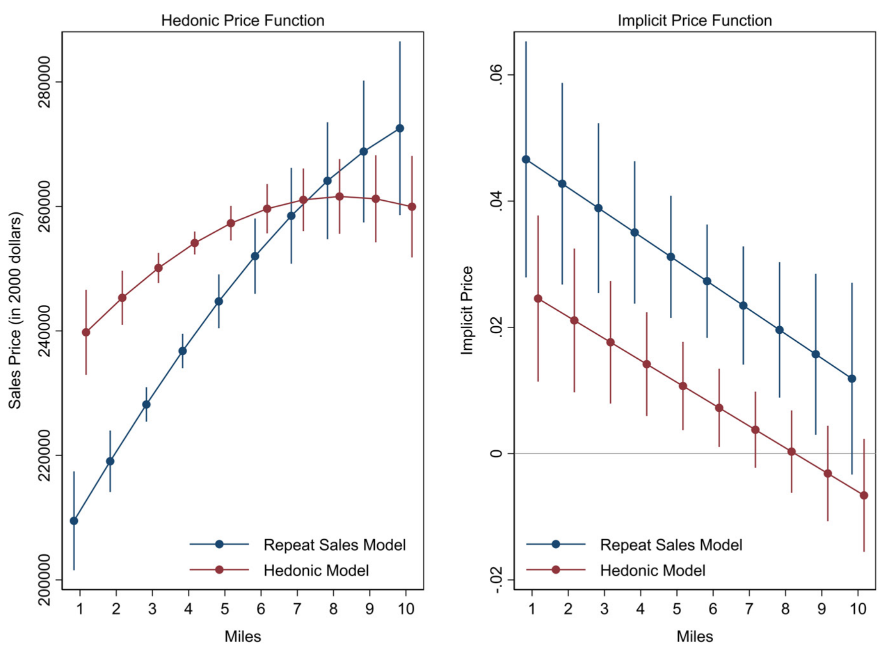

Figure 4. Hedonic and implicit price functions

Note: Sales price in 2000 dollars.

Turning to the implicit price functions, the marginal effects are higher for the repeat sales model across distances, but the patterns are otherwise similar, leading to two key observations. First, the marginal effects are greatest closest to the station, suggesting that nuisance elements may be strongest right next to the station. This is not surprising given that certain nuisance elements, such as unsightliness and

[9] I generated the implicit price function by taking the partial derivative of price with respect to distance.

increased utilization of street parking, may be directly attributed to the station. This finding is consistent with previous studies that find that nuisance elements have the potential to offset accessibility benefits for properties near the station (Billings, 2011; Wagner, 2013; Yan et al., 2012). Second, I estimate statistically significant marginal effects beyond walkable distances, up to six miles with the hedonic model and nine miles with the repeat sales model, albeit effect sizes are relatively small at greater distances. This observation suggests that certain negative externalities from the station may have a wider sphere of influence. Certain negative elements such as, pollution, crime (or perception of crime), and traffic, could extend beyond walkable distances. Additionally, the station could attract development not just in areas adjacent to the station, but in more intermediate distances. These developments have the potential to lead to additional negative externalities.

Beyond the potential for direct and indirect nuisance elements to be affecting properties at farther distances, I also expect differential sorting across distances to play a role. Different sets of households are bidding in specific distances based on their preferences for a specific level of access. Certain household types may have a preference for properties beyond walkable distances but within driving distance of a station. In addition, households who are induced by the improved accessibility may induce additional re-sorting. For example, wealthier households may be induced by the improved accessibility benefits and lower levels of nuisance elements at farther distances, further attracting other households who wants to live near the new wealthier households.

Although the new stations have the largest impact on proximate properties, they still effect properties at farther distances. Statistically significant effects beyond walkable distances suggest that previous studies may have been premature in limiting study areas to within walkable distances, especially when considering the suburban environment. There are several mechanisms underlying the net effect of proximity and these mechanisms can vary across distances; however, my study is unable to disentangle the different mechanisms. Future study is warranted to better understand the mechanisms that are driving the relationship in the suburbs.

I've identified two potential explanations that could have led to differences between the hedonic and repeat sales estimators. First, it is possible that the repeat sales model is suffering from selection bias. The repeat sales model could be overstating the positive relationship between proximity and housing prices relative to the hedonic model if, on average, the omitted single-sale properties were sold at higher prices and located at farther distances relative to repeat sale properties. However, the descriptive statistics and consistency of the estimate when running the hedonic model on the repeat sales sample provide evidence that the two datasets are not systematically different. Therefore, I do not believe that the repeat sales model is biased due to selection. Second, it is possible that omitted observable bias is relatively greater for the hedonic model. As discussed earlier, the hedonic model requires a comprehensive set of controls to reduce the threat of omitted variable bias as it compares properties that are close to the station to properties that are farther away. For example, the hedonic model could be understating the positive relationship between distance and housing prices relative to the repeat sales model if households are willing to pay more for certain housing features that happen to be more prominent in houses near the station. Lacking a comprehensive set of controls, I feel that the repeat sales model is the preferred specification as the model is able to reduce omitted variable bias by controlling for time-invariant factors.

7 Robustness checks

I employ several robustness checks to test the sensitivity of my results to alternative samples. Table 4 presents the results of these robustness checks.[10] I apply the repeat sales specification to each of the robustness check.

Table 4. Summary of robustness checks

Variable	Regression Models						
	1	2	3	4	5	6	7[a]
Distance	0.050***	0.044***	0.058+	0.078***	0.062***	0.042***	0.019
	(0.011)	(0.01)	(0.031)	(0.021)	(0.012)	(0.007)	(0.012)
Distance squared	-0.002*	-0.001+	-0.000	-0.005*	-0.003**	-0.001*	-0.001
	(0.001)	(0.001)	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)
Marginal effects	.046	.042	.058	.068	.056	.042	.017
Joint F test	19.95	20.98	16.51	17.21	21.44	20.98	1.16
Observations	16,511	11,243	8,956	12,132	15,980	32,231	32,231

Note: The dependent variable is the natural logarithm of sales price, adjusted to 2000 dollars. Each column is a separate regression that applied equation 2 to alternative repeat sales samples: 1=preferred repeat sales sample; 2=limit to properties built before 1990; 3=limit to properties less than 5 miles; 4=limit to properties less than 7 miles; 5=limit to properties to less than 10 miles; 6=expand to include all properties sold between 1994-2011; 7=treatment date based on construction groundbreaking. Controls include house fixed effects, parking is represented by the number of all-day spaces in parking lots/garages within one mile of the station, time fixed effects represented by sales year and quarter, and ZIP code-specific linear time trends. Robust standard errors in parenthesis.

[a] Includes all properties that sold more than once between 1994-2011.
*** Statistical significance level at *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

For Model 2, I remove properties that could have potentially responded to the announcement and construction of the new stations by limiting the sample to properties that were built before 1990. The results are consistent with the main estimate. For Models 3-5, I restrict the sample to only include properties that were within the following distances – five, seven, and ten miles of the nearest station – to assess sensitivity to distance thresholds. I estimate the same general pattern when omitting farther properties, supporting the main finding that proximity to rail is considered a disamenity and effects should eventually level off. Furthermore, the greater marginal effects relative to the main estimate provide evidence that properties from farther distances are not driving my results. For Model 6, I extend the pre- and post-periods by four years to assess if the window of time being studied explains the results.[11] The marginal effects and general patterns are consistent with the main estimate. For Model 7, I test for anticipatory effects to ensure that the estimated effects are in response to the opening. I use the extended sample of repeat sales transactions but change the treatment date from its opening to its construction date, artificially assigning post treatment distance to properties sold during construction years even though the stations are not yet in operation.[12] A joint hypothesis test reveals that the study cannot reject the null hypothesis that both distance coefficients are zero at the 10 percent level, providing evidence that the increase in housing prices estimated by the main analysis is in response to the opening of the new stations.

[10] For Table 4, figures of the hedonic price and implicit price functions are available upon request.
[11] I select four years given that the northern end of the Green Line expanded in 1993.
[12] I artificially change the treatment date from opening, 2001, to groundbreaking, 1995, for the Green Line and change the treatment date from opening, 2005, to groundbreaking, 2001, for the Blue Line.

I also consider the robustness of my model to the quadratic distance specification. A key concern in using the hedonic framework is using the appropriate functional form (Yinger & Nguyen-Hoang, 2016; Yu et al., 2017). As Yinger and Nguyen-Hoang (2016) underscored, a nonlinear hedonic specification is required for the bid function and associated envelope to be mathematically consistent and allow for sorting. I selected a quadratic specification due to the shape of my underlying data, but another commonly used nonlinear form in the literature is a categorical distance term.[13] I decided not to use a categorical distance measure as it excludes useful identifying variations. In a repeat sales model with a categorical distance measure, my identification strategy would be based off houses that sold more than once and changed distance categories between sales as a result of the new stations; therefore, properties that changed distance but not categories would not be contributing to the model. However, as an additional robustness check, I assess if my findings are sensitive to the selection of functional form by estimating my hedonic and repeat sales models using a categorical distance specification. The results of the categorical distance models provide support for a quadratic distance specification and similarly conclude that distance to the station is considered a disamenity.[14]

Overall, the robustness checks provide further evidence that the introduction of the new stations is not endogenous to recent trends in price and that sample selection and functional forms are not driving my results. The preferred repeat sales specification makes a strong case for causal inference as it controls for all time-invariant housing and locational characteristics, time-specific shocks, and time-varying characteristics that follow a linear trend within a ZIP code; however, bias can stem from time-varying housing and locational characteristics that are not accounted for by the various covariates and fixed effects in the model. Data limitations prevented the inclusion of specific time-varying housing and locational characteristics and contextual limitations did not allow for the inclusion of a difference-in-differences strategy, which would have further reduced the threat of omitted variable bias.

8 Discussion and conclusions

This study sheds light on how the suburban context may complicate or even reverse findings on the well-studied relationship between proximity to rail and housing prices. I use hedonic and repeat sales models with an unrestricted distance specification to estimate the impact of improved access to public transportation produced by the opening of new Metro stations in Prince George's County. This study contributes to the literature by focusing on the suburban environment and employing models that are better suited for the car-centric suburbs.

Both the hedonic and repeat sales models suggest that being near the station is considered a disamenity in Prince George's County with the preferred repeat sales model estimating larger marginal price increases. It appears that households are evaluating the tradeoffs between the costs and benefits of living near a rail station and the negative elements may be offsetting accessibility and other benefits. The main findings are inconsistent with previous studies on central cities that find a premium for properties located near stations. I argue that the suburban context may be critical in explaining the overall trend of higher prices for houses located farther from the stations.

When comparing the urban and suburban context, a critical element to take into account is the mode of access to the rail stations. A 2012 survey of riders conducted by the WMATA revealed that the majority of the riders from Prince George's County rely on cars to access the Metro (Metropolitan Wash-

[13] Appendix Figures A3 and A4 show that the underlying data supports a quadratic specification.

[14] Appendix Table A3 presents the regression results for models using distance categories where houses were assigned to one-mile interval distance categories based on their distance to the nearest station. Appendix Figure A5 plots the coefficients and associated 95 percent confidence intervals from the hedonic and repeat sales models.

ington Council of Governments, 2013). About two-thirds used the Park and Ride or were dropped off. Additionally, only 11 percent of Prince George's County riders walked to the stations, compared to 70 percent of DC riders. Unlike the central cities, driving plays a larger role in accessing public transportation in the suburbs and suburban stations facilitate access to parking. All new stations in Prince George's County offered a Park and Ride, while only six of 40 stations in DC offered Metro-operated parking.

One possible interpretation of the findings is that the suburban environment provides greater opportunities for residents to use a car to access public transportation. By being able to drive to stations, residents can still obtain the accessibility benefits without having to live right next to the station and experience the nuisance elements. The steeper slopes in proximate distances to the stations support the hypothesis that households do not want to live next to the noise, pollution, traffic, and other negative externalities associated with the station. However, in the suburbs, having access to public transportation is not defined by living right next to the station. Households can pay to minimize their exposure to nuisance elements associated with station areas. The fact that the preferred model still estimates statistically significant marginal price increases up to nine miles from the nearest station implies that accessibility to the Metro is still relevant for properties within driving distances. This interpretation is consistent with other studies that have found negative capitalization effects from stations that offer a Park and Ride (Kahn, 2007; Lieske et al., 2021).

Similar to city residents, suburban residents are considering competing positive and negative factors when valuing proximity to rail. However, this study suggests that differences between the urban and suburban environments may influence how residents consider these tradeoffs. In the suburbs, negative externalities from station areas play a relatively different role at proximate distances since the more car-friendly environment offers residents opportunities to avoid these negative externalities without giving up improved access. The findings highlighted by this study identify several areas of further research. First, we need to gain a better understanding of who is affected by the improved access to public transportation in the suburbs. The estimated effects from this study are a combination of the effect of proximity and differential sorting. A critical next step would be to gain a better understanding of differential sorting and its implications for residents and neighborhoods. Are we seeing differential sorting based on income? Glaeser et al. (2008) argued that public transportation plays a central role in the concentration of poverty in cities. Lower income households are willing to pay more to live in central cities and be able to access public transportation, while higher income households who are able to afford cars are willing to pay more to live in the suburbs with greater land. Are we seeing a similar trade-off in the suburbs where lower income households are paying more to live near public transportation even with the nuisance effects, while higher income households are paying more to avoid the nuisance effects since they can afford to drive to the station and pay the fees to park near the station? This trade-off may help explain the observed spatial pattern of lower income tracts surrounding the stations in Prince George's County.

Second, we need to understand the implications of the findings on wealth building through home equity across race and income groups. Although, on average, housing prices increased during the study period, properties near the stations — areas with the highest concentration of Black and lower-income residents — see lower property appreciation relative to properties that are farther away from the stations. This can have critical implications for wealth building in Black communities as housing is one of the main sources of wealth. What role do the Green and Blue Lines expansions play in depressing housing appreciation near the station areas? What role does the demographic make-up of Prince George's County play in the lower property values around the stations? Studies in transit-oriented development argue that the built-environment, such as walkability, retail services, and street design, around stations helps offset the nuisance effects and positively contributes to the values of properties near stations (Bartholomew & Ewing, 2011; Duncan, 2011). However, it is well documented that Black neighborhoods also face additional difficulties in attracting quality retail and neighborhood investments. In Prince George's County, policy makers have continued to optimistically point to the station areas for their development potential but struggle to attract funding and developers to translate plans into reality (Hernández & O'Connell, 2016; Spivack, 2013).

Lastly, future research should assess the external validity of the findings across suburbs. Prince George's County is not a good representation of American suburbs. It is a predominantly Black suburb that boasts a higher-than-average household income. Will we see the same capitalization effects in predominantly White suburbs? Working class suburbs? Researchers should delve into how the willingness to pay for public transportation in the suburbs varies by income and race.

This study is one of the few studies that directly examines suburban access to public transportation. The main findings underscore that we cannot generalize findings from central cities to the suburbs and bring to the forefront important questions regarding interactions between race, income, and access to public transportation in the suburbs. Although these factors have always been part of the discourse on assessing the costs and benefits of public transportation in central cities, findings from this study suggest that we should expand these conversations to include the suburbs. As cities expand their current rail networks and city dwellers migrate to the suburbs, many of the new infrastructure investments are being constructed in the suburbs; therefore, the findings of this study contribute to a critical area of research on the relationship between proximity to rail and housing prices in the suburbs.

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Appendix

Appendix available as a supplemental file at https://jtlu.org/index.php/jtlu/article/view/2199.

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