Let It Be, Let It Move

Regression Discontinuity Insights on Demand-Responsive Transit and Property Value Changes

KEYWORDS

DRT Property RDD

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Introduction

Problem Statement

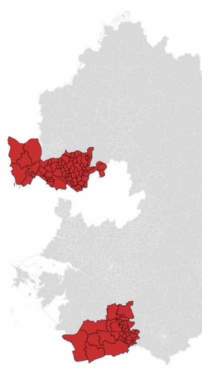
In areas with insufficient transportation infrastructure, limited mobility constrains access to opportunities, thereby influencing local property values. While Demand-Responsive Transit (DRT) has recently been introduced to improve accessibility in such areas, its actual economic impact has yet to be fully understood.

Research Objectives

- This study **identifies transportation-disadvantaged areas and examines how DRT introduction influences property values.**
- In particular, this research places emphasis on clarifying the clear causal link between accessibility improvements and property value shifts through rigorous statistical inference.

Scope

- The analysis focuses on **Goyang, Gimpo, and Pyeongtaek in Gyeonggi Province**, analyzing transportation accessibility and property transaction data at the district level.
- This study utilizes the monthly average price per pyeong across various housing types, including apartments, detached housing, row houses, multi-household housing, multi-family housing, and officetels.



Sources

- Administrative Boundaries: District-level shapefiles of Gyeonggi Province provided by GIS Developer
- Bus Stop Locations: Nationwide Bus Stop Location Information provided by the Pubic Data Portal
- Subway Station Locations: Integrated dataset compiled from multiple subway lines across Gyeonggi Province, including metropolitan, regional, and airport lines, provided by the Public Data Portal
- Demand-Responsive Transit (DRT) Service Areas: Operational areas of the Ddokbus (똑버스) service provided by Gyeonggi Transportation Research Institute
- Property Transaction Data: Housing transaction data provided by the Real Transaction Price Disclosure System

Literature Review

- Yoo and Yeon (2021) calculated an Accessibility Index by analyzing transit variables (e.g. route counts) within grid cells. This index was utilized to identify transportation-disadvantaged areas. Adopting this methodology, this study defined transportation-disadvantaged areas by calculating an Accessibility Index at the administrative dong level, based on accessible subway stations and bus stops.
- Byun and Ko (2019) analyzed the determinants of apartment sales and *Jeonse* prices in non-capital metropolitan areas, revealing that public transportation accessibility significantly influences price determination. Extending beyond this focus on apartments, this research expands the analytical scope to include a diverse range of housing types to comprehensively examine the market-wide impact of accessibility.
- Kang et al. (2024) applied a Regression Discontinuity Design to examine how the COVID-19 pandemic, real estate regulations, and monetary policies affected apartment prices in Korea. Following this methodological approach, this study uses real transaction data and employs RDD to identify the causal impact of DRT implementation on property values.

Identification of Transportation Disadvantaged Areas

Definition

Transportation-disadvantaged areas were defined as districts with low accessibility to public transit.

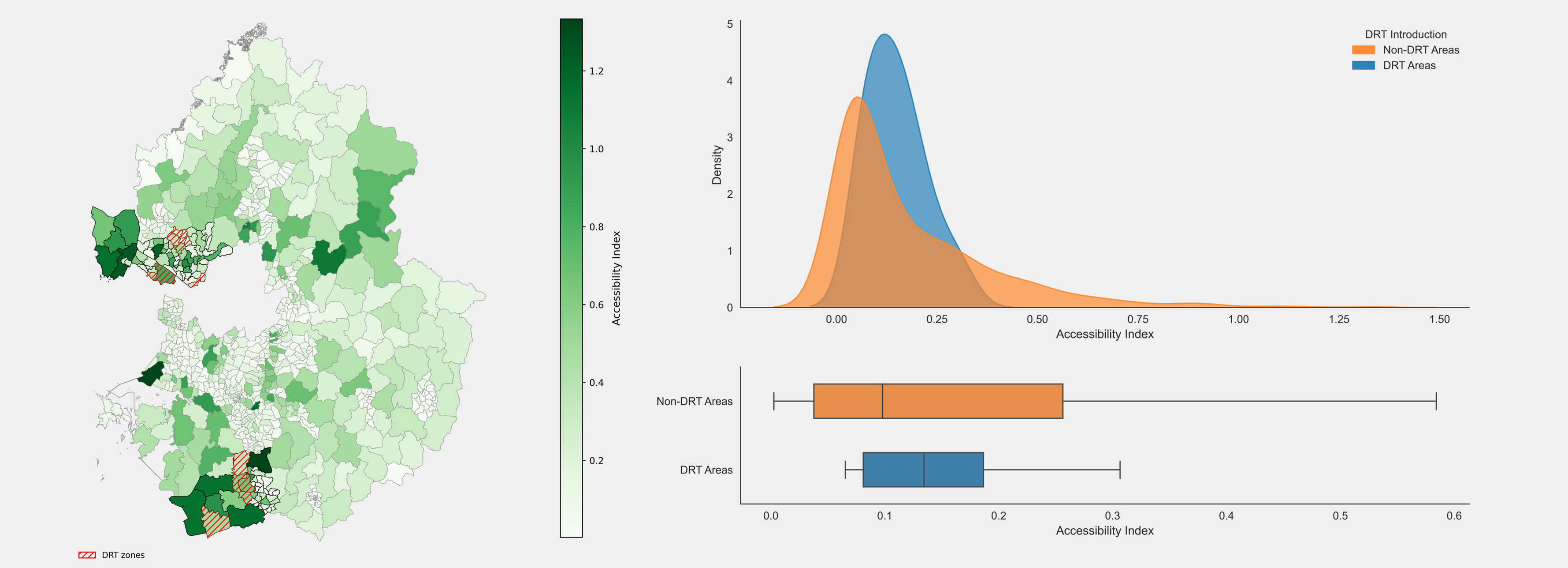
- Accessibility indicates how easily residents can reach nearby bus and subway services. By measuring the spatial distribution of transit facilities, it provides an objective way to identify areas with limited mobility.

$$\text{Accessibility Index}_d = \frac{\text{BusStops}_d}{\max(\text{BusStops})} + \frac{\text{Stations}_d}{\max(\text{Stations})}$$

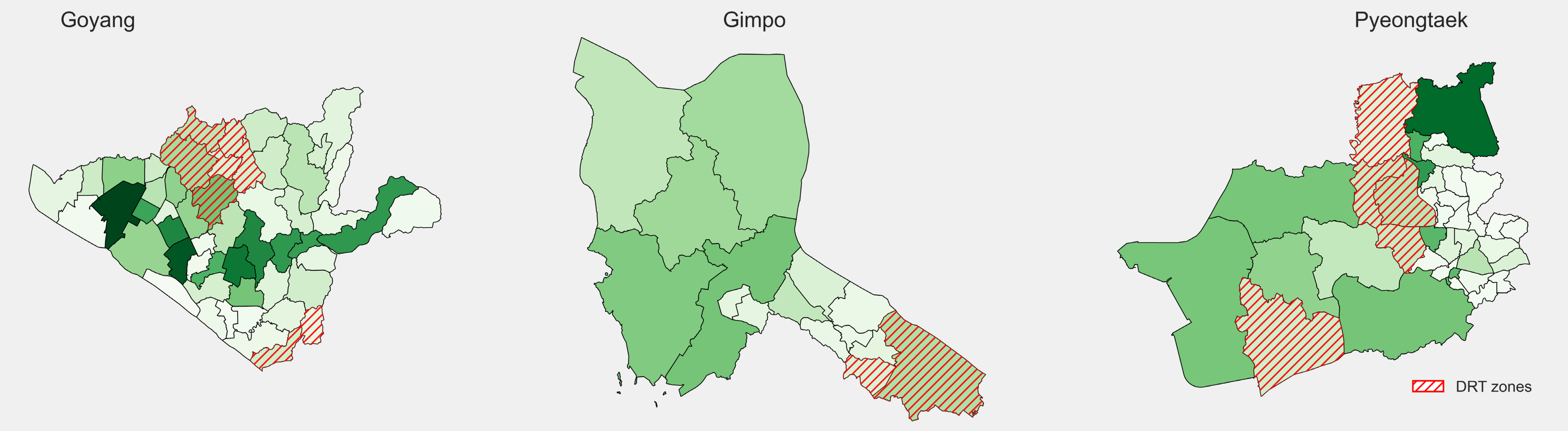
- The accessibility index was constructed using two factors: number of bus stops, number of subway stations
- Equal importance was assigned to both factors, and values were normalized within each comparison group to ensure interpretability.

Spatial Distribution of Accessibility

The spatial distribution of accessibility across Gyeonggi Province revealed pronounced geographic disparities. Accessibility was generally high near major transit corridors, while many northwestern and southern districts exhibited particularly limited access to bus and subway infrastructure. These differences highlight structural imbalances in transit provision across the region.



To provide a fair basis for comparison in the subsequent analysis, accessibility indices were recalculated at the city level. Because each city differs in its overall infrastructure density and urban scale, direct comparison of districts across cities could be influenced more by structural characteristics than by the effect of DRT itself. **City-level normalization ensured that each district was evaluated relative to others within the same urban context.**



The resulting city-specific indices allowed the study to match districts with similar levels of transportation disadvantage. This step minimized confounding differences in baseline accessibility and created a more comparable analytical frame, enabling a clearer examination of how the introduction of DRT influenced subsequent changes in property values.

Research Design and Method

Quasi-Experimental Design

This study employs a quasi-experimental approach to estimate the causal impact of DRT introduction on property values where randomized assignment is not feasible.

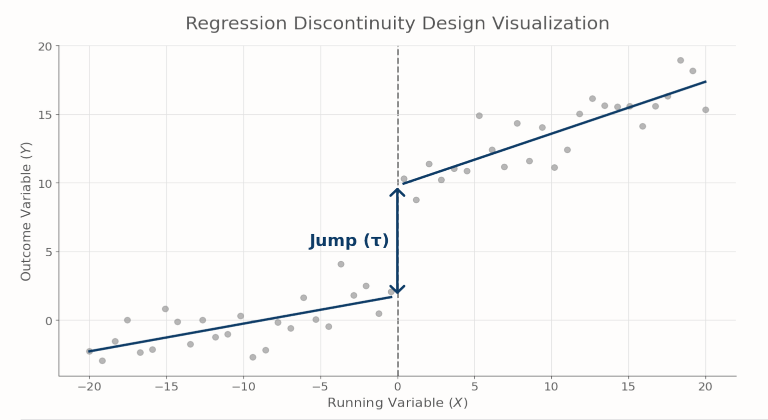
- To ensure valid comparisons, **administrative districts were matched using the city-level accessibility index**, which groups areas with similar levels of transportation disadvantage.
- Under this framework, districts that adopted DRT were classified as the treatment group, while the most comparable non-adopting districts served as the control group.

City	Treatment Group (Implementation Date, Index)	Control Group (Non-Implementation, Index)
Gimpo	Pungmu-dong (Aug 2023, 0.341)	Unyang-dong (0.335)
	Gochon-eup (Jul 2023, 0.654)	Haseong-myeon (0.749)
Pyeongtaek	Godeok-dong (May 2023, 0.434)	Bijeon-dong (0.461)
	Godeok-myeon (May 2023, 0.370)	Yongi-dong (0.274)
Goyang	Deokeun-dong (Nov 2024, 0.413)	Yongdu-dong (0.413)
	Hyangdong-dong (Oct 2024, 0.198)	Wondang-dong (0.190)
	Siksa-dong (Jun 2023, 1.000)	Pung-dong (1.000)
	Sarihyeon-dong (Jun 2023, 0.387)	Goyang-dong (0.388)
	Jiyeong-dong (Jun 2023, 0.373)	Sinwon-dong (0.371)
	Seolmun-dong (Jun 2023, 0.560)	Daeja-dong (0.570)
	Munbong-dong (Jun 2023, 0.347)	Jeongbalsan-dong (0.293)
	Seongseok-dong (Jun 2023, 0.693)	Jugyo-dong (0.595)

Regression Discontinuity Design

What is RDD?

- **Cutoff-based identification:** Treatment status changes at a predefined threshold.
- **Local comparability:** Units near the cutoff share similar characteristics.
- **Causal inference:** Discontinuities in either the level or slope of the outcome at the threshold indicate the policy's effect.



Weighted Least Squares Method

WLS was applied to obtain stable estimates of monthly average transaction prices. Because transaction volumes vary substantially across months, periods with fewer sales are more prone to random fluctuations. By assigning greater weights to months with higher transaction counts, **WLS prevents low-volume periods from exerting outsized influence on the results.** This approach reduces heteroscedasticity and enhances the overall robustness of the estimation.

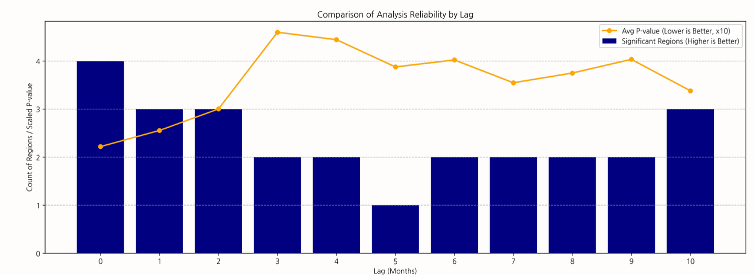
The Basic Estimation Model

$$\text{Price} = \beta_0 + \beta_1 \cdot \text{timeVar} + \beta_2 \cdot \text{postTreatment} + \beta_3 \cdot (\text{timeVar} \times \text{postTreatment}) + \epsilon$$

- β_0 : property price at the time of cutoff
- β_1 : price trend before the cutoff (pre-treatment trend)
- β_2 : immediate change in price at the time of cutoff (jump effect)
- β_3 : change in price trend after the introduction (post-treatment slope change)

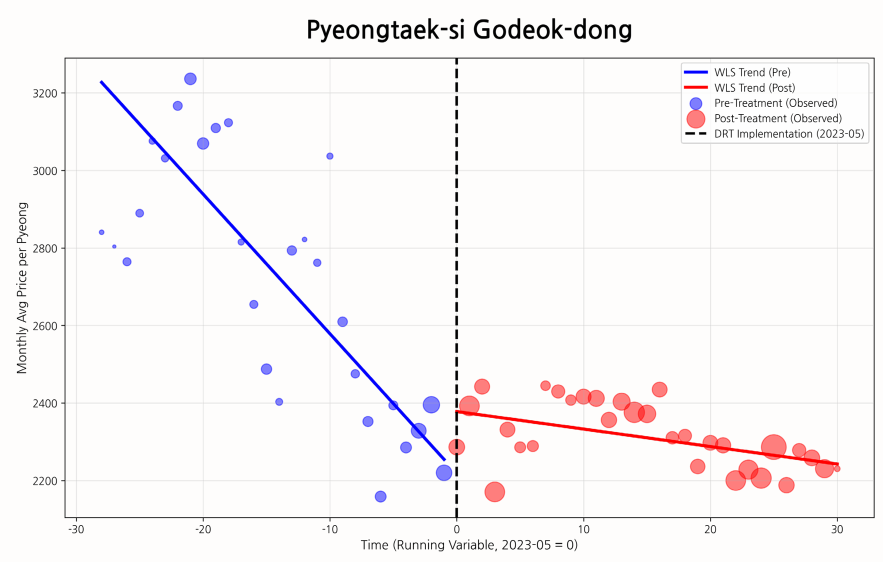
In other words, a significant β_2 indicates a sharp price shift at the time of cutoff, whereas a significant β_3 suggests a change in the rate of price increase or decrease following the introduction.

Considering Lag



Because the effects of DRT may not appear immediately, property value changes were tested across 0 to 10 months after introduction. **Month 0 was selected as the cutoff** because it showed the lowest average p-values and the largest number of districts with significant price changes, indicating the clearest treatment response.

Empirical Results

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                            WLS Regression Results
==============================================================================
Dep. Variable:        price_per_pyeong   R-squared:                       0.776
Model:                             WLS   Adj. R-squared:                  0.764
Method:                  Least Squares   F-statistic:                     63.64
Date:                 Wed, 19 Nov 2025   Prob (F-statistic):           6.88e-18
Time:                         06:08:12   Log-Likelihood:                -368.73
No. Observations:                   59   AIC:                             745.5
Df Residuals:                       55   BIC:                             753.8
Df Model:                            3
Covariance Type:             nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept            2218.4251     49.038     45.239      0.000    2120.150    2316.700
time_var              -36.0182      3.559    -10.120      0.000     -43.151     -28.886
post_treatment        159.3814     59.463      2.680      0.010      40.215     278.547
time_var:post_treatment 31.5101     4.019      7.840      0.000      23.456      39.564
==============================================================================
Omnibus:                        2.076   Durbin-Watson:                   1.075
Prob(Omnibus):                  0.354   Jarque-Bera (JB):                1.611
Skew:                          -0.404   Prob(JB):                        0.447
Kurtosis:                       3.052   Cond. No.                         115.
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Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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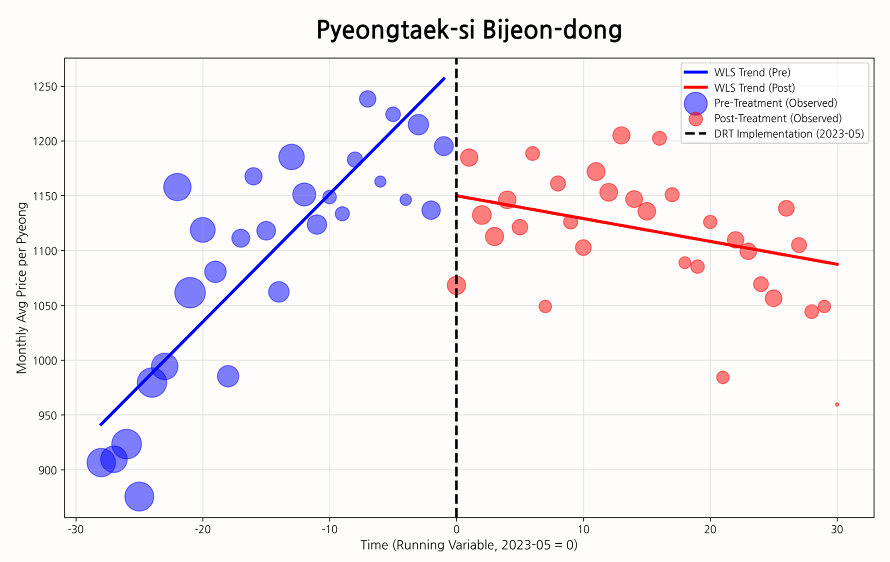


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                            WLS Regression Results
==============================================================================
Dep. Variable:        price_per_pyeong   R-squared:                       0.667
Model:                             WLS   Adj. R-squared:                  0.648
Method:                  Least Squares   F-statistic:                     36.66
Date:                 Wed, 19 Nov 2025   Prob (F-statistic):           3.74e-13
Time:                         06:08:12   Log-Likelihood:                -327.19
No. Observations:                   59   AIC:                             662.4
Df Residuals:                       55   BIC:                             670.7
Df Model:                            3
Covariance Type:             nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept            1268.2109     23.661     53.599      0.000    1220.793    1315.629
time_var               11.6672      1.212      9.624      0.000       9.238      14.097
post_treatment       -118.2977     33.300     -3.552      0.001    -185.033     -51.563
time_var:post_treatment -13.7499     1.896     -7.253      0.000     -17.549      -9.951
==============================================================================
Omnibus:                       12.101   Durbin-Watson:                   1.447
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               20.750
Skew:                           0.611   Prob(JB):                     3.12e-05
Kurtosis:                       5.635   Cond. No.                         96.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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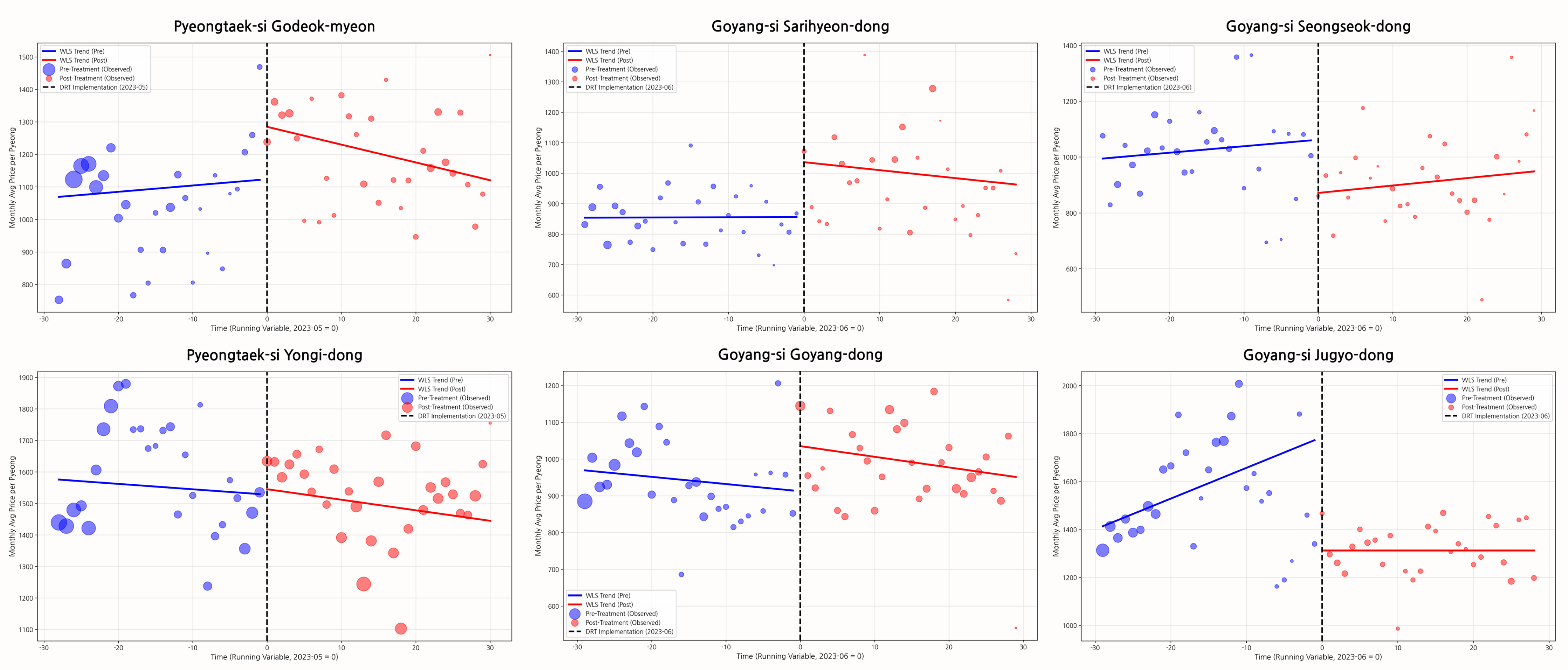

City	Group	District	Price Change (Intercept)	Trend Change (Slope)
Pyeongtaek	Treatment	Godeok-dong	+1.59 million KRW (p=0.010)***	+31.51 (p<0.001)***
	Control	Bijeon-dong	-1.18 million KRW (p=0.001)***	-13.75 (p<0.001)***
	Treatment	Godeok-myeon	+1.61 million KRW (p=0.065)*	-7.42 (p=0.099)*
	Control	Yongi-dong	+17.27 (p=0.848)	-1.63 (p=0.739)
Goyang	Treatment	Sarihyeon-dong	+1.80 million KRW (p=0.009)***	-2.70 (p=0.494)
	Control	Goyang-dong	+1.23 million KRW (p=0.042)**	-0.93 (p=0.766)
	Treatment	Seongseok-dong	-1.91 million KRW (p=0.017)**	0.33 (p=0.940)
	Control	Jugyo-dong	-4.73 million KRW (p<0.001)***	-12.83 (p=0.022)**

p*** <= 0.01, p** <= 0.05, p* <= 0.1

Among the twelve matched pairs of transportation vulnerable areas, four pairs showed statistically significant differences between treatment and control districts. These significant cases were found in Pyeongtaek and Goyang, with two pairs identified in each city.

The results show that DRT introduction has a positive and measurable impact on property values in the districts where it was implemented.

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Conclusions

Direct Value Appreciation

In Godeok-dong in Pyeongtaek, where market conditions were generally weakening, the introduction of DRT corresponded with a clear shift toward price improvement. While the matched control group, Bijeon-dong, recorded declines in both price and growth trend, the treatment group showed the opposite pattern. After implementation, Godeok-dong registered an increase of 1.59 million KRW in average price and a growth trend of 3.51, reflecting a strong upward response. This contrast suggests that improved mobility from DRT can stimulate housing demand even in soft market conditions.

Market Amplification Effect

In Sarihyeon-dong in Goyang, where the overall housing market was on an upward trend, the treatment area displayed a notably stronger increase than its matched control group.
The average transaction price rose by 1.80 million KRW in the DRT-introduced district, which is approximately 1.5 times the increase observed in Goyang-dong, the control group. This difference, despite both districts being exposed to the same broader market conditions, suggests that the added accessibility provided by DRT strengthened local housing demand.

Mitigation of Decline

In Seongseok-dong in Goyang, which experienced a general decline in market prices, the introduction of DRT was associated with a noticeably smaller drop in property values. The treatment group saw a decrease of 1.91 million KRW, whereas the matched control group, Jugyo-dong, recorded a much steeper decline of 4.73 million KRW. This contrast indicates that enhanced mobility provided by DRT can moderate the extent of price depreciation during downturns.