1F or B1: Where should Subway Stations be Built?

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Abstract

Cities today have a larger demand for land than before, even stretching down to the underground. Many have suggested the need to bury upper-ground subway stations underground to allow more economic activities on land. I provide pieces of evidence of how the upper and underground stations could have different economic impacts locally in two aspects: employment growth and local asymmetry. Using the difference-in-differences strategy and OLS estimation on local asymmetry, I suggest underground stations could be more helpful for local employment than upper-ground stations, but whether upper-ground stations exacerbate local asymmetry remains unclear. This paper also relates to the current literature on 'staggered treatments', incorporating the Callaway-Sant'Anna estimator for ATT estimation.

Keywords: Public Transits, Staggered Difference-in-Differences, Regional Employment

JEL classification: L92, R42

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1 Introduction

Many have suggested that public facilities such as subway stations and railroads should be put underground, and very recently, discussions have been made on Seoul's metro facilities. In October 2024, the local government of Seoul proposed a 25 trillion KRW (approximately 17.5 billion USD) plan for subway railroad embedment, the act of burying existing subway stations built above the ground. Such a large-scale project was based on the notion that upper ground stations and railroads, according to Se-hoon Oh, the mayor of Seoul, "deter the communication and regional economic growth". The municipality also suggested that the embedment would create new spaces for both commerce and green areas and alleviate congestion. However, there are concerns about the plan as it would bring immediate railroad unavailability and high cost, which per se calls for economists' careful analysis of the "causal impact" that the embedment would bring.

The comparison of upper-ground and underground transits hasn't been studied as extensively as the impact of transits on local growth and disparity. Positive impact on regional economic development and property value of transportation facilities has been widely recorded(Marein, 2022; Dewees, 1976), although its impact on local population growth has had mixed evidence(Gonzalez-Navarro and Turner, 2018; Mayer and Trevien, 2017). Gonzalez-Navarro and Turner (2018) suggests that larger cities are more likely to have subway stations, but the stations do not necessarily lead to population growth. This paper differs from Gonzalez-Navarro and Turner (2018) in two ways. First, their analysis focuses on the 'between-cities' comparison of growth, whereas this paper conducts a 'within-city' comparison of different EMDs(comparable to the US Census blocks) in Seoul. Second, whereas they use residential data to measure population growth, this paper relies on census data containing the employment information of all firms in South Korea to measure local employment growth. The microscopic study of this paper contributes to the literature on public transit and regional growth by investigating how public transit affects the very close vicinity.

This paper also contributes to the literature on artificial barriers. As Ahlfeldt et al.

(2015) proposes, the Berlin Wall in the Cold War period served as an artificial barrier to economic activities. Although upper-ground subway stations in my study aren't as rigid barriers to economic behavior as the Berlin Wall, they certainly impose additional costs on economic activity, such as residents on one side being reluctant to engage in commercial activities on the other. I illustrate such impact with simple comparative statics, assuming that upper-ground stations cause moving costs, and confirm such asymmetries in commerce using geographic data of Seoul's restaurants.

In this paper, I document upper and underground stations' causal impact on local employment growth and local asymmetry(or inequality) in commerce. Using the 'difference-in-differences' approach, I suggest that underground stations might better increase local employment than upper-ground stations, although upper-ground stations do not necessarily deter economic growth. Also, through OLS estimation using location data of restaurants in Seoul, I suggest that commerce asymmetry is more pronounced in the vicinity of upper-ground stations than its underground counterpart.

The rest of this paper is as follows. Section 2 describes the data used in this research with detailed summary statistics. In section 3, I elaborate on the empirical strategy to obtain a careful causal estimation of treatment effects and a model that illustrates the effects on regional asymmetry. I provide the results in section 4. In section 5, I conclude the results.

2 Data

2.1 Subway Transit Data

The subway transit data primarily consists of information on location and transit lines from Seoul municipal open data. The data collectors, including the author, have added variables *'year built'*, *'ground status(upper = 1, under = 0)'*, *'side 1'*, and *'side 2'* through

Google Maps' open APIs.[1] Combining the stations' location data from Google Maps with the location data of small establishments, I analyze the asymmetric pattern of commercial activities surrounding the stations. The summary statistics of the data are in table 2.1.

	level	year_built	asymmetry	firms_in_200m
Min	0.000	1906	-63.000	0.00
Median	0.000	1996	-1.000	47.00
Mean	0.378	1992	1.243	53.56
Std. Dev.	0.485	22.2	25.1	41.4
Max	1.000	2024	98.000	202.00
No. Obs.	656	653	189	189

Table 1: Subway Transit Data: Summary Statistics

2.2 Employment Data

The employment panel data across different years and districts are based on South Korea's establishment-level census data(전국사업체조사). The data is available from 1994 to 2022, inclusive, and includes all establishments conducting economic activities in South Korea. I aggregate their employment levels to calculate the total employment of a particular combination of district and year. The data provides the EMD-level location of establishments, which allows us to compare the EMD-level transit status and EMD-level employment.[2] The summary statistics of the data are in table 2.2.

	year	employment	log(employment)	treated year	(upper=1)
Min	1994	7	1.946	1917	0.00
Median	2008	3184	8.066	1994	0.00
Mean	2008	5410	7.952	1986	0.44
Std. Dev.	7.97	9054	1.17	25.3	0.497
Max	2021	125624	11.741	2018	1.00
No. Obs.	13310	13310	13310	1181	1181

Table 2: Employment Data: Summary Statistics

[1]Most of such information required manual data collection even after incorporating the *ggmap* package in R.

[2]For readers who are more comfortable with the US units, the location levels of our data are EMD(eup-myeon-dong), SGG(si-gun-gu), and sido, which are respectively equivalent to block, tract, and county(or province).

2.3 Location Data of small establishments

To capture the local asymmetry around subway stations in microscopic detail, I use the location data of small establishments provided by Small Enterprise and Market Service(SEMS). This data includes the longitude and latitude information of every small enterprise in South Korea, enabling detailed analyses of the location decisions of establishments affected by surrounding facilities, including transits.

3 Empirical Strategy

3.1 Endogeneity Issues

Estimating and comparing the economic impacts of upper-ground and underground stations suffer from two possible sources of endogeneity.

1. Upper-ground stations tend to be built on more vacant lands.

2. Economic variables also affect the disposition of subway transits. (Reverse Causality)

Figure 1 illustrates well both of the concerns. It shows that compared to the outer area of Seoul[3], there is more favor for underground stations in the core area. This could be true because the government tends to build underground (upper-ground) stations in the core (respectively, suburb). Another reason is the core area's high concentration of economic activities pushing the subway transits underground (the second source). Tackling such endogeneity issues requires a careful choice in researchers' identification strategy.

3.2 Specification for ATT of Subway Stations

I tackle such endogeneity issues using the 'difference-in-differences' strategy to estimate the average treatment effect of subway station construction. The goal of 'difference-in-differences'

[3] In this paper, I do not discriminate between Seoul and the outer capital region as they share the same labor market. It is a common practice in urban economics to define a city as a geographic unit sharing the same labor pool.

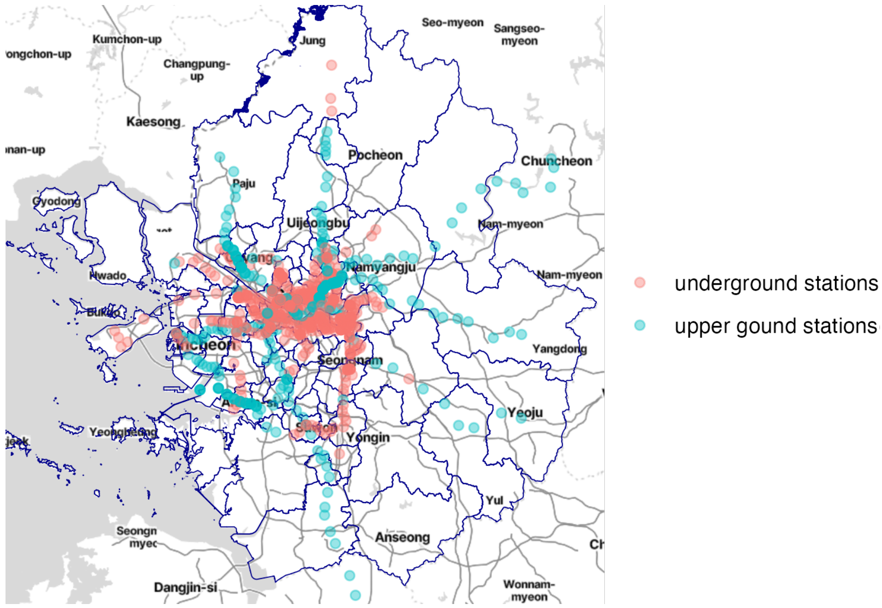

Figure 1: Spatial Distribution of Subway Stations in Seoul

is to consistently estimate the average treatment effect on the treated(ATT):

$$\text{ATT} = \text{E}\left[Y_i(1)|D_i = 1\right] - \text{E}\left[Y_i(0)|D_i = 1\right] \tag{1}$$

where $\text{E}\left[Y_i(1)|D_i = 1\right]$ is the outcome of the treatment group after treatment and $\text{E}\left[Y_i(0)|D_i = 1\right]$ is the potential outcome of the treatment group if it hadn't been treated.

In the case of canonical difference-in-differences where the researcher has a single treated group and a single comparison group, the estimate for ATT is equivalent to β in the following two-way fixed effects regression:

$$\log(\text{employment})_{i,t} = \delta_i + \delta_t + \beta \cdot D_{i,t} + \varepsilon_{i,t} \tag{2}$$

Here, i and t denote the individual and the time, respectively, and $D_{i,t}$ is the treatment status of an individual at a given time period. In our context, δ_i is the EMD fixed effects, and δ_t is the year fixed effects. We are performing three different regressions to obtain β_0, β_{up}, β_{un}

where each of these coefficients captures the ATT of (1) subway station construction, (2) upper-ground station construction, and (3) underground construction, respectively. Our objective is to understand how subway stations affect the EMD's employment level and compare how it differs according to whether the station is built on the upper-ground or not.

However, in our analysis, the β coefficients from the two-way fixed effects regression could be a biased estimate for the ATT(Chaisemartin and D'Haultfœuille, 2020; Borusyak et al., 2024). Such bias in a difference-in-differences approach comes from two sources: (1) treatment effect heterogeneity and (2) staggered treatment designs. Treatment effect heterogeneity implies that ATT could differ across different groups and periods. In this case, the estimand is not a single value of ATT, but multiple ATT(g,t)'s. Staggered treatment designs mean that multiple groups are treated on different dates. In our study, the treatment date (i.e., the date that a particular EMD constructed its first subway station) differs among different EMDs, leading to a bias in regression (2) unless ATTs are constant across time and region. Figure 2 illustrates the distribution of treatment dates of the EMDs with subway stations.

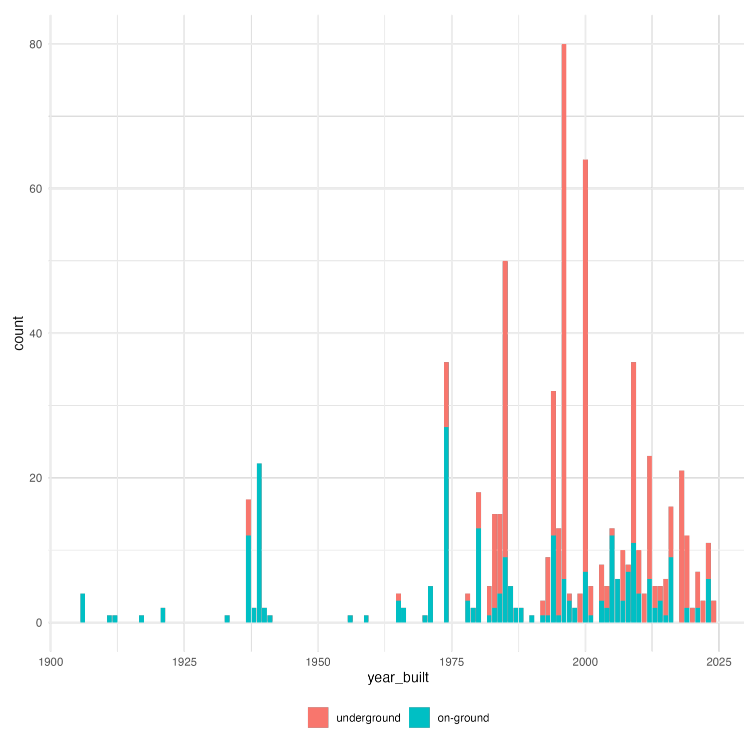

Figure 2: Distribution of treatment dates

To tackle such an issue, I present both the β of regression (2) and the alternative robust estimate from Callaway and Sant'Anna (2021). The doubly robust estimator introduced in Callaway and Sant'Anna (2021) performs a cell-by-cell difference-in-differences between a treated group at a certain period and a 'not-yet-treated' group to obtain the estimate of each of the $\mathrm{ATT}(g,t)$'s.[4] A common practice in the staggered difference-in-differences literature is to report the summarized values of $\mathrm{ATT}(g,t)$'s in two levels: (i) the overall value of ATT (equation 3) and (ii) the event-study values (equation 4).[5]

$$\mathrm{ATT}_{\text{overall}} := \sum_{g=2}^{T} \frac{1}{T-g+1} \sum_{t=2}^{T} I\{g \leq t\} \mathrm{ATT}(g,t) P(G=g) \tag{3}$$

$$\mathrm{ATT}(e) := \sum_{g=2}^{T} I\{g+e \leq T\} \mathrm{ATT}(g,g+e) P(G=g|G+e \leq T) \tag{4}$$

3.3 Local Asymmetry Effect

3.3.1 Identification

To identify the stations' effects on local asymmetry in commerce, I regress the level of asymmetry on the dummy variable of whether a transit was built upper-ground. Here, the observation level of our data is a subway station, and I gathered the location information of all restaurants in a 200-meter radius around the station in 2021. Figure 3 depicts an example with 'Konkuk University Station'.[6]

The asymmetry degree is defined as below:

[4] In their study, 'not-yet-treated' groups consist both of 'never' treated groups which would never be treated in the sample period of the data, and the groups that are not yet treated in the period of interest, but would eventually be treated in the sample period of the data.

[5] The notations are slightly modified from the original text of Callaway and Sant'Anna (2021). In my equation, T denotes the final period of the panel and g denotes a particular group defined by its treatment date.

[6] The red circle is the 200m radius from the station's center, and each black point on the map denotes a restaurant. Here, we can see that there are much more establishments on the NE side of the platform than on the SW side.

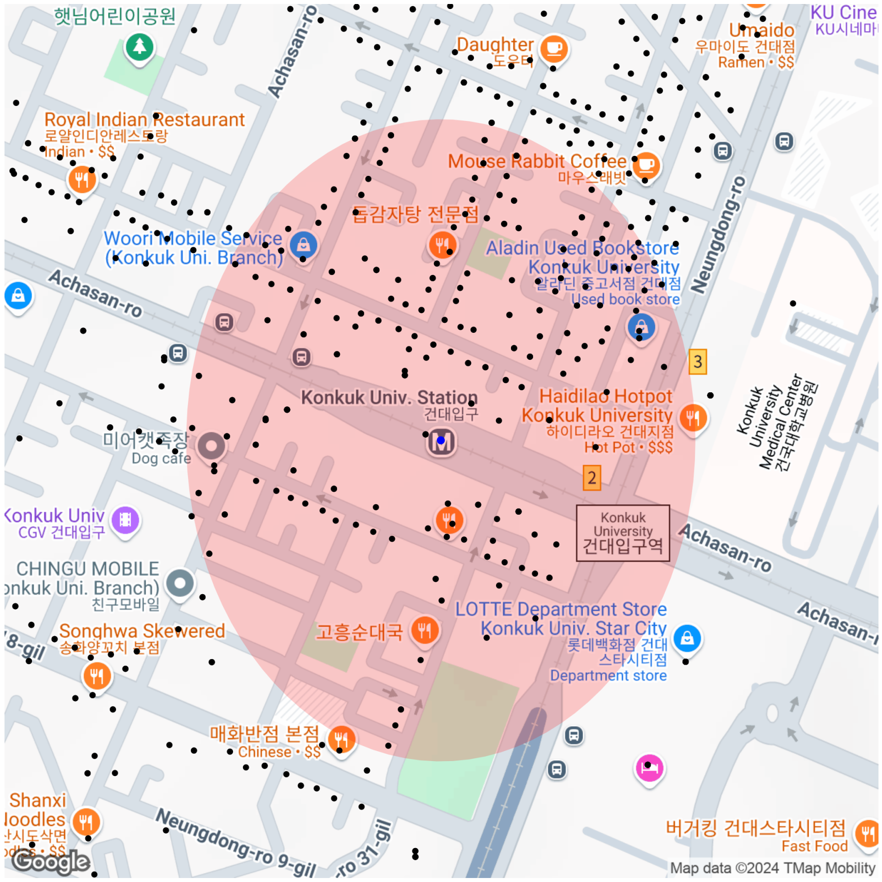

Figure 3: Konkuk University Station(Upper-ground Station)

$$Y_i = |N_1 - N_2| \tag{5}$$

where i denotes each station and N_1, N_2 are the numbers of restaurants on each side of the subway station. The coefficient θ_1 of regression 6 captures the conditional difference of asymmetry level between upper-ground and underground stations, and δ_{SGG} denotes the SGG-level fixed effects.

$$Y_{i,SGG} = \theta_0 + \theta_1 D_{\text{upper}} + \delta_{SGG} + \eta_i \tag{6}$$

Endogeneity issues are well controlled in this OLS regression and are hardly a concern. Three potential causes of endogeneity are well-controlled in the following sense.

1. Reverse Causality - We can say that Subway stations are 'predetermined' in the sense that it is difficult to assume that the local asymmetry per se calls for station construction.

2. Measurement Error - Measurement error correlated with the error term(η_i) is unlikely as my data of D_{upper} is manually collected from Google Maps and photos data. Unless the data collectors, including the author, had a priori intention to fill in incorrectly, the measurement errors are unlikely and nearly impossible to be correlated with the error term.

3. Omitted Variables - The last concern is the biggest. It might be true that upper-ground stations might have characteristics that affect the local asymmetry indirectly. For example, upper-ground stations might be more often built in riverside areas. Alternatively, upper-ground stations might be in a more/less agglomerated part of cities, where the economic density changes more drastically. To control for such sources, I filter all stations with major natural constraints, including historical sites and rivers, in their 200m radius. To control for other economic sources, I add SGG-level fixed effects to balance different economic conditions of SGGs.

3.3.2 Model

The 'moving cost' channel can explain such asymmetry with a simple representative consumer model. Suppose a district d can be divided into two zones, θ_d^W andθ_d^E. A single subway station, $T_d(j)$ divides the two zones and could either be upper-ground(j =1F) or underground(j =B1). If $D = 1$, The representative consumer is stochastically spawned at either west or east with equal probability, with the inverse demand for the amenities of the spawn zone being $p_i = D_i^{-1}(q)$. If $T_d(j = 1\text{F})$, moving from θ_d^i to θ_d^{-i} incurs a cost of $c > 0$, whereas $T_d(j = \text{B1})$ does not. We assume that there is no production advantage of one zone against another, implying that the supply curve for both zones would be equal.

In such a simple model, the consumer's willingness to pay decreases by c for the other zone if $T_d(j = \text{1F})$. This creates an asymmetry in both prices and quantities due to a shift in the demand curve—for example, figure 5 depicts the case when the consumer was located at E, leading to a fall in inverse demand for W. Note that $P^*_E - P^*_W \leq c$ where equality is satisfied if the supply is perfectly inelastic.

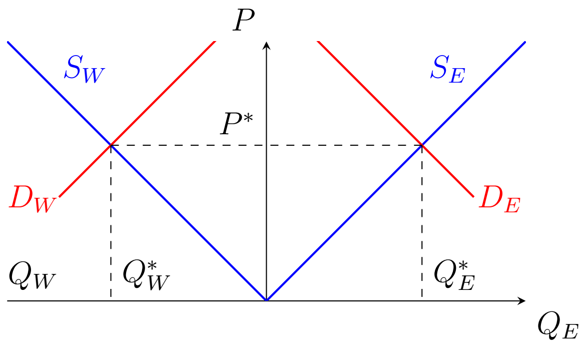

Figure 4: $T_d(j = \text{B1})$

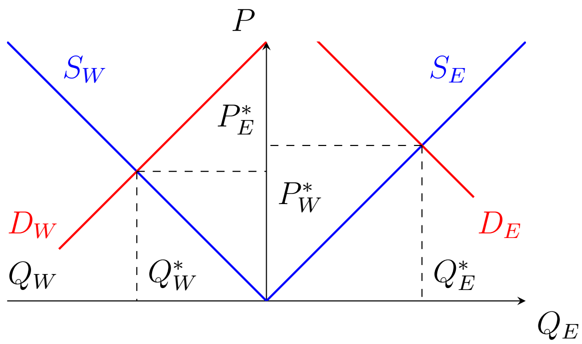

Figure 5: $T_d(j = \text{1F})$

4 Results

4.1 ATT of Subway Stations

The main results of ATTs are presented in Table 4.1. The ATT of subway station construction is presented in the first and second columns; the ATT of upper-ground stations are in the third and fourth columns, and the ATT of underground stations are in the final two. The odd columns show the results from two-way fixed effects regressions, and even columns are from Callaway and Sant'Anna (2021) estimator.

The results show two significant estimate values: (1) ATT of transit allocation in CS estimation and (2) ATT of underground transit allocation in TWFE estimation. However, upper-ground stations are insignificant in both specifications. The CS estimate coefficient of 0.156 in the second column can be interpreted as the difference in log employment due to the subway station allocation. That is, an EMD with a subway station has $e^{0.156}(\approx 1.17)$ times larger level of employment than the case if it hadn't had a subway station.

	Total		Upperground		Underground	
	TWFE	CS	TWFE	CS	TWFE	CS
ATT	0.153	0.156^{**}	0.022	0.187	0.223^{**}	0.142
	(0.095)	(0.081)	(0.144)	(0.128)	(0.113)	(0.105)
Num. obs.	13310		12649		12790	
Num. groups: EMD	593	562	565	543	566	557
Num. groups: year	28	27	28	27	28	27
R^2	0.889		0.891		0.892	
Adj. R^2	0.884		0.885		0.887	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3: Main Results

In addition to baseline ATTs, figures 6 to 8 show the event-study plots from Callaway and Sant'Anna (2021), which depicts the values of ATT(e)'s in equation 4. Although all three plots show insignificant coefficients post-treatment[7], there is a much clearer pattern of

[7] I presume that such large confidence intervals and low significance are due to the sample size. Although the data consists of more than 10,000 observations, Callaway and Sant'Anna (2021) estimator subsamples the data to produce a 'clean' comparison between the treated and the control group, which omits most of

increasing average treatment effects in figures 6 and 8, implying more positive and growing employment effects from underground stations than upper-ground stations.

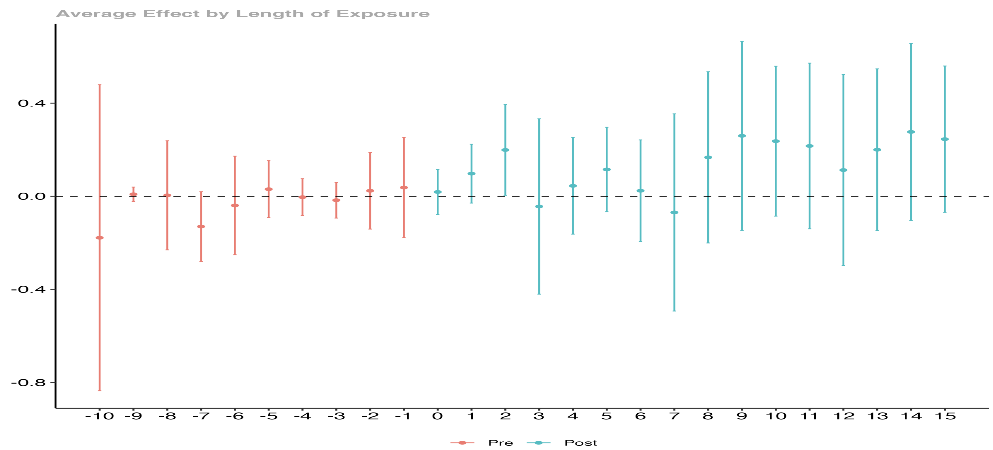

Figure 6: Event-Study(Subway Transits)

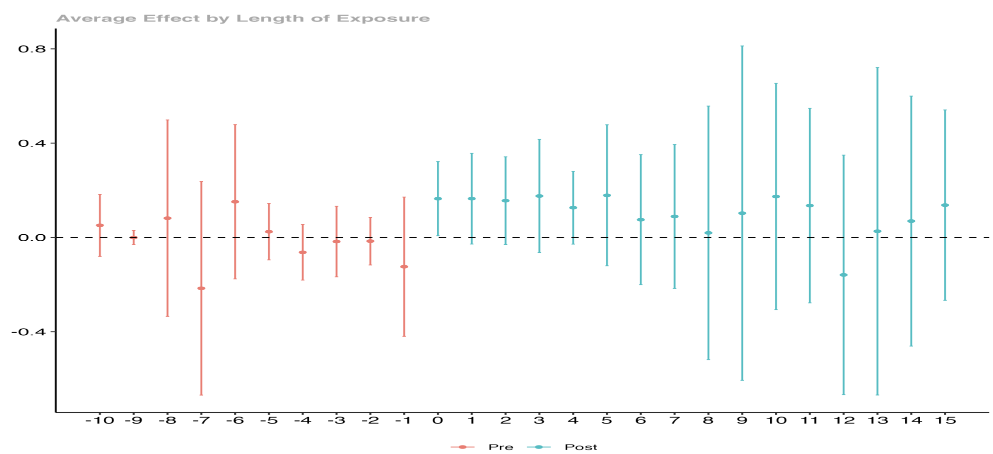

Figure 7: Event-Study(Upper-ground Transits)

the observations in estimating each event-study plots.

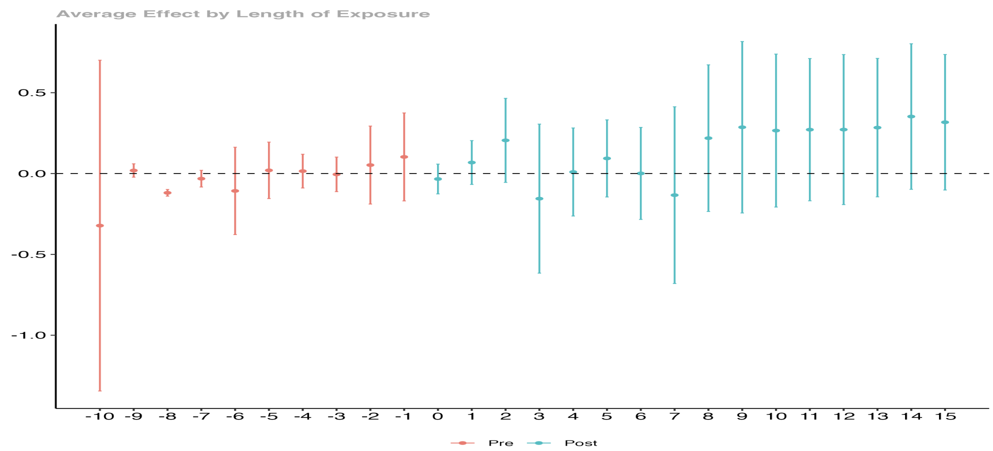

Figure 8: Event-Study(Underground Transits)

4.2 Asymmetric Allocation

The results in table 4 show no firm evidence that upper-ground stations encourage local asymmetry. However, the positive coefficient of 'level'(upper = 1, under = 0) suggests that if one of the two station types displays asymmetric business allocation, it would be the upper-ground transits. However, one must be careful to support this claim, as the regression does not claim that there is a statistically significant difference between the two.

	With Fixed Effects	Without Fixed Effects
level(1=upper)	3.490	2.052
	(5.610)	(4.519)
(Intercept)		0.820
		(2.053)
Num. obs.	189	189
Num. groups: location	25	.
R^2	0.119	0.001

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 4: Regression on Asymmetry Levels

5 Conclusion

To summarize the main results, underground stations and subway stations overall report statistically significant average treatment effects for encouraging local employment in different specifications. However, upper-ground stations did not. Further examining event-study figures, there is a consistent pattern in the overall subway station and underground station construction, which is not observed in upper-ground construction. Although these event-study ATTs aren't statistically significant, it is interesting that the ATTs of underground transits differ from upper-ground counterparts, suggesting that underground transits may be more helpful for local employment in the long run.

In addition to local growth, I model and examine whether upper-ground transits induce local asymmetry. Although the empirical results are unsatisfactory, the model shows that upper-ground transits might operate as a moving cost, lowering the willingness to pay on the opposite side of the spawning zone. However, the empirical results show no substantial evidence that such moving cost is incurred, most likely due to the small sample size. Thus, future research regarding this subject should include more relevant samples.

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Based on his contributions to collecting data and his allowance for using the data freely, I could write this research paper for the final Econometrics(2) class assignment.

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[8] The presentation slides are in my GitHub repository.