The Determinants of the Transit Accessibility Premium

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Motivation

(Classic) Research question

How does accessibility by transit affect residential rents?

1. Theory: Better Transit $\rightarrow$ utility to residents $\rightarrow$ higher rents
2. Empirics: Significant and largely unexplained variation in the 'Transit Accessibility Premium'.

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3. My take: not surprising, treatment effect very context specific.
4. More interesting: what determines this variation?

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4. More interesting: what determines this variation?
5. Implications: Effective transit, transit-oriented urban planning, taxation.

Data

Transportation

Entire transit and road networks 2013-2019 $\rightarrow$ Actual travel times between each two points in space by mode and time of day throughout the research period

Rents

Ads scraped from all major websites in Israel. After cleansing, geo-referencing, etc. $> 700,000$ ads in 100,000 unique addresses

Origin-Destination matrix

Cellular survey, monitoring roughly half of all cellular phones in Israel 2018-2019. Flows between 1,250 polygons by time of day.

Outline

Step 1: Estimate the idiosyncratic elasticity of rents wrt transit (transit accessibility premium).

$$log(rent) = g\left(\underbrace{log(accessibility)}_{\tau_i}, \overbrace{\mu_j}^{\text{Address FE}}, \underbrace{\psi_{rt}}_{\text{District-specific trend}}, \overbrace{X_{ijrt}}^{\text{Ad specific and spatial time-variant characteristics}}\right)$$

Step 2: Explore the Transit Accessibility Premium as a function of dwelling and urban characteristics.

$$\tau_i = f\left(\chi_{ijrt}\right)$$

Challenges: Exogeneity of allocation, define accessibility, estimate τ_i, confoundedness.

Linear models

Basic approach:

Estimate for ad i in address j, in district r, at time t:

$$log(rent)_{ijrt} = \alpha + \tau * log(RCMA_{jt}^{PT}) + \mu_j + \psi_{rt} + \beta X_{ijrt} + \upsilon_{ijrt}$$

X includes all dwelling-specific and time-variant spatial characteristics: Best-Linear-Approximation/Automatic Selection of controls

Limitations:

- Poor performance when Y is a non-trivial function of X
- Can estimate the Transit Accessibility premium only pre-defined groups
- Can't estimate the effect of covariates on the transit accessibility premium.

Causal Forest

A standardized machine learning model designed for estimation of heterogeneous treatment effects.

- Basic idea in Athey & Imbens, 2016. Current form in Athey, Wager, Tibshirani, 2019
- Quickly popularized
- Idiosyncratic treatment effects: $\tau \rightarrow \tau_i$ or $\tau(\chi)$
- No need to predefine groups of interest
- Reasons for heterogeneity: The effect of χ on τ_i

Challenges to estimation

From the introduction:
Accessibility, τ_i estimation, confoundedness, exogeneity of allocation.

What else?

- Asked rents versus market rents.
- Supply-side response to transit.
- Anticipation.
- Transit disamenities.

The Average Treatment Effect

Table 3

The Average Treatment Effect of Transit Accessibility on Rents

	Baseline	LASSO	IV	LASSO-IV	CF
Average Treatment Effect	0.005 (0.004)	0.005 (0.004)	0.031 (0.09)	-0.043 (0.088)	0.017*** (0.006)
R^2 (Within, adjusted)	0.583	0.600	0.583	0.599	
N - observations	731,564				
N - unique addresses	107,879				

Note: Models are described in the text. Standard errors clustered by address id are shown in parentheses.

The Average Treatment Effect is economically insignificant

Best Linear Projection of τ_i

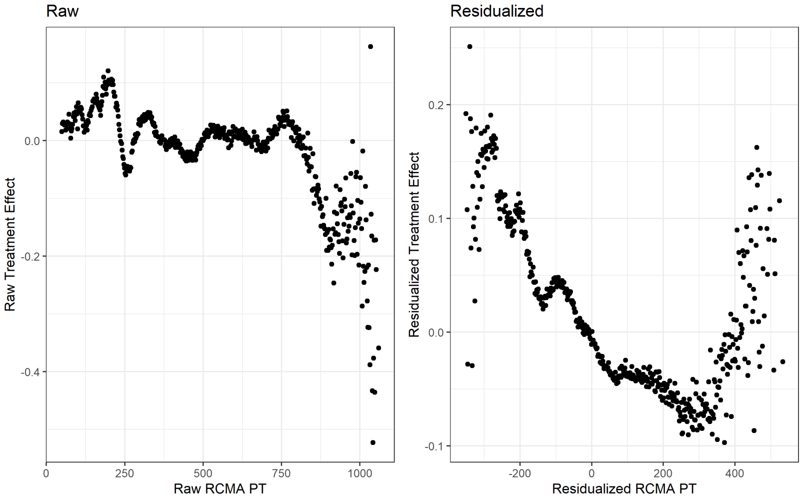
Table 6

Best linear projection of the transit accessibility premium, Top 15 features by absolute magnitude of the coefficient

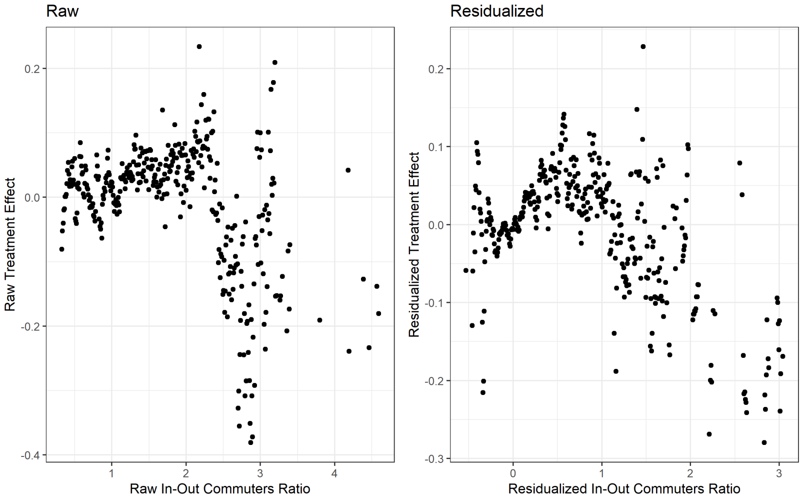
	Coefficient	Robust Standard Error
RCMA_PT	-0.11***	(0.019)
Out-commuters density	0.07**	(0.034)
Near Metronit	-0.038***	(0.007)
Share of population aged 40-59	-0.038***	(0.01)
Evening commuters	-0.035	(0.044)
Socioeconomic Status	0.033***	(0.01)
Share males	-0.03***	(0.011)
Share of population aged 20-39	0.02	(0.015)
Size in square meters	0.018***	(0.006)
Near Light Rail	0.018**	(0.008)
Share of population aged 0-19	-0.018	(0.012)
RCMA_car	0.015	(0.018)
In-commuters density	0.014	(0.019)
Share Ultra Orthodox	0.01	(0.011)
Renovation status	-0.008	(0.005)

Note: Doubly robust estimation, all variables standardized to have a mean of zero and variance of 1.

τ_i - Level of accessibility



τ_i - Mixed Use Zoning



What is measured?

The Transit Accessibility Premium reflects the utility potential residents of an area perceive that they get from transit.

But:

1. Perceived Level of service $\neq$Level of service
2. Perceived utility $\neq$Utility
3. Utility to residents $\neq$Social welfare
4. Short-term social welfare $\neq$Long-term social welfare

Still an important concept: effective transit, transit-oriented development, take-up.

Why heterogeneity matters?

1. Explanation of significant variation in previous literature.
2. Average Treatment Effect too context-dependent.
3. Possibly improved external validity.
4. Allows better understanding of the effect.
5. More important policy implications and research insights.

Main Findings

Higher effect found for areas with:

1. High density of potential users.
2. Mixed-Use zoning.
3. Proximity to Light rail or new train stations.
4. $RCMA^{PT}$ below threshold level.
5. $RCMA^{PT}$ either lower or (to a lesser extent) exceptionally higher than expected.

Another finding: estimated effect is usually modest.

Policy implications

1. Effective public transit requires densification.
2. Car-Transit infrastructure trade-off: can't have both.
3. Mixed-Use zoning
4. Rail Systems are more valued than same-level bus services.
5. Land Value Uplift taxation should not be large, should quickly decay with distance.

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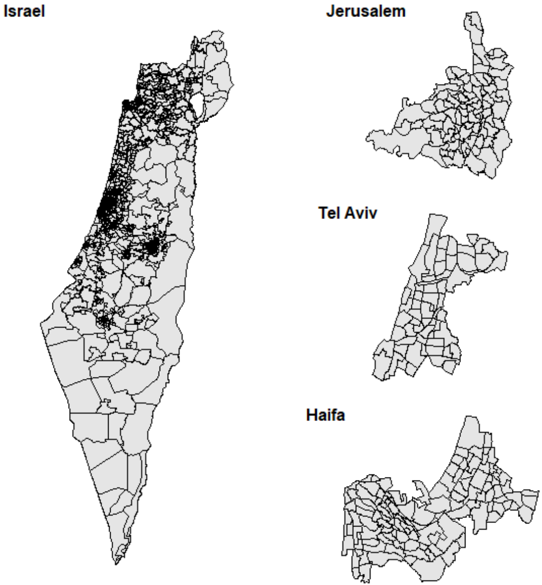
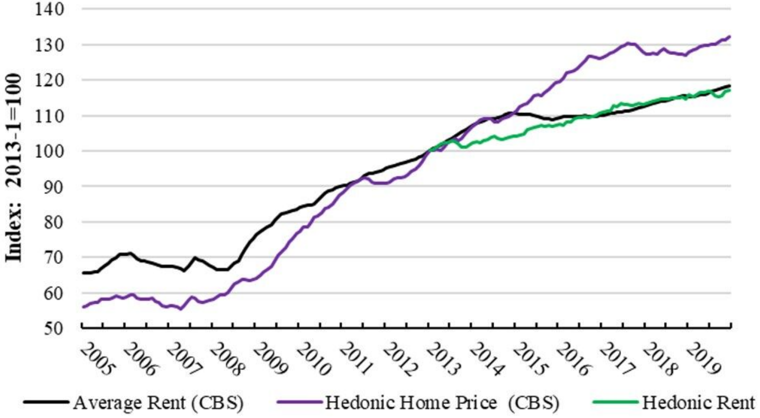
Transportation polygons



Residential costs

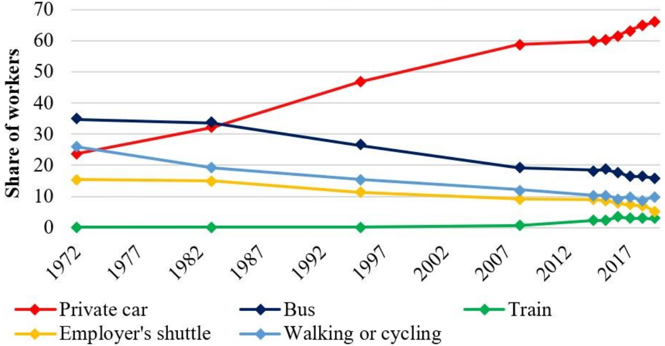
Figure 2
Residential cost indices, 2005-2019



Source: Israeli CBS, hedonic rents estimated with data in the paper.

Transportation: Long run trends

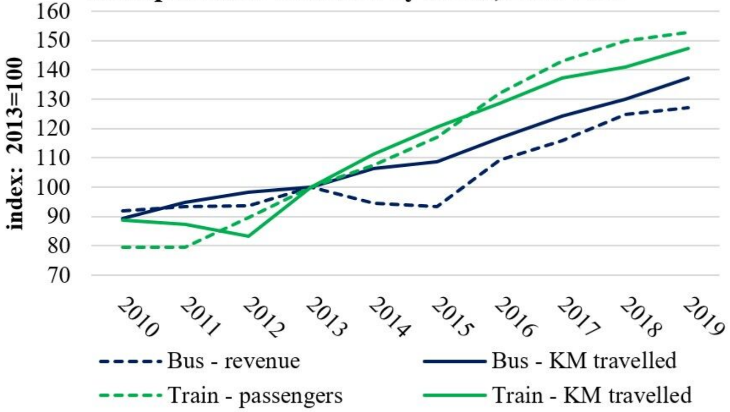
Figure 3
Mode of Commuting in Israel, 1972-2019



Note: The 1972 census had no seperation between public buses and employer's shuttles. I divided the unified category based on the stable ratio between them in later years.The 1983 survey had no seperate category for train passengers. I've assumed linear progress between the 1972 and 1995 censuses. Source: Israeli Central Bureau of Statistics censuses and social surveys.

Figure 4

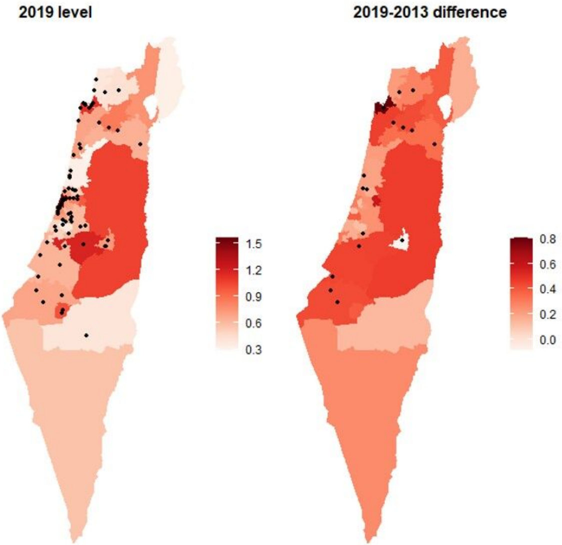
Transportation statistics by mode, 2010-2019



Note: Bus revenue is deflated using the bus rides price index to reflect changes in the number of passengers. Source: Israeli Central Bureau of Statistics annual reports.

Figure 6

Bus activity and active train stations, 2019 level and change during the period



Transport allocation process

Bus

- Operational clusters, $\sim$ 70 in 2019
- Competitive tendering, operation of clusters for $\sim$ 10 years
- Improvements in services implemented in tenders

Train

- Long construction and development projects
- Major schedule overruns, 72% for rail projects

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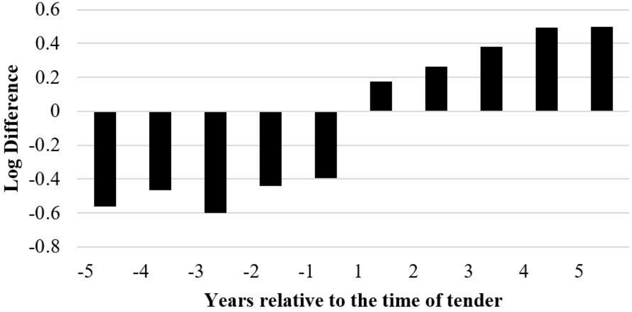
Claim: Timing of allocation plausibly exogenous

1. Hard to match timing of transportation events to other spatial developments
2. Improvements to the network largely result from these events

Figure 5

Log difference of average bus activity compared to time of tender



Note: Activity is defined as the number of times a bus stops at the station during a regular weekday.The presented difference is the average of log differences in each station's activity relative to the time of tender.

Commuter Market Access

Concept based on Tsivanidis (2019): A sufficient statistic for the effect of accessibility on welfare in a large class of urban models.

Composed of two terms:

Residential Commuter Market Access

$$\underbrace{RCMA_o}_{\text{Variable of Interest}} = \sum_d \frac{\overbrace{L_{F_d}}^{\text{workers in d}}}{FCMA_d} \underbrace{\kappa_{od}}_{\text{Connectivity measure}}$$

Firm Commuter Market Access

$$\underbrace{FCMA_o}_{\text{Accesibility from firms' point of view}} = \sum_d \frac{\overbrace{L_{R_d}}^{\text{Residents in d}}}{RCMA_d} \kappa_{do}$$

κ_{od}: Measure of connectivity

As in Dingel & Tintelnot (2020)

Travel time to commuting cost: $t_{od} \rightarrow \delta_{od}$

$$\delta_{od} = \frac{H}{H - t_{od}}$$

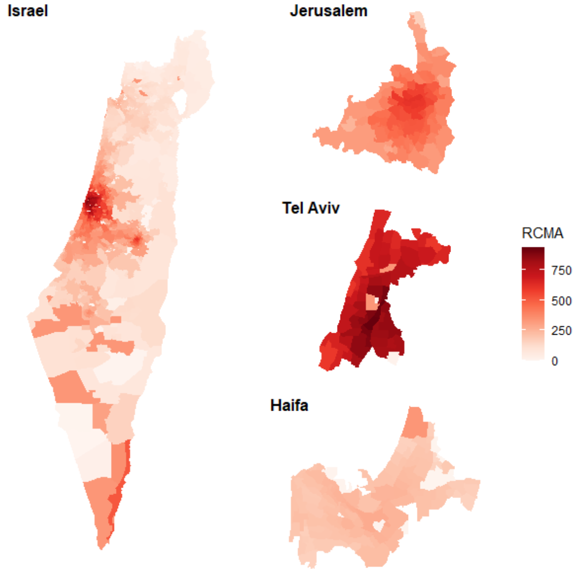
H is the daily time a worker spends on working and commuting. Empirically H=9.7, for consistency with prior research I define H=9.

Commuting cost to connectivity: $\delta_{od} \rightarrow \kappa_{od}$

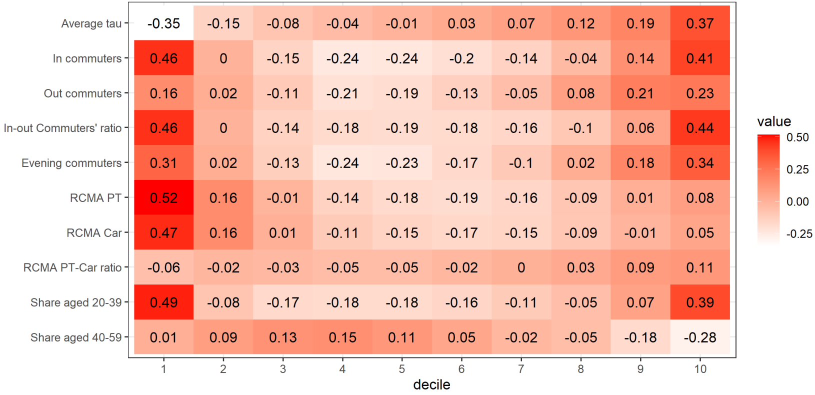
$$\kappa_{od} = \delta_{od}^{\epsilon}$$

ϵ estimated in a PPML gravity model.
$RCMA_i$ calculated using ad specific travel times and $FCMA_o$.

RCMA: Residential Commuter Market Access



Ad characteristics by deciles of τ_i



Heterogeneity in specified subgroups

Table 4

Heterogeneity in the transit accessibility premium - specified subgroups

Heterogeneity group	Baseline	Population density	Workers density	Socioeconomic Status	$RCMA^{Car}$	$RCMA^{PT}$
Definition	All	Top Quartile	Top Quartile	Top Quartile	Top Quartile	Top Quartile
Causal forest: base effect	0.017*** (0.006)	0.012* (0.006)	0.008 (0.005)	0.013** (0.006)	0.027*** (0.006)	0.027*** (0.006)
Causal forest: difference		0.021 (0.015)	0.036** (0.017)	0.014 (0.015)	-0.039** (0.017)	-0.041** (0.017)
Linear model: base effect	0.005 (0.004)	0.004 (0.004)	0.002 (0.004)	0.029*** (0.004)	0.005 (0.004)	0.006 (0.004)
Linear model: interaction term		0.019* (0.011)	0.083*** (0.012)	-0.101*** (0.007)	-0.000 (0.000)	-0.001*** (0.000)
R^2 (Within, adjusted)	0.58264	0.58264	0.58269	0.58285	0.58264	0.58265
N - in interaction group		182891	182894	182892	182891	182891
N - observations	731564					
N - unique addresses	107879					

Note: Standard errors clustered by address id are shown in parentheses. Causal forest estimates are obtained using a doubly robust estimation.

Heterogeneity by proximity to Mass Transit Systems

Table 5

Heterogeneity in the transit accessibility premium, by proximity to mass transit systems

Heterogeneity group	Baseline	Near Train	Near Light rail	Near BRT
Definition	All	0-1000m	0-1000m	0-1000m
Causal forest: base effect	0.017*** (0.006)	0.022*** (0.006)	0.015** (0.006)	0.019*** (0.006)
Causal forest: difference		-0.035** (0.018)	0.078* (0.041)	-0.022 (0.021)
Linear model: base effect	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	-0.003 (0.004)
Linear model: interaction term		-0.000 (0.001)	0.037 (0.024)	0.092*** (0.011)
R^2 (Within, adjusted)	0.58264	0.58264	0.58264	0.58272
N - in interaction group		101006	20677	63583
N - observations	731564			
N - unique addresses	107879			

Note: Standard errors clustered by address id are shown in parentheses. Causal forest estimates are obtained using a doubly robust estimation.

Proximity to new train stations: Diff in Diff

Found an increased effect of accessibility for dwellings adjacent to Light Rail or BRT, but not to train stations.
No increased effect for trains?

$$log(rent)_{ijrt} = \alpha + \rho * post_{rt} + \tau * [proximity_j * post_{rt}] + \mu_j + \lambda_t + \beta X_{ijrt} + \upsilon_{ijrt}$$

- Restrict sample to addresses within a 3km radius from a new train station.
- Compare addresses close to the station to addresses in the outer circle
- The model doesn't rely on improved accessibility.
- Emphasizes patterns of re-organization.

Proximity to new train stations: Diff in Diff

Table A.6

The effect of proximity to train stations on rents

	Constant effect	Heterogeneity by distance				
Interaction group (distance in meters from station)	0-1000	0-200	200-400	400-600	600-800	800-1000
Difference in Differences	0.013** (0.005)	-0.007 (0.032)	0.022* (0.013)	0.015* (0.009)	0.012 (0.009)	0.010 (0.008)
R^2 (Within, adjusted)	0.600	0.600				
N - observations	45,614	45,614				
N - unique addresses	7,389	7,389				
N - observations in treatment group	10,045	62	1,076	1,833	3,044	4,030

Note: Standard errors clustered by address are shown in parentheses. The control group is always defined as observations located 1000-3000 meters from stations.

A modest significant effect, (almost) monotonically decreasing with distance.

Proximity to new train stations: Diff in Diff

So why I haven't found an increased effect of accessibility?

- Once there's accessibility to a train station, little added value from additional accessibility.
- New VS old stations: different contexts
- Different control groups
- Effect goes through non-accessibility channels