Transit and rents: patterns of heterogeneity

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Abstract

Accessibility is a key factor in the utility from living in different areas. In urban models, accessibility is theoretically expected to be internalized by the residential market, creating an 'accessibility premium' in areas with improved accessibility. Previous case-study literature found significant and largely unexplained variation in the transit accessibility premium in different urban contexts. This paper proposes a new approach to uncovering the determinants of this variation in a unified framework, utilizing a theoretically grounded measure of accessibility, and both causal machine learning and standard econometric methods to highly granular nationwide data on the transit and roads network, cellular location, and asked rents.

I find that high residential density, Mixed-Use zoning, and a demographic composition more reflecting typical transit users imply a larger transit accessibility premium. This premium is also higher in areas with a low level of services compared to a reasonable reference point, and positive only up to a threshold level of services. There is some evidence that proximity to rail systems implies a premium over and above the expected premium implied by a reduction in travel times alone. The estimated effect is usually modest.

JEL Codes: R40, R32, R23, R12

[1]Bank of Israel and The Hebrew University.

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Introduction

The 'transit accessibility premium' - the effect of accessibility by public transportation on residential rents has an important economic interpretation: the utility perceived by potential residents of an area from transit services near their residence. This utility is theoretically expected to widely vary depending on geographic, urban, and demographic contexts, rendering the average effect in a specific context uninformative in other urban contexts or even in specified sub-groups of the same sample.[2] Accordingly, a vast case-study literature and several meta-analyses found significant and largely unexplained variation in this premium.

This paper aims to uncover the determinants of the variation in the transit accessibility premium. I apply both causal machine learning and traditional econometric methods to highly granular nationwide panel data on transportation and asked rents to unveil the patterns of dependence of the transit accessibility premium on different urban and demographic characteristics. These patterns likely display external validity superior to an average treatment effect in a specific sample and can better inform planners, researchers, and policymakers when considering alternative transit allocations.

To study this effect, this paper utilizes variation stemming from a rapid improvement in public transportation in Israel in 2013-2019. During the research period, train and bus activity improved nationally by 47% and 37% accordingly.[3] Such a rapid nationwide improvement is unusual and allows a unique opportunity to examine transit effects using a large margin of change in a developed economy context. I find that a higher transit accessibility premium is associated with high residential density, Mixed-Use zoning,[4] and a demographic composition representing typical transit users. I also find a larger premium when the level of services is either lower or exceptionally higher than a reasonable reference point, an absolute upper bound for the level of services still affecting rents, and a proximity to rail stations effect over and above the effect implied by a reduction in travel times alone. The estimated effect is usually economically small.

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[2] Redfearn (2009) empirically demonstrates this non-trivial variation using ex-ante innocuous choices of subsamples in the same empirical context.

[3] Here, for expositional purposes defined as Total KM travelled as reported in the Israeli Central Bureau of Statistics' annual reports. The analysis in the rest of the paper relies on a different, theoretically grounded, measure of accessibility. Other notable improvements are the opening of Israel's first Light Rail (2011) and Bus Rapid Transit (2013) systems. See more at the empirical context section.

[4] The blending of different uses such as residence, employment, education, and commerce in the same area.

This paper is part of a growing literature applying newly developed causal machine learning methods to address urban economic questions, one of a few papers utilizing granular cellular location data to address urban economic questions,[5] and to my knowledge, the first paper constructing and utilizing a panel of granular transportation data in a nation-wide analysis of the transit-accessibility premium.

The urban economic theory attributes significant importance to accessibility in determining an area's attractiveness and cost of residence . The higher residential cost is due to utility from improved access to the labor market and other opportunities, allowing firms and individuals to utilize economies of scale and reduce the cost of consuming amenities in other parts of the city. In that sense, transit services and a developed road network are substitutes for downtown residence.

The accessibility-residential cost relationship is a central result both in the canonical monocentric city model (AMM),[6] where accessibility is typically measured by distance to the Central Business District, and in more recent quantitative urban models where accessibility is defined using more granular concepts of urban pull factors and travel costs.[7] The aggregation of travel times to different parts of the city to a single accessibility measure in these models is non-trivial. I rely on a recent sufficient statistic result developed by Tsivanidis (2019), showing that in a large class of quantitative general equilibrium urban models a single concept, Commuter Market Access, is sufficient to summarize the impact of the entire transit network on equilibrium outcomes.

Empirically examining the effect of transportation on economic phenomena entails an inherent difficulty in identification: possible endogeneity of transportation allocation. Common approaches account for this using institutional arguments, instrumenting for current transportation infrastructure with planned or historical routes,[8] or restricting the

[5]Prominent examples are: Büchel et al (2020), Athey et al (2021), Hausman et al (2021), Kreindler & Miyauchi (2021), Gupta et al (2022), Miyauchi et al (2022).
[6] Alonso (1964), Mills (1967), Muth (1969).
[7] See Ahlfeldt et al (2015), Albouy & Lue (2015), Diamond (2016), Ahlfeldt & Feddersen (2017), Monte et al (2018), Dingel & Tintelnot (2021), Severen (2021), Hausman et al (2021), Gaigné et al (2022).
[8] See review at Redding & Turner (2015), other prominent examples are Baum-Snow (2007, 2010), Duranton & Turner (2011,2012), Duranton et al (2014), Baum-Snow et al (2017), Severen (2021). Brooks & Lutz (2019) Argue that due to path-dependence historical routes should be used for sample selection and not as instrumental variables.

analysis to regions enjoying allocation inconsequentially.[9] In the specific literature on the transit accessibility premium, standard procedure constitutes of either a difference-in-differences design or cross-sectional hedonic regressions for the effect of proximity to a single transportation project on the value of nearby properties.[10] Identification is usually claimed relying on institutional knowledge, or without accounting for endogeneity. In this paper, I apply a difference-in-differences framework and make an institutional argument for exogeneity in the timing of transit allocation in Israel.

The empirical literature generally finds a small positive accessibility premium.[11] Usually, treatment is defined by proximity to stations, and the response is measured using residential property values. Proximity to Bus Rapid Transit (BRT), light rail, or train stations implies a 12%, 4%, or 6% increase in property values accordingly,[12] though there is considerable variation between studies, including many studies that find a zero, or even a significant negative effect. This large variation is discussed and addressed in reviews using a meta-analytic regression approach across papers. Only a few common patterns emerge using this approach - a stronger effect for Mass Transit Systems compared to regular bus services, an effect rising with proximity to stations and a moderating effect of high private-car accessibility. The literature lacks analyses that systematically test for different sources of variation and their relative importance in a combined framework.

In the Israeli context, some papers examine the effects of transportation on residential and employment location choices: Leck et al (2008) find that rail transit diminished periphery-core wage disparities in southern and central Israel. Israel & Blankshtain-Cohen (2010) find suburbanization and counter-urbanization effects of rail services in the Tel Aviv metropolitan area. Frisch & Tsur (2010) finds that new road and rail infrastructure contributed to long-distance commuting from their catchment areas. Bleikh (2018) explores long-term trends in commuting.

Other prominent papers include Ida & Talit (2018), who describe and examine the effect of an ongoing reform in bus operation in Israel, and Soffer & Suhoy (2019) who

[9] E.g., Chandra & Thompson (2000), Mayer & Trevien (2017), Banerjee et al (2020). A less common approach is examination of obviously exogenous shocks to transportation; A key example is the division and re-unification of Berlin. See Redding & Sturm (2008), Ahlfeldt et al (2015).
[10] A less common approach also allows for spatial dependence between units, see Diao et al (2017).
[11] See Wardrip (2011), Mohammad et al (2013), Ingvardson & Nielsen (2018), Zhang & Yen (2020), Rennert (2022) for recent reviews.
[12] Median values from papers included in tables 2-4 in Ingvardson & Nielsen (2018).

use survey data to construct relative accessibility indices by transportation mode and examine determinants of modal transportation choice. They find an increase in recent years in rail use among all income groups. Several papers[13] examine the employment and education effects of the penetration or massive improvement of bus services to Arab localities following Israeli Government Decisions: No. 1539 (2009), and No. 922 (2015), aimed specifically to manifest economic development in those localities. Findings imply a negligible positive effect on employment.

The paper proceeds as follows: section 1 describes the data used for the analysis, section 2 describes the Commuter Market Access concept and its estimation, section 3 describes the empirical context, section 4 the methodology, sections 5 and 6 present and discuss the results, and section 7 concludes.

1. Data

This section describes the assembled dataset by main subjects: transportation, rental ads, the cellular location-based Origin-Destination matrix, and additional data. A summary of the data sets appears in appendix table A1.

1.1 Transportation

I observe the entire transportation network in Israel throughout the research period. This includes granular information on roads, schedules, routes, and travel times, allowing me to calculate effective travel times by public transportation and private cars between any two points in space throughout the research period. These travel times include switches and real in-ride, walking, and waiting time. See appendix A for a thorough description of the data, a detailed definition of travel times, and a description of the procedures applied to obtain them.

1.2 Rental ads

The RENTS dataset is collected by a private firm scraping rental ads from all popular sites in Israel. RENTS is regularly used by the Israeli CBS, the Bank of Israel, and other public organizations and is available to me for ads published since 2013. It contains information on the ad's publication date, asked rent, address, and other characteristics.[14]

[13]Greenwald et al (2018), Abu-qarn & Lichtman-Sadot (2022), Barak (2020), Avivi et al (2021).

[14] I use characteristics that are non-missing in more than 90% of the ads in the dataset: rent, size, number of rooms, floor, number of floors in the building, number of toilet rooms, and dummies for renovation status and the existence of: air conditioner, lift in the building, parking, balcony, security room, new kitchen, and barred windows.

RENTS may contain multiple spans of the same ad if it was updated or changed. I use the last appearance of an ad to diminish noise from errors and idiosyncratic beliefs on the actual market value. I keep only successfully geo-referenced ads[15] and further cleanse RENTS by filtering out ads that have no access to public transportation,[16] or ads containing missing, clearly wrong, or unusual characteristics.[17] This procedure results in a final dataset of 760,568 ads in 147,283 unique addresses.

1.3 Origin-Destination matrix

The OD_MAT dataset, received from the Israeli Ministry of Transportation, is the product of a large-scale project continuously monitoring the location of roughly half of all mobile phones in Israel.[18] OD_MAT is based on data from 3.77 million unique cell phones and roughly 2.75 billion human days. After appropriate weighting, OD_MAT describes a total of 15.76 million journeys in an average weekday – roughly 2.1 daily journeys per person in the entire adult Israeli population.

Since OD_MAT is collected using cellular location data, feasible polygon size is determined by the density of cellular antennas in the area, with sizes ranging between 0.12 to 1,079 Square KM. The median polygon's size is almost two square KM and inhabited 6,244 residents in 2018. Polygons in populated areas are smaller than polygons in rural areas, as presented in appendix figure A1. The three largest cities in Israel: Jerusalem, Tel-Aviv, and Haifa are divided into 83, 63, and 69 polygons accordingly. I observe the 2018-2019 weekday average flows in half-hour intervals between the 1,250 polygons in the dataset.

There is no direct way to reveal the purpose of rides or individual round-trip journeys from the data. Therefore, one must choose times of day that most likely represent pull factors, such as a residence-workplace commute. I define the relevant flow between

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[15] Geo-referencing is done using the ADDRESSES dataset (see appendix table A.1), and Google Maps and Open Street Map API's when geo-referencing using ADDRESSES failed. 97.3% of the ads were successfully geo-referenced.

[16] I examine the effect in terms of elasticity, keeping ads without any access to public transportation would cause modest improvements in services to show up as huge change in log points.

[17] Apartments with less than 1, or more than 6.5 rooms, or apartments whose rent per square meter is not within the 10-200 NIS (roughly 2.7-54 US dollars) interval. I preform finer filtering by comparing the rent and size of the apartment to the corresponding median value of the 100 geographically closest similar apartments, only keeping ads where the ratio between the ad and the median value is within the 0.5-1.5 interval.

[18] A presentation of the project appears in Matat (2021). Almost 3% of all journeys in the dataset were blanked due to confidentiality issues.

every pair of polygons proxying for typical pull factors as the sum of all journeys between them originating between 6:30-9:30.[19]

I also use the sum of in-flows to a polygon originating between 19:30-21:00, which I observe as largely consisting of journeys to leisure activity, to proxy for amenities in the polygon. A similar measure of amenities is developed and rationalized by Hausman et al (2021).

1.4 Additional data

I extract the following publicly available annual data from the Israeli Central Bureau of Statistics: Population count, Socio-Economic status,[20] the share of non-Jews, ultra-orthodox, males, and each of the following age groups: 0-19,20-39,40-59, over 60 in each statistical area.[21] Other data includes dates of all bus tenders in Israel since the beginning of the reform, which is used to construct the instrumental variable later described, and the CBS Labor Force and Social surveys and Population Censuses used for calibration and stylized facts.

2. Commuter Market Access

2.1 Framework

I adopt the Commuter Market Access (CMA) framework developed in Tsivanidis (2019) to define accessibility. CMA for a spatial unit is given by Residential Commuter Market Access (RCMA), representing accessibility of residents in the unit to pull factors (e.g., possible employers), and Firm Commuter Market Access (FCMA) which represents how accessible are the pull factors within that unit (e.g., the accessibility of firms within it to possible employees). Tsivanidis (2019) shows that in a wide class of quantitative urban models, CMA is a sufficient statistic summarizing the impact of travel costs on economic equilibrium outcomes. In the rest of this section, I describe CMA in labor market terms, though its interpretation in my context is more general.

The Commuter Market Access is defined by the following set of equations:

[19] According to the 2008 Israeli Population Census, the most relevant dataset covering the distribution of commutes throughout the day in Israel, this interval covers two thirds of all workplace commutes.
[20] I use the 2017 level for the entire sample.
[21] The smallest spatial unit in Israel, resembling US census tracts. The average statistical area in 2019 contained 3,016 residents.

$$(1)\ \ RCMA_o = \sum_d \frac{LF_d}{FCMA_d} \kappa_{od}$$

$$(2)\ \ FCMA_o = \sum_d \frac{LR_d}{RCMA_d} \kappa_{do}$$

LF_d and LR_d are the number of workers and residents in polygon d, accordingly. κ_{od} is a measure of connectivity between polygons o and d discussed below. The connection to polygon d contributes more to $RCMA_o$ when the trip from polygon o to polygon d is short, the number of workers in d is high, and d isn't easily accessible to workers from other areas.

2.2 Definition of Connectivity

Following Dingel & Tintelnot (2021), I parametrize travel times, as defined in Appendix A, to commuting costs as:

$$(3)\ \ \delta_{od}^m \equiv \frac{H}{H - t_{od}^m}$$

t_{od}^m is the roundtrip travel time between polygons o and polygon d by transportation mode m.[22] m can take one of three values: PT for public transportation, car for private car, or all for a mode-unified measure. Specifically, t_{od}^{all} is the average of travel times by public transportation and private cars, weighted by the national share of commuters using each mode.[23] H represents the daily sum of hours a worker dedicates to working and commuting. Hence, the commuting cost between polygons o and d, δ_{od}^m, is the inverse of the share of time a worker making this commute spends on working during a workday. The average full-time worker in Israel works 8.7 hours and has a one-direction commute time of 30.7 minutes, leading to an empirical $H = 9.7$.[24] For consistency with prior research, I impute $H = 9$.[25]

Connectivity between polygons o and d by transportation mode m is defined in equation (4). ϵ^m is the elasticity of commuting with respect to commuting costs. Since

[22] Whenever $t_{od}^m > H$, I truncate travel times to 539 - 1 minute less than 9 hours.
[23] The average 2014-2019 share of car commuters using the Israeli Social Survey is 67.7%
[24] Average values from the 2018-2019 Israeli Labor Force survey. The Commute time is relatively long compared to a rough OECD average of 20 minutes (OECD, 2011).
[25] Estimates where I assumed $H = 10$ or $H = 8$ yielded practically identical connectivity measures.

ϵ^m is negative, κ_{ij}^m is bounded between 0 and 1. Zero travel time implies a connectivity measure of 1.

$$(4)\ \kappa_{od}^m \equiv [\delta_{od}^m]^{\epsilon^m}$$

2.3 Estimation of Commuter Market Access

I estimate the elasticity of commuting with respect to commuting costs using a standard gravity model and a Pseudo Poisson Maximum Likelihood estimator:[26]

$$(5) Flow_{od} = \exp(\epsilon^m * RCMA_{od}^m + \gamma_o + \omega_d) + \upsilon_{od}$$

$Flow_{od}$ is the number of journeys from polygon o to polygon d during the morning peak, and γ_o and ω_d represents origin and destination fixed effects accordingly. Since OD_MAT represents average 2018-2019 values, I use average 2018-2019 travel times for estimation. Results using travel times by different modes of transportation are presented in table 2, and implied connectivity measures $\kappa_{od}^m(t_{od}^m) = [\delta_{od}^m]^{\epsilon^m}$ in appendix figure A.2. The Estimated elasticities are of similar magnitude to those reported in Dingel & Tintelnot (2021).[27] The model estimated with mode-unified commuting costs has the best goodness of fit, lending support to its construction.

Table 1

Commuting elasticity estimates

	Mode-Unified	PT	Car
Elasticity	-10.96*** (0.228)	-9.182*** (0.445)	-10.17*** (0.247)
Pseudo R^2	0.728	0.639	0.701
Location pairs	1,464,100		
Commuters	2,592,630		

Note: Standard errors are shown in parentheses.

I proceed by defining mode-unified Residential and Firm Commuter Market Access measures ($RCMA^{all}, FCMA^{all}$) for all polygons using equations (1), (2), and κ_{od}^{all} as the connectivity measure. Figure 1 presents the spatial distribution of the estimated

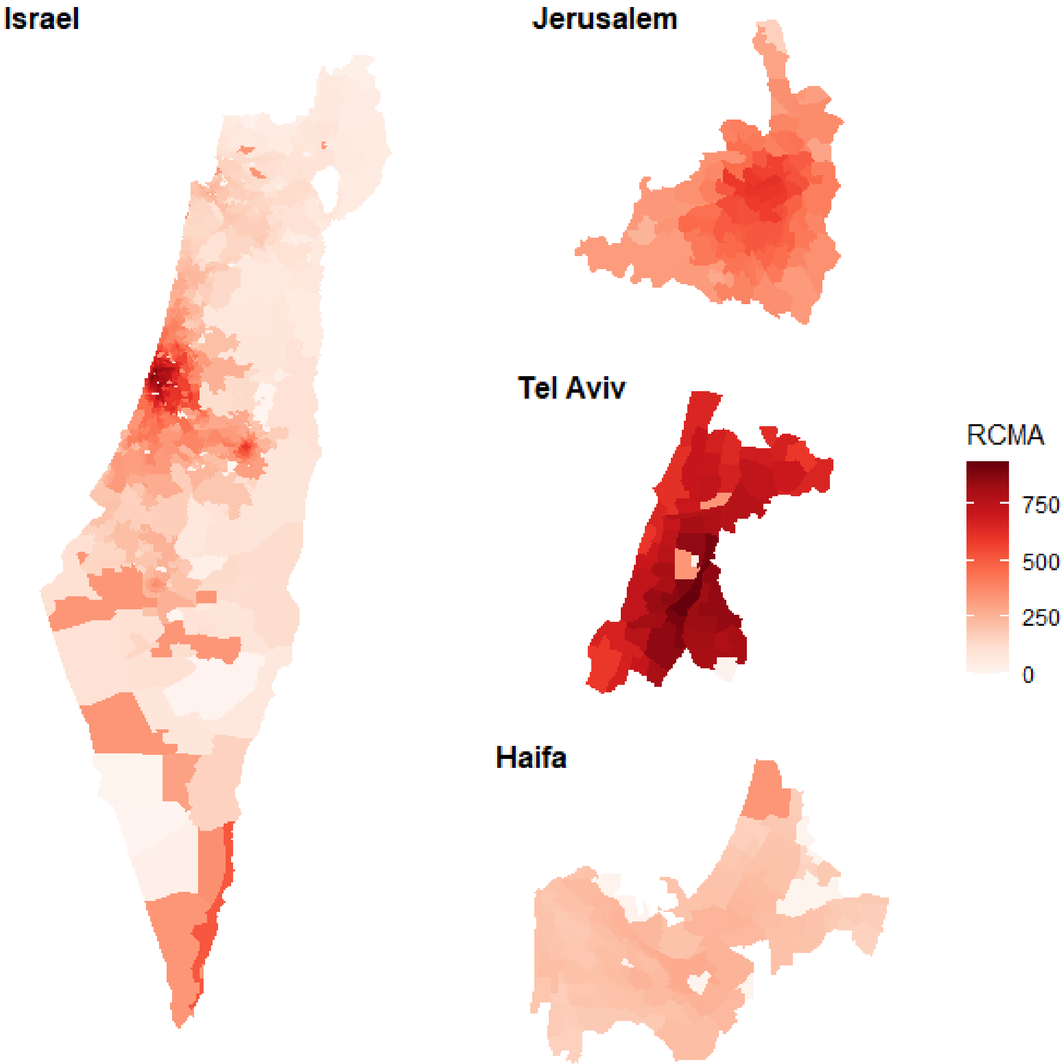
[26]Specifically, I use the PPMLHDFE command available in Stata (Correia et al, 2019). See Silva & Tenreyro (2006) for discussion of the shortcomings of estimating gravity equations with OLS, and Dingel & Tintelnot (2021) for a discussion specifically on granular settings.

[27] Dingel & Tintelnot (2021) reports elasticities ranging between -7.99 to -19.81.

$FCMA^{all}, RCMA^{all}$. As expected, both in the national and metropolitan level accessibility escalate near important economic centers.[28]

Figure 1.a

Estimated Residential Commuter Market Access

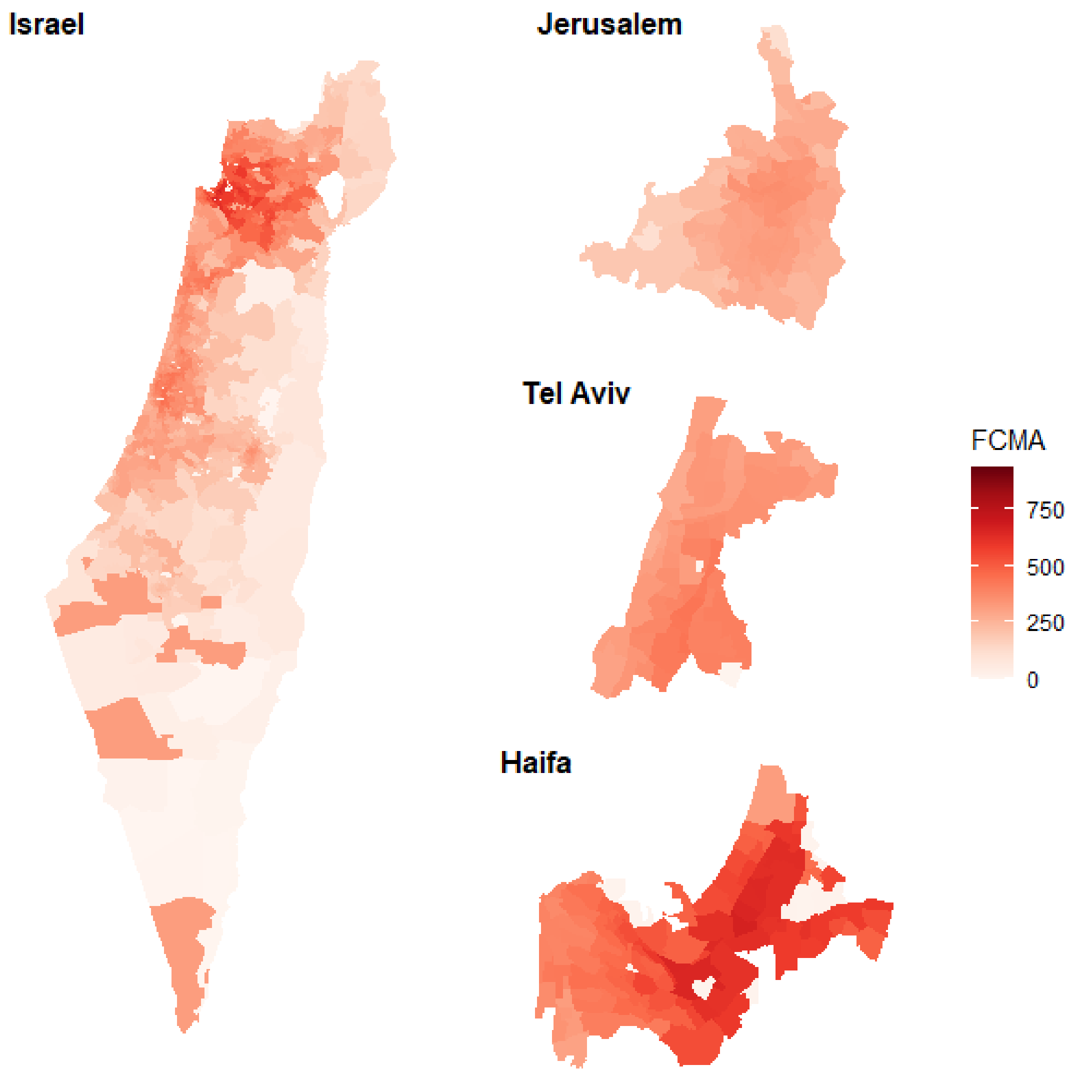


Note: No data was received for flows from and to 40 polygons due to confidentiality issues. These areas are plotted with the average value of Residential Commuter Market Access in their region.

[28] Also note a surprisingly high Firm Commuter Market Access in eastern Haifa, which might drive some of the results later presented concerning the proximity to the Metronit, and high Residential Commuter Market Access near Eilat (an important tourism town in the southern end of Israel). This might be the result of leisure rides to Eilat originating during morning rush hours, which are indistinguishable from commutes in my dataset. This phenomenon should not affect results since there are almost no ads in areas relevant for a commute to Eilat in the RENTS dataset.

Figure 1.b

Estimated Firm Commuter Market Access



Note: No data was received for flows from and to 40 polygons due to confidentiality issues. These areas are plotted with the average value of Firm Commuter Market Access in their region.

Lastly, I use the mode-unified Firm Commuter Market Access measure, $FCMA_d^{all}$, to assign Residential Commuter Market Access by transportation mode m for each address j that appears in the dataset at transportation period t, using the following equation:

$$(6)\ \ RCMA_{jt}^{m} = \sum_{d} \frac{LF_d}{FCMA_d^{all}} \kappa_{jdt}^{m}$$

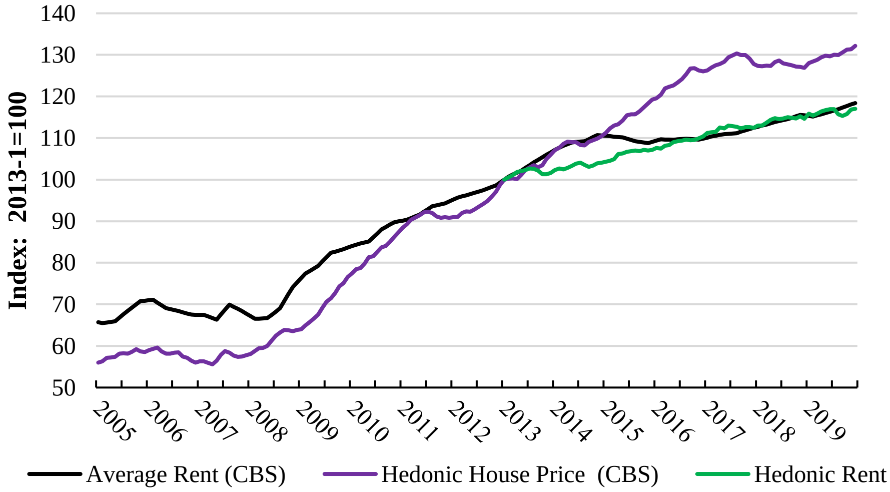
Where κ_{jdt}^{m} is the connectivity from address j to area d, at transportation period t, by transportation mode m. Note that $FCMA_{d}^{all}$ and LF_{d} are constant across time and transportation modes. Hence, variation in $RCMA_{jt}^{m}$ is the result of changes in travel times alone and does not reflect dynamics in the attractiveness of commuting destinations.

3. Empirical setting

3.1 Housing and rents

Economic activity and population in Israel are concentrated around three metropolitan areas of descending economic importance: Tel Aviv, Jerusalem, and Haifa. Rents and housing prices, as theory suggests, are higher around the metropolitan areas, especially Tel Aviv. Residential costs hiked mainly before, but also throughout the research period (2013-2019).[29] House prices rose by 27% and rents by a modest 12.9% during the research period. The appreciation is visualized in figure 2.[30]

Figure 2
Residential cost indices, 2005-2019



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

[29] Several papers examined whether this hike represents a price bubble and concluded that it is not the case; Yakhin & Gamrasni (2021) argue that the price level in 2019 is only 5.5% higher than the long-run equilibrium price. Also see Dovman et al (2012), Caspi (2016), Arestis & Gonzalez-Martinez (2017) for analysis of the major hike in the early period.

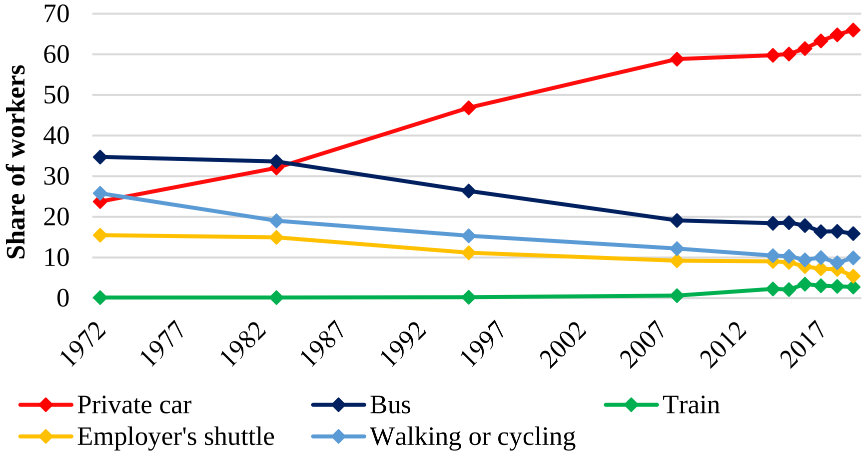
[30] The hedonic rent index produced by the Israeli CBS have been shown to be biased due to exclusion of new tenants from estimation (Raz-Dror, 2019). Therefore, I display the average rent index reported by the CBS, and a hedonic index estimated with regional fixed effects and all physical and spatial variables described below using my data.

3.2 Transportation in Israel

Improvements in the standard of living alongside an auto-oriented planning policy, resulted in a consistent and significant incline in the motorization rate and private car commuting (figure 3).[31] By the late 1990s rail infrastructure suffered from neglect and bus services were operated almost exclusively by two cooperatives.[32] The operators' market power, accompanied by weak regulation led to complete dependence on the cooperatives which in turn led to a gradual decline in the quality of service. Following government decision 1301 (1997), the right to operate bus lines was gradually tendered to new firms in a model similar to that prevalent in many European countries. The bus reform was accompanied by large investments in rail infrastructure inducing continued substantial improvement in services and efficiency.[33]

Figure 3

Travel to work mode 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 Beaurau of Statistics censuses and social surveys

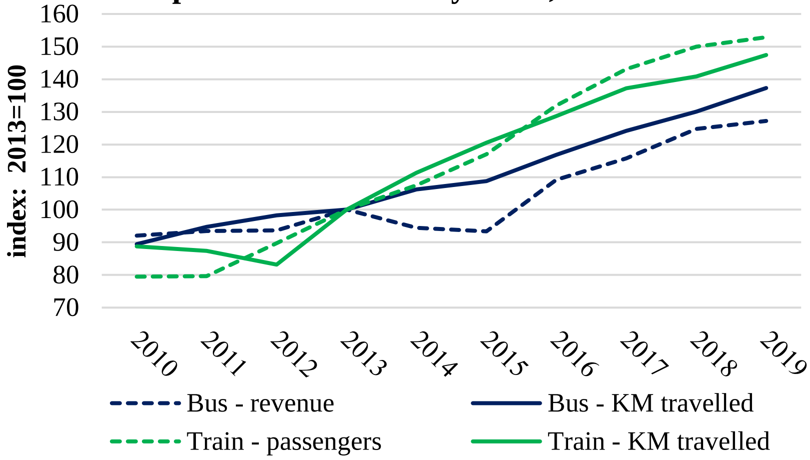
The results of the ongoing reform are apparent during the research period: considerable growth in the supply of public transportation, and to a lesser extent in the number of passengers (figure 4). Improvements in train services seem more effective, with train ridership hiking considerably higher than bus ridership in the last decade.

[31] These trends in the past two decades are discussed at Friedman (2019).
[32] Egged and Dan provided 95% of all bus passenger rides in Israel in 1997 (Shiftan & Sharaby, 2006).
[33] The process of tendering all services is longer than originally expected and is still undergoing. Tenders that took place are considered a success, improving the level of service, and narrowing costs. A Thorough review can be found at Ida & Talit (2018).

Improvements in the bus network and rail services were more pronounced in Haifa and its surroundings, in Judea & Samaria, and the Ashdod greater area (figure 6). Out of 68 now-active heavy rail stations in Israel, 15 were inaugurated during the research period: stations in the new "Rakevet HaEmek" line connecting Haifa to the Jezreel valley and Bet-Shean, the rail to Karmiel, the new southern rail, a new station in Jerusalem,[34] and a few suburban stations in central Israel.

Figure 4

Transportation statistics by mode, 2010-2019



Bus revenue is deflated using the bus rides price index to reflect changes in number of passengers.

Source: Israeli Central Beaurau of Statistics annual reports

3.3 The process of public transportation allocation

To identify the transit accessibility premium I rely on the exogeneity of the timing of public transit allocation. This section argues that the timing of allocation of both bus and train services is indeed exogenous.[35]

Bus[36]

The planning of the entire bus network in Israel is under the responsibility of the National Public Transport Authority (NPTA).[37] The network is divided into operational

[34] Jerusalem was connected to rail services since 1892, but the old rail and stations' location didn't allow quick travel to major economic centers. Many new rails follow the path of historical rails built by former sovereigns of the region as an extension of the Hejaz railway and for British military purposes.

[35] The Jerusalem Light Rail is not discussed here. It is operated by a private firm under the supervision of the Jerusalem Transport Master Plan Team. There was no change to its rails since its inauguration in 2011, though there is as an improvement in frequency and travel times due to transit signal prioritization.

[36] This section heavily relies on Ida & Talit (2018) and on conversations with officials at the Ministry of Transportation and Adalya (a consulting firm providing services to the NPTA).

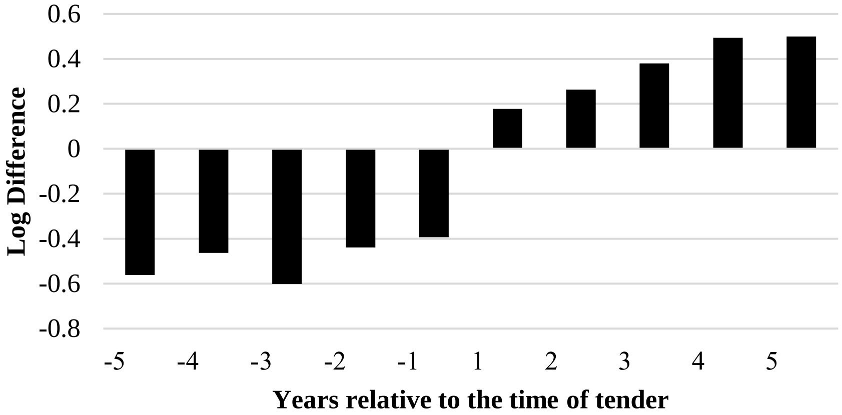
[37] A rather new authority under the responsibility of the Ministry of Transportation. established in 2012 as a result of government decision No. 3988 (2011).

clusters of different size.[38] Services are operated by private firms, competing off the road in public tenders for exclusive rights to operate a cluster for a period of 12 years.[39] At the end of 2019, the bus network was divided into 71 clusters, 18 of which, covering 44% of all weekday activity in the network, were tendered during the research period (2013-2019).

A new operation agreement typically implies an immediate improvement, followed by an upward trend in services in the cluster. Figure 5 displays the average of log differences in a station's activity by time from the tender taking place.[40] The long duration of the operating agreements implies that the starting date of a new operating agreement, hence the timing of service improvement begins is predetermined over a decade before taking place. This long lag implies that planners are practically unable to time major changes to the network to coincide with other spatial 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

Train

Railway development in Israel is co-planned by Israel Railways Ltd., and the NPTA. Operation and scheduling decisions are under the responsibility of Israel Railways, with

[38] A cluster usually includes a share of services in a metropolis, all service in a large locality, a group of close localities or a specified non-urban region, or a specific important bi-regional link.

[39] Formally the winner will operate the cluster for 6 years. At the end of the first 6 years the NPTA can choose to extend the operation period twice for 3 years at a time. The NPTA never chose not to extend an operation period. Toward the end of the research period the NPTA changed the operation period in new tenders to a fixed duration of 10 years, with no extensions.

[40] Appendix figure A.4 presents the change in $RCMA^{PT}$ in the affected area following each of the major transportation events during the research period.

NPTA supervision. Like similar transportation projects worldwide, the time between the beginning of the planning process of a new station to planned inauguration is long. On top of the long planning time, there is large uncertainty about the projects' schedule. The Bank of Israel (2010) puts a lower bound on the duration of average schedule overrun for rail projects in Israel at 72%.[41] This implies no ability to effectively schedule improvements in the rail network to match other spatial developments.

4. Methodology

I focus on rents instead of the sales price to mitigate threats to identification arising from anticipation.[42] Since the research period is relatively short, and spatial reorganization is a slow process, the estimated effect is not likely to include utility stemming from long-term spatial effects of transit allocation like zoning, sorting, densification, or gentrification. Hence, the estimated effect should be interpreted as a short-term transit-accessibility premium representing the utility perceived by potential residents from accessibility by public transportation and internalized into rents.

4.1. Linear Models

As a benchmark to the heterogeneity analysis, I apply a standard Two-Way Fixed Effects model to estimate the average effect of the log of $RCMA_{jt}^{PT}$ on the log of asked rents. This approach utilizes within-address variation in accessibility and rents over time, conditional on district-specific trends to identify a causal effect. I partial-out apartment-specific and time-variant spatial confounders using several flexible approaches discussed below. Specifically for an ad i, located in address j, within region r, at year t. The estimated linear models take the following form:

$$(7)\ \log(rent)_{ijrt} = \alpha + \tau * \log(RCMA^{PT})_{jt} + \mu_j + \psi_{rt} + \beta X_{ijrt} + \upsilon_{ijrt}$$

With μ_j representing address fixed effects, ψ_{rt} a set of district-year dummies, X_{ijrt} a set of apartment-specific characteristics,[43] and υ_{ijrt} an ad-specific error term.

[41] More information on the uncertainty in the planning schedule can be found at Bank of Israel (2015)

[42] A thorough discussion of the different interpretation of the effect on rents and property values appears in Gupta et al (2022).

[43] Including $log(RCMA_{jt}^{car})$, population density, the number of floors in the building, the apartment's floor, number of rooms and toilet rooms, the apartment's size in square meters, the ratio of its size to the size of similar nearby apartments, and dummies for: a new kitchen, air conditioner, parking, barred windows, balcony, security room and renovation status.

I estimate this model both with OLS and by instrumenting for $\log\left(RCMA_{jt}^{PT}\right)$ with information on major transportation events. Specifically, the instrument is a dummy variable indicating that the apartment is in an area where either bus services were tendered[44] or a new train station opened[45] since the beginning of the research period. This approach estimates a Local Average Treatment Effect exploiting only conditional within-address variation in transit services and rents. Compliance with the Rank Condition depends on the correlation between the conditional instrument and treatment variables. This correlation is visualized in figure 5 above. More formally, first-stage F statistics for the estimated models exceed 1,000 (appendix table A.2). It is also worth noting that even though the F-statistics are high, overall goodness of fit of the first stage is poor, leading to inaccurately estimated effects in the second stage.

As argued in the empirical context section. The timing of major transportation events is plausibly exogenous; hence during a long enough research period, the exclusion restriction will be satisfied. Since my research period only spans 7 years, in which only 44% of the activity in the network was tendered,[46] there might be a spurious correlation between the rent trend and the areas affected by tenders, biasing the IV estimation in an unknown direction. This drawback, alongside noisy estimates in practice, leads me to attribute low importance to the IV analysis, which I only view as complementary evidence supporting the notion that the average effect is economically insignificant.

The choice of controls and their functional forms is not trivial. Misspecification of functional forms might pose a threat in my context since rent could be a non-trivial function of apartment characteristics. If mis-specified, a possible correlation between changes in accessibility and the prevalence of certain characteristics would bias the estimated effect. I address this issue using two approaches: (1) relying on a best-linear-approximation argument,[47] and estimating a linear model with all ad-specific, and time-variant spatial characteristics as controls, (2) augmenting the dataset with all possible two-way interactions between ad-specific and spatial time-variant characteristics and

[44] Specifically: the share of bus stops-at-station within a one-kilometer radius from the address that were tendered since the beginning of the research period exceeds 50%.
[45] Within a one-kilometer radius from the apartment.
[46] Tenders during the research period took place in many different urban contexts, but not in Tel Aviv, Haifa, or Jerusalem composing a large share of the ads in the dataset.
[47] Angrist & Pischke (2008).

applying automatic selection of controls using the double and triple selection LASSO methods (Belloni et al ,2014; Chernozhukov et al, 2015).

4.2 Causal Forest Model

In my context heterogeneity in the effect is difficult to uncover with traditional methods. Linear regressions, the almost exclusive workhorse in the literature, only allow shallow exploration of heterogeneity across a small number of predetermined dimensions. To better explore heterogeneity in the transit accessibility premium I estimate a Causal Forest[48] - a standardized machine-learning model specifically designed for the estimation of heterogeneous treatment effects.

I estimate the model with a set of spatial time-invariant variables[49] and the same set of time-variant variables described above. I apply a newly developed procedure to incorporate fixed effects into the model. The procedure aims to incorporate information about location and district-dependent trends when partialling-out confounders, while maintaining the ability to estimate the role of time-invariant features in the determination of heterogeneity. The procedure can be seen as an extension to the semi-parametric difference-in-differences estimator presented in Abadie (2005)[50] for data with multiple periods and groups.

Estimation Procedure:

Denote X the set of controls, Y the dependent variable (log asked rents), and W the treatment variable ($\log(RCMA^{PT})$).

1. Divide the covariate matrix X to time-variant and time-invariant features, X^{var} and $X^{constant}$ accordingly.
2. Demean X^{var}, Y, W by address id and time-district group membership,[51] denote $X^{var,demeaned}, Y^{demeaned}, W^{demeaned}$ accordingly.
3. Orthogonalize the demeaned dependent and treatment variables with separate regression forests, using $X^{var,demeaned}$:

[48] Wager & Athey (2018), Athey et al (2019).
[49] Spatial variables are defined as the average values of the variable within 500, 1500 or 5000 meters radii centered around the apartment. 2018-2019 level time invariant variables originate from OD_MAT and include: density of morning in and out-commutes proxying for population and workers' density, and evening in-commuters. Time variant annual variables originate from CBS_DATA and include: population density, Socio-Economic Status, share non-Jewish, male, ultra-orthodox, and in the age groups: 0-19, 20-39, 40-59, 60 and above. Distance to the nearest coast is also included.
[50] A first-differences application of Causal Forests using similar arguments appears in Wang (2019).
[51] I apply the implemented procedure available in R's the fixest package (Berge, 2018).

$\hat{Y}_i^{demeaned} = f\left(X_i^{var,demeaned}\right), \widehat{W}_i^{demeaned} = g(X_i^{var,demeaned})$

4. Estimate a causal forest using the demeaned original and predicted dependent ($Y_i^{demeaned}, \widehat{Y}_\iota^{demeanded}$) and treatment ($W_i^{demeaned}, \widehat{W}_\iota^{demeanded}$) variables, and the original, not demeaned, covariate matrix X.

This procedure offers a semi-parametric estimation of heterogeneous treatment effects. Address information and district-specific trends enter the model linearly when partialling-out confounders. Partialling-out of time-variant confounders and estimation of the role of all characteristics in the determination of heterogeneity is performed a-parametrically as in standard Causal Forests. In addition, I recognize that addresses can entail information on heterogeneity by considering address clusters in the sampling and estimation procedures of the causal forest.

Appendix table A.3 presents summary statistics for the estimated Causal Forest (CF) model.[52] I assess the models' fit using the omnibus test developed by Chernozhukov et al (2018).[53] The test results show that the model captures the average treatment effect and heterogeneity in the underlying signal quite well. The magnitude of the effect is usually small, as visualized in figure A.4. Only 16.4% of the observations' point estimates are of absolute elasticity larger than 0.25.[54]

4.4. Difficulties in estimation

Measurement error[55]

I estimate the transit accessibility premium using asked rents. Asked rents are owners' perceptions of the market value of the residence in their advertised apartment, which are noisy signals of the actual market value that better reflects the implied utility to the average resident. Hence, this issue can be viewed as a measurement error in the dependent variable.[56] Importantly, the magnitude of the idiosyncratic perception bias might be systematically smaller in thick markets. Since transit improvements are

[52] I use the implementation in R's grf package (Tibshirani et al, 2021). Parameters were chosen using the tuning decision rule developed at Nie & Wager (2021), which is readily implemented in R's grf package.
[53] This test is discussed specifically for Causal Forests in Athey & Wager (2019).
[54] This cutoff implies a 0.057 change in log rents for the national average 2013-2019 $RCMA^{PT}$ difference.
[55] A more general method to approach measurement error is Instrumental Variables estimation. This approach also yields economically small average treatment effects, but the estimation is too imprecise to conduct a reliable heterogeneity analysis which is the heart of this paper.
[56] I somewhat mitigate this concern by always using the last appearance of an ad in the dataset to determine its asked rent. This step should reduce noise from prior idiosyncratic beliefs of the owners after gaining some experience in the market.

plausibly positively correlated with market thickness, they can reduce the asked rent-market-value spread, raising concerns of a non-classical measurement error in the dependent variable, upward biasing τ.

A possible approach to address this concern is to include a measure for market thickness in the estimated models, eliminating the induced correlation between transit improvements and the magnitude of the measurement error term. But, since market thickness is known from previous literature to have a positive correlation with housing prices,[57] it is also a mediating variable, and including it would downward bias τ. On the other hand, as discussed before and due to attenuation bias, excluding it from the estimation would upward bias τ.

Assuming market thickness only affects the magnitude of the perception bias and not its direction, the real effect can be bounded by estimating models both with and without a market thickness measure.[58] I find supporting evidence for this assumption by examining the correlation between market thickness and the difference in the asked rent between the first and last appearances of an ad in the dataset. This difference reflects the adjustment to the perception of the market price after gaining time and experience in the market. Though there are plausible arguments to expect a higher tendency of homeowners in either thick or thin markets to over-value their property, I find no correlation between market thickness and the adjustment to asked rent.[59] This finding lends credibility to the upper and lower bounds interpretation presented above.

In practice, including the market thickness variable in the estimation further reduces the already economically insignificant average treatment effect in all estimated models, but has no other important effect on the results. Estimation results including the market thickness variable are available upon request.

Other types of endogeneity

The allocation process described in the empirical context section supports the notion that planners can't effectively time major allocations such that they will correspond to

[57] Early work includes Stein (1995), Genesove & Mayer (1997, 2001). More recent analysis include Andersen et al (2022) and DeFusco et al (2022). To the best of my knowledge, there are no papers examining this relationship specifically for the rents market.
[58] The number of similar-sized apartments advertised in the same month as the ad's last publication date and located within 500 meters from it.
[59] Correlation coefficients range between (0.003, 0.017) when using either logs or raw values for each variable. I also find no correlation (0.014) between a binary indicator for ads where the rent was adjusted in any direction and the market thickness variable.

other events. The timing of new bus operation agreements is predetermined roughly a decade before the tender's formulation. The argument for rail services lies in similar reasoning, supported by observed schedule overruns. This does not rule out minor changes in the network corresponding to other unobserved events. I acknowledge that this type of fine-tuning to the network is possible in my institutional context, but it is small-scaled and thus unlikely to influence rents. Whatever bias remains is accounted for in the Instrumental Variable model by exploiting only variation stemming from the timing of major transportation events.

Anticipation

The housing market can react to expected changes in transit services years before they occur.[60] I address anticipation by estimating the effect on rents instead of the sales prices.[61] Tenants gain no extra utility from living near an inactive transportation project. Thus, they will not be willing to pay more for apartments near those projects. This choice largely mitigates, though does not eliminate the problem. Some anticipation effects could rise due to increasing house prices resulting in tougher negotiation by landlords, or by households looking to settle in an area expecting improvement in allocation, willing to absorb poor services in the early period. There can also be a reduction in rents in apartments adjacent to large still inactive projects due to noise or other disamenities from living near a construction site. This argument is mainly relevant to rail projects and should not pose a major problem in my context since most rail stations opened during the research period are located on the outskirts of the urban area, not manifesting major disturbances during construction. Also note that construction disamenities are prominent mainly in the early stages of heavy construction (Gupta et al, 2022), generally not included in my research period.

5. Results

5.1 Descriptive statistics and the average treatment effect

Table 2 reports average values and standard errors for important features of the sample. The sample is composed of rental ads scraped from major websites and is not representative of the entire Israeli residential market. Since the goal of the empirical

[60] E.g., Yiu & Wong (2005), Agostini & Palmucci (2008), Liang et al (2018), Hoogendoorn et al (2019), Gupta et al (2022).
[61] See similar argument in Gupta et al (2022).

exercise is to identify patterns of heterogeneity, and there is considerable variation along all dimensions of urban form in the sample, I don't view these differences as problematic. It is important to note that the Average Treatment Effects reported should not be taken as informative for the entire Israeli residential market.

Table 2
Summary statistics

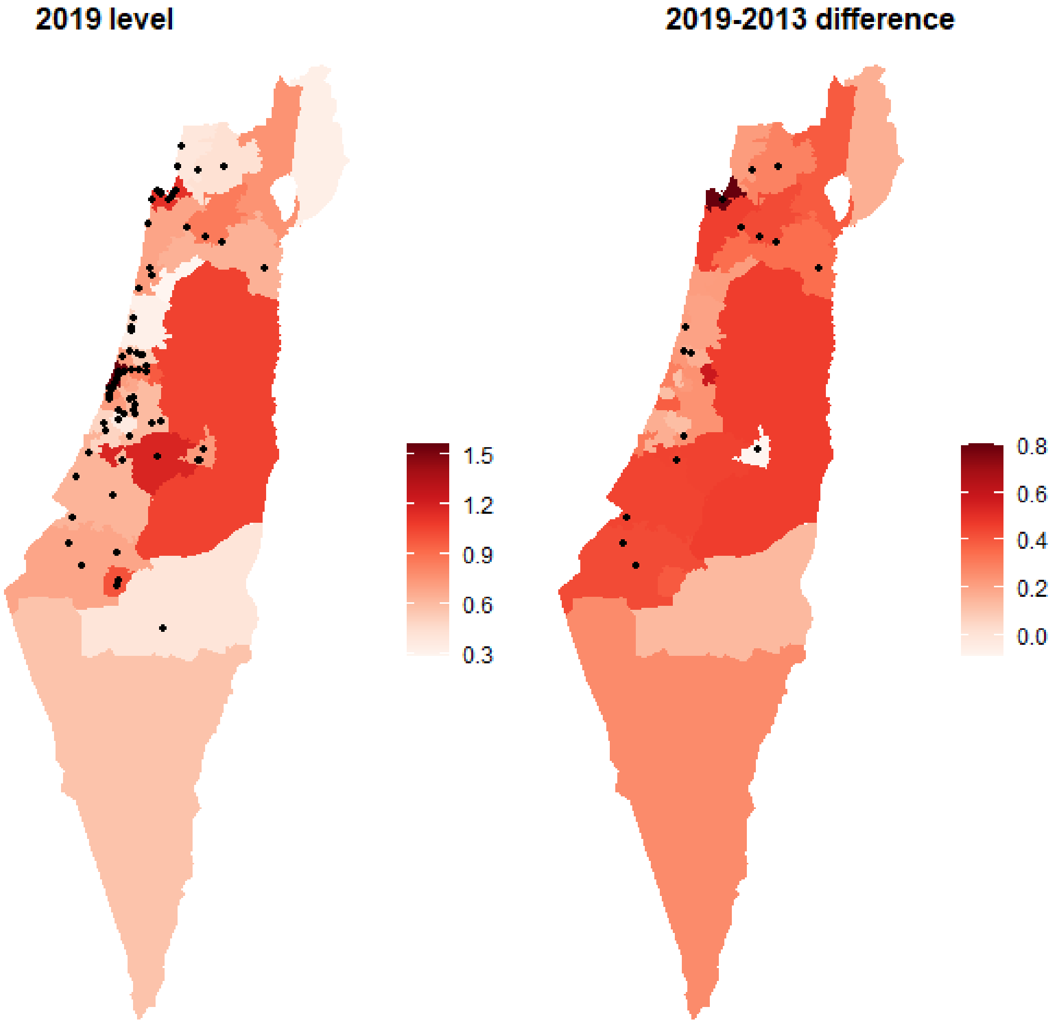
	National Average	Sample average	Low treatment	High treatment
$RCMA^{PT}$ (2013)	347.58 (251.06)	472.46 (257.27)	374.62 (236.56)	566.09 (240.93)
$RCMA^{PT}$ (2013-2019 log difference)	0.23 (0.31)	0.13 (0.13)	0.08 (0.11)	0.18 (0.13)
$RCMA^{Car}$ (2013)	643.51 (437.56)	838.85 (487.25)	644.06 (403.65)	1025.27 (487.48)
$RCMA^{Car}$ (2013-2019 log difference)	0.02 (0.19)	0.02 (0.11)	0.03 (0.11)	0 (0.1)
Rent per square meter (2013-2019)		55.28 (17.27)	50.11 (15.94)	60.24 (17.05)
Socio-Economic status (CBS, year)	0.01 (1.16)	0.45 (0.84)	0.29 (0.78)	0.61 (0.86)
Population density (Cellular survey,2018-2019)	2233.6 (2041.8)	3198.18 (2063.32)	2901.34 (2031.62)	3436.98 (2057.63)
Employment density (Cellular survey, 2018-2019)	1862.04 (2299.43)	3038.96 (3100.81)	2803.08 (2864.54)	3228.71 (3266.2)
Amenities measure (Cellular survey, 2018-2019)	956.14 (930.83)	1383.66 (971.74)	1260.61 (998.03)	1482.65 (938.42)

Note: values are computed at the statistical area or transportation polygon level to maintain consistency with the national sample.

Areas with advertised apartments in the sample are on average wealthier, denser, more urban and accessible, and experienced a smaller improvement in transit services than the national average during the research period. Haifa and several peripheral regions composing a relatively small share of my sample experienced the largest improvements both in bus activity and new train stations opened during the research period (figure 6). Within the sample, apartments in areas experiencing larger accessibility improvements were located on average in denser, wealthier, and more central areas than apartments experiencing lower treatment intensity. Though there are differences in the average characteristics, there is substantial variation in all displayed features in both groups (as apparent from the standard errors), allowing examination of heterogeneity in the treatment effect along different empirical contexts.

Figure 6

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



Note: Activity is defined as the daily number of times a bus stops at any station in the region and is displayed in per capita terms.

Table 3 presents estimates of the average transit accessibility premium estimated using the models described above. Point estimates of the elasticity of rents with respect to $RCMA^{PT}$ lie within the (-0.046, 0.027) interval, where both extremes are results of the inaccurately measured Instrumental Variable models. Point estimates excluding them, but including different geographic and temporal aggregations,[62] lie within the (-0.017, 0.017) interval. Hence, the estimated Average Treatment Effect is always of an

[62] Results reported in appendix table A.4.

economically negligible magnitude. Explicitly, the national average 2013-2019 log difference in $RCMA^{PT}$ is 0.23. Applying the estimated elasticities, the effect of transit improvements throughout the research period on the average ad in the sample can be roughly bounded to a modest (-0.39%, 0.39%) of its rent.

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)	0.027 (0.091)	-0.046 (0.089)	0.017*** (0.006)
R^2 (Within, adjusted)	0.583	0.600	0.583	0.599	
N - observations	731,548				
N - unique addresses	107,875				

Note: Models described in the text, standard errors clustered by address id shown in parentheses.

5.2 Patterns and determinants of heterogeneity

Though the average transit accessibility premium is small, there is important heterogeneity. I explore patterns of heterogeneity by estimating the effect in several groups of interest using both variants of the Baseline model,[63] and a Doubly Robust estimator with the Causal Forest model. I then proceed to uncover determinants of the observed heterogeneity – ceteris paribus, what is the effect of specific characteristics of an apartment or an urban context on the transit accessibility premium. I conduct this exercise with a Doubly Robust estimation of covariates of interest on the idiosyncratic premium as estimated by the Causal Forest model.

As displayed in table 4, apartments located in areas with high residential, and even more so, high employment density experience a larger effect than apartments in low-density areas. On the other hand, apartments located in areas with high accessibility, both by car and by public transportation, experience a lower effect on rents following an improvement in services, I will later discuss this relationship in more detail. There is a disagreement between the models on the transit accessibility premium along values of the Socio-Economic Status, and I abstain from further interpretation of this result.

[63] Including an interaction term between the treatment variable and group membership: $\log(rent)_{ijrt} = \alpha + \tau * \log\left(RCMA_{jt}^{PT}\right) + \gamma * \left(\log\left(RCMA_{jt}^{PT}\right) * \xi_i\right) + \mu_j + \psi_{rt} + \beta X_{ijrt} + \upsilon_{ijrt}$ where ξ_i represents groups membership.

Table 4

Heterogeneity in the transit accessibility premium - Specified subgroups

Heterogeneity group	Baseline	Population density	Workers' density	Socio Economic 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)	-0.041** (0.017)	-0.039** (0.017)
Linear Model: Base Effect	0.005 (0.004)	0.004 (0.004)	0.002 (0.004)	0.029*** (0.004)	0.006 (0.004)	0.005 (0.004)
Linear Model: Interaction term		0.019* (0.011)	0.082*** (0.012)	-0.101*** (0.007)	-0.001*** (0.000)	-0.000 (0.000)
R^2 (Within, adjusted)	0.583	0.583	0.583	0.583	0.583	0.583
N - in interaction group		182,889	182,887	182,889	182,887	182,887
N - observations	731,548					
N - unique addresses	107,875					

Note: Standard errors clustered by address id shown in parentheses. Causal Forest estimates are obtained using Doubly Robust estimation.

Table 5 displays the estimated effect for apartments located near Mass Transit Systems.[64] Importantly, these models estimate the effect of improved accessibility for apartments enjoying proximity to Mass Transit Systems, not the effect of improved services specifically in those Mass Transit Systems. Apartments located near the Jerusalem Light Rail experience a higher effect compared to the rest of the sample. The linear model also estimates a strong effect for apartments near the Metronit, though there is a disagreement between the models on this result - probably due to the flexible form of the Causal Forest better picking up other margins of change responsible for the hike in rent in this area. Apartments near rail stations seem to experience a lower (or similar) effect compared to the rest of the sample. This finding echoes the similar result regarding the largely overlapping group of apartments in highly accessible areas.

In a traditional case study analysis, not relying on the CMA concept guiding the rest of the analysis in this paper, I find a small positive train-station proximity premium,

[64] Proximity is defined as being located up to 1,000 meters from an active station, consistent with standard practice in the literature (see in Ingvardson & Nielsen, 2018).

monotonically decreasing with the distance from the station.[65] (See analysis in Appendix B). The reason the positive effect was not found for trains in the main analysis can be due to train stations affecting the rents market through channels other than accessibility, the different comparison group (namely, focusing on the variance between the core and the periphery of the new stations' catchment areas emphasizes patterns of re-organization),[66] improved visibility, or the different geographic contexts – new stations are mostly spread across peripheral and suburban regions, and mostly at the outskirts of the urban area. In contrast, most existing stations that drive the results in the main analysis, are in central regions and within cities.

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)	0.036 (0.024)	0.092*** (0.011)
R^2 (Within, adjusted)	0.583	0.583	0.583	0.583
N - in interaction group		100,996	20,675	63,578
N - observations	731,548			
N - unique addresses	107,875			

Note: Standard errors clustered by address id shown in parentheses. Causal Forest estimates are obtained using Doubly Robust estimation.

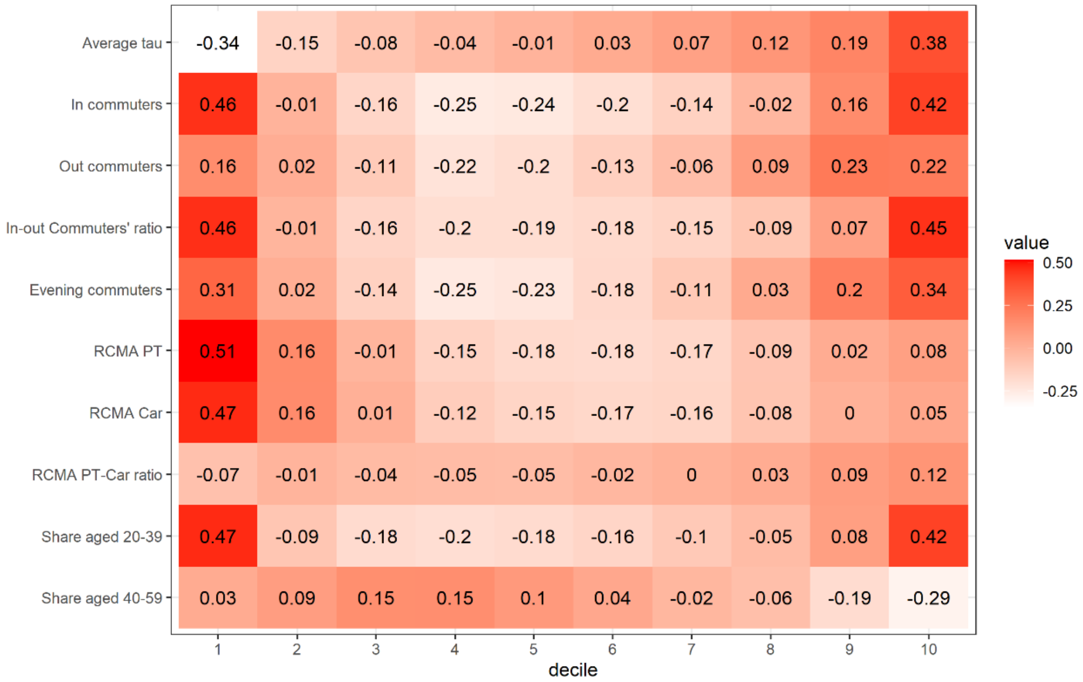
I now turn to the examination of the premium's heterogeneity with the Causal Forest model. Figure 7 displays characteristics of observations divided by deciles of the estimated idiosyncratic premium as estimated with the Causal Forest model. The figure

[65] I could not conduct a similar analysis for the Jerusalem Light Rail and Haifa's BRT system (Metronit) since they opened either before or shortly after the beginning of my research period.
[66] A thorough discussion of Growth Versus Re-Organization in the effect of transportation on economic phenomena appears in Redding & Turner (2015).

presents the average premium and normalized values of some of its speculated determinants in each decile.

Figure 7

Normalized ad characteristics in deciles of the treatment effect



Apartments in particularly dense areas can be found at both ends of the distribution of the estimated premium. Apartments in highly accessible areas are in the lower part of the estimated distribution, echoing the results reported in table 4. The figure also reports the values of the ratio between $\frac{RCMA^{PT}}{RCMA^{Car}}$. Apartments with a higher ratio, enjoying high transit accessibility relative to the accessibility enabled by their location and road network, display a higher estimated premium. Apartments in areas with an age distribution more reflecting typical transit users (lower share of the population aged 40-59, higher share aged 20-39) also have a higher estimated premium.

To understand the determinants of this observed heterogeneity I estimate the Best Linear Projection of covariates of interest on the transit accessibility premium using a doubly robust estimator (Augmented Inverse Probability Weighting). The coefficients' interpretation is similar to the interpretation of a linear regression of the estimated idiosyncratic premium on chosen covariates. I use a set of covariates similar to the set used for the estimation of the Causal Forest.[67] I also add the level of $RCMA^{PT}$ and dummies for addresses located less than a kilometer from any of the Mass Transit System's stations. All variables are standardized to conduct a meaningful comparison of magnitudes. Top 15 variables by absolute coefficient magnitude are presented in table 6.

Table 6

Best Linear Projection of the treatment effect,
Top 15 features by absolute magnitude of the coefficient

	Coefficient	Robust Standard Error
$RCMA^{PT}$	-0.108***	(0.019)
Out-commuters density	0.068**	(0.034)
Share of population aged 40-59	-0.04***	(0.01)
Near Metronit	-0.038***	(0.007)
Socio Economic Status	0.035***	(0.01)
Evening-commuters	-0.032	(0.044)
Share males	-0.03***	(0.011)
Share of population aged 20-39	0.022	(0.015)
Near Light Rail	0.018**	(0.008)
Share of population aged 0-19	-0.018	(0.012)
Size in Square meters	0.017***	(0.006)
$RCMA^{Car}$	0.013	(0.018)
In-commuters density	0.012	(0.019)
Share Ultra-Orthodox	0.011	(0.011)
Renovation status	-0.007	(0.005)

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

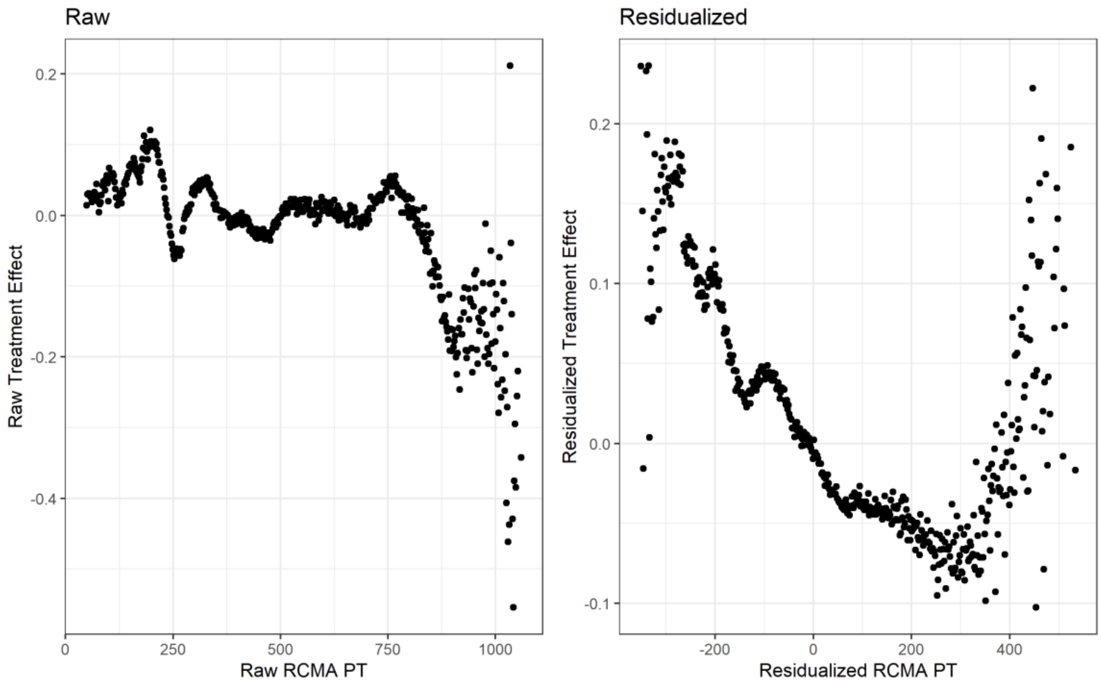
The rents market internalizes utility to residents in areas that have many possible users. A one standard deviation increase in residential density[68] causes a 0.068 increase in the elasticity of rents with respect to $RCMA^{PT}$. Similarly, a composition of the population more prone to using public transportation (A higher share of the population aged 20-39, ultra-orthodox, and a lower share aged 40-59, children, males) also support a higher transit accessibility premium, though not all coefficients are statistically significant.

[67]To reduce collision, I omit population density defined by CBS statistical areas, one of two parking indicators, number of rooms and toilet rooms, and spatial variables not defined by the 1500 meters radius. I also omit variables whose interpretation is vague or too context-specific: district dummies, proximity to shore, apartment's floor and dummies indicating the existence of a new kitchen, a lift in the building, an open balcony, an air conditioner, and a security room.
[68] Proxied for using the number of individuals leaving the area for their morning commute.

A higher level of accessibility causes a significantly lower transit accessibility premium. This finding complements the results in table 4 and figure 7 and might hint at diminishing returns to accessibility or the existence of an upper bound for the level of accessibility still influencing rents. To inspect this relationship further, figure 8 presents a binned scatterplot of the raw and residualized[69] relations between accessibility by public transportation and the estimated treatment effect.

Figure 8

The relationship between the level of $RCMA^{PT}$ and the treatment effect



Note: The plots are based on all (731,548) observations in the dataset, binned to 500 dots based on their level of $RCMA^{PT}$. Residualization in the residualized plot is performed using linear regressions of the level of $RCMA^{PT}$ and of the treatment effect on the same variables used for the Best Linear Projection (table 6) except for $RCMA^{car}$.

The treatment effect is relatively constant along most of the distribution of $RCMA^{PT}$, until a clear threshold after which the estimated treatment effect declines. This implies an upper bound for the level of service still appreciated by residents. Only 9.3% of the ads in the dataset are located in areas that enjoy a level of service above that cutoff

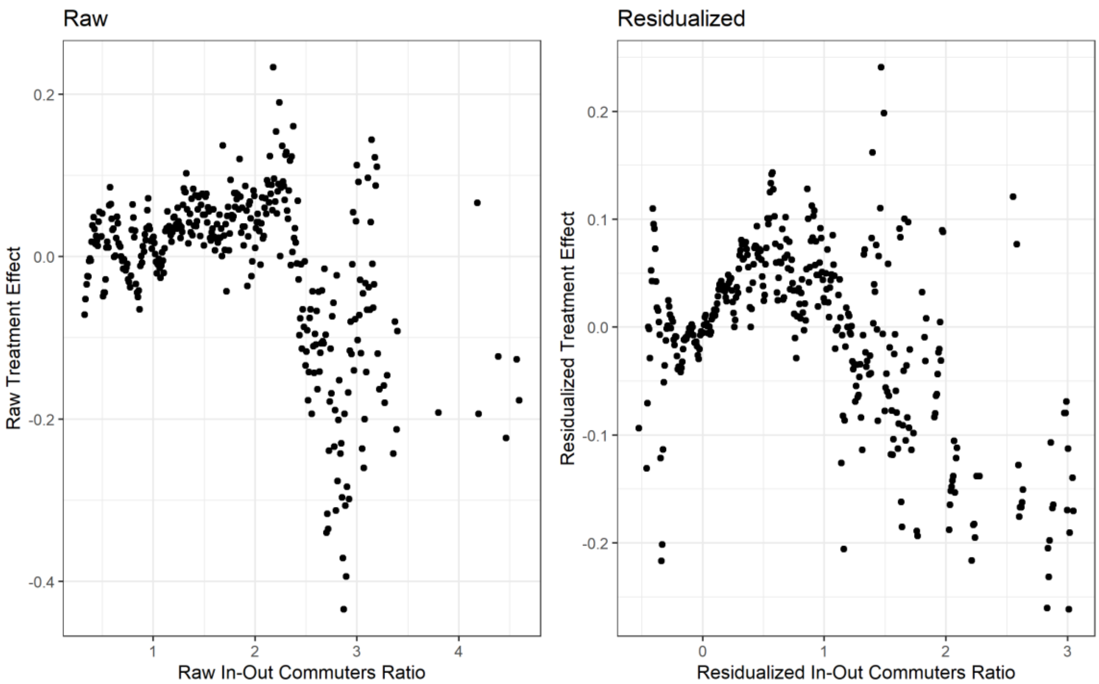
[69] Residualization is performed with a linear regression of all variables used in the Best Linear Projection model appearing in table 8 (except for $RCMA^{car}$) on both $RCMA^{PT}$ and the estimated treatment effect. $RCMA^{car}$ is excluded to focus on similar neighborhoods neglecting location, its inclusion doesn't make any important difference in the results.

($RCMA^{PT}$ larger than 750), hence the absolute level of accessibility in my sample is usually not a binding constraint to the utility perceived by residents from improved services. The relation between τ and $RCMA^{PT}$ in residualized form displays a clear U-shape. Residents are willing to pay more for improved transit services when they are either lower, or (to a lesser extent) when they are exceptionally higher than expected given area characteristics. A level of service that is higher than that reasonable reference point, but not exceptional is not valued by residents.

Both the lower premium for apartments located near the Metronit, and the higher premium for apartments located near the Jerusalem Light Rail reported in table 5 hold even after accounting for other area characteristics (table 6). The effect of proximity to a train station is small, hence not presented here. This is consistent with results from the linear model reported in table 5, and the absolute threshold result reported in figure 8, implying that the lower treatment effect estimated for this group is not caused by the proximity but by other characteristics of these areas.

Figure 9

The relationship between in-out commuters' ratio and the treatment effect



Note: The plots are based on all (731,548) observations in the dataset, binned to 500 dots based on their in-out commuters' ratio. Residualization in the residualized plot is performed using linear regressions of the in-out commuters' ratio and of the treatment effect on the same variables used for the Best Linear Projection (table 6).

Another possibly important determinant of heterogeneity is the type of zoning in the area. I examine the level of the treatment effect along the distribution of the ratio between in-commuters and out-commuters. Extreme levels of that ratio represent apartments in areas with separate-use zoning, where low values represent residence-oriented areas, and high values represent employment-oriented areas. I present binned scatterplots of the relation between the in-out commuters' ratio and the estimated transit accessibility premium in figure 9.

The relationship, both in its raw and residualized forms, reveals the existence of an optimum ratio between residence and employment in an area regarding the effect of transit on rents. This implies lower utility to residents from public transit services in areas with separate-use zoning such as suburbs, or employment hubs. The highest effect is estimated for areas with Mixed-use zoning, emphasizing its importance in creating an effective public transportation network.

The causal forest approach also allows an ex-post evaluation regarding the extent to which the treatment intensity during the research period was correlated with the transit accessibility premium. Or more simply put, to which extent did transit allocation during the research period aimed toward areas where the expected effect on rents was higher? I find no such correlation. I calculate the log of the difference of $RCMA_j^{PT}$ for addresses appearing in the dataset both in 2013 and 2019 and the average treatment effect for all ads in those addresses and find a raw correlation of 0.007. Hence, there is no evidence that during the research period transit allocation was aimed toward areas expected to experience a higher transit accessibility premium.

6. Discussion

This paper explores the determinants of heterogeneity in the transit accessibility premium – the effect of accessibility by public transportation on residential rents. Within a hedonic framework, this effect represents perceived utility to potential renters from improved transit allocation. There are some important margins on which this effect differs from social welfare. Renters are not a random sample of the population, and they might attribute different importance to transit compared to homeowners. The renters also do not necessarily have a good evaluation of both the actual accessibility and its effect on their utility before moving into the area. Thus, there might be a difference between their perceived and actual utility benefits. Lastly, this framework neglects the important aspects of long-term effects of transit, externalities, and utilities to non-residents, which in some cases could outweigh the short-term utility to residents.

These caveats imply that the results reported here should not be interpreted as the effect of transit on welfare. Even so, these results still identify an important concept that can inform both policy and future research. A higher treatment effect implies that potential residents view transit allocation in the area as effective for their own needs. Directing allocation towards areas with a high estimated effect thus implies a higher predicted take-up, which is an important indication for policymakers. Examination of the characteristics associated with a high premium, and the causal effect of those characteristics on the estimated premium provides a useful indication of the possibility of transit-oriented development in different urban contexts.

I find six key results: (1) The transit accessibility premium is usually modest. (2) There is a clear threshold for the absolute level of transit services positively affecting rents. (3) The premium is higher when services are either lower, or exceptionally higher than expected given a reasonable reference point. (4) Densification, and especially a higher density of potential users (as observed by the demographic composition of residents in the area) implies a larger premium. (5) Mixed-use zoning implies a higher premium, and (6) The premium is higher in apartments located near Rail systems, specifically near the Jerusalem Light Rail, and with somewhat weaker evidence apartments located near new train stations.[70]

The U-shaped relation between the residualized level of accessibility and the idiosyncratic premium implies two interpretations of the effect: a penalty for subpar services, and a small premium when the level of service is exceptional compared to areas with similar characteristics. The upper bound on the absolute level of services still positively affecting rents probably indicate the adverse effects on residents from proximity to important transportation hubs, e.g., noise, pollution, crowdedness, or more infrastructure dedicated to public transportation at the expense of private cars.[71] Reliance on urban rail systems, more careful planning of bus infrastructure, or reliance on many smaller transportation hubs might mitigate those adverse effects.

[70] For new train stations, the effect is estimated using proximity, and not the accessibility measure used in the rest of the paper. The estimated proximity effect declines with distance from the station. The gradient and small magnitude of the effect can inform ongoing policy discussion regarding the value uplift tax schedule from proximity to Israel's planned metro system.

[71] See analysis of such effects in Gaduh et al (2022), or at Portnov et al (2009) in the Israeli context.

The significantly higher effect in dense, mixed-use areas combined with the established relationship between automobile infrastructure and sprawl[72] implies that improvement to the car infrastructure crowd-out transit investments. My results demonstrate that even if transit travel times are not affected, the effects of car infrastructure on the urban form can diminish the value of transit to residents, on top of the direct effect of improving the prominent alternative.[73] Even given large monetary investments, car-centric cities will face considerable difficulties developing effective transit due to their typically low density and separation of residence from other uses. This finding implies that cities aspiring to increase transit's modal share due to congestion, pollution or any other reason should generally refrain from parallel major investment in new roads.

Lastly, the estimated effect of accessibility by public transportation on residential rents in this paper is usually economically small. I estimate an average elasticity within the (-0.017, 0.017) interval, and an idiosyncratic elasticity smaller than 0.25 in absolute size in 83.6% of my sample. This magnitude is consistent with previous literature estimating project-specific effects of transit on residential costs, and small compared to estimates of the effect of other types of neighborhood amenities, allowing policymakers to neglect short-term residential-market considerations when examining competing transit allocations.

7. Conclusion

Theoretical urban economic models predict that utility to individuals from public transit in their residential area would be internalized by the rents market. This transit accessibility premium is expected to vary depending on geographic and urban contexts. This paper utilizes high-resolution nationwide granular data, a theoretically grounded measure of accessibility, and both causal machine learning and standard econometric methods to explore the determinants of heterogeneity in the transit accessibility premium in a unified framework. This framework offers a new approach to exploring the significant variation in transit proximity premiums as observed, but not coherently explored, in a vast case-study literature and meta-analyses conducted on it.

I find a larger premium in areas hosting a large pool of potential users (higher residential density, and a demographic composition more reflecting transit users), and areas with

[72] See Glaeser & Kahn (2004), Garcia-López (2019), Fretz et al (2022), Ostermeijer et al (2022).
[73] In the opposite direction, higher density only marginally reduces driving. (Duranton & Turner, 2018)

mixed-use zoning. I also find an upper threshold for the level of accessibility above which improving transit services entails no added value to residents, and a higher premium in areas with a low, or an exceptionally high level of accessibility relative to the expected level given area characteristics. This last finding implies that the estimated effect is usually either a penalty for subpar services or (to a lesser extent) a premium for services that are exceptional relative to a reasonable reference level. There is some evidence of a higher premium for apartments located near rail systems, in my context primarily for the Jerusalem Light Rail. The premium in the entire sample is usually modest.

These findings could better inform planners and researchers considering the effect of alternative transit allocations and urban development plans compared to previous case-study literature focusing on the average accessibility premium in one specific context.

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Appendix tables and figures

Figure A.1

Transportation polygons in Israel

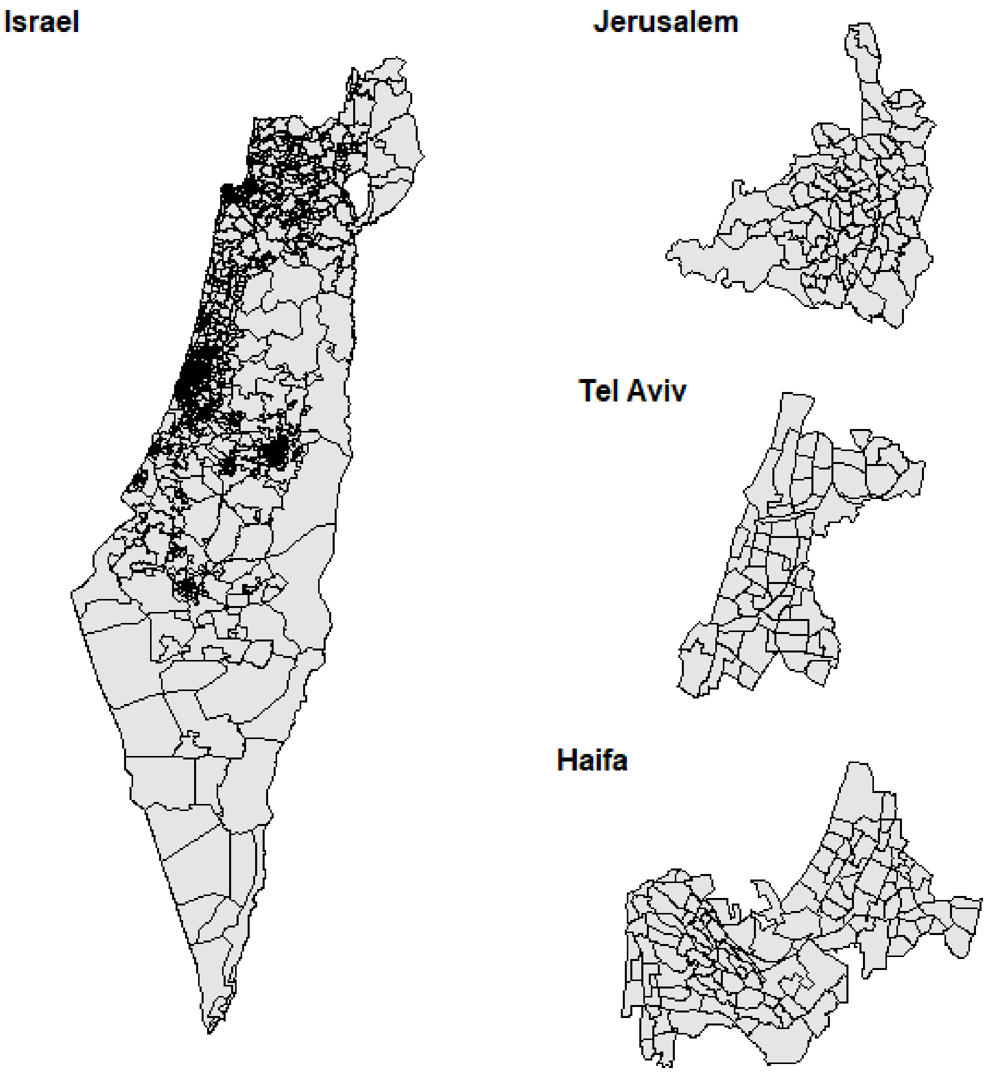


Figure A.2

Implied connectivity by different elasticities

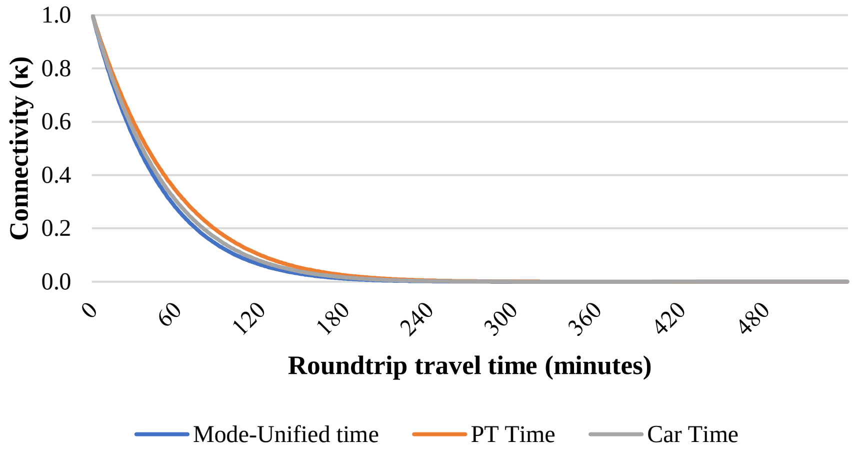
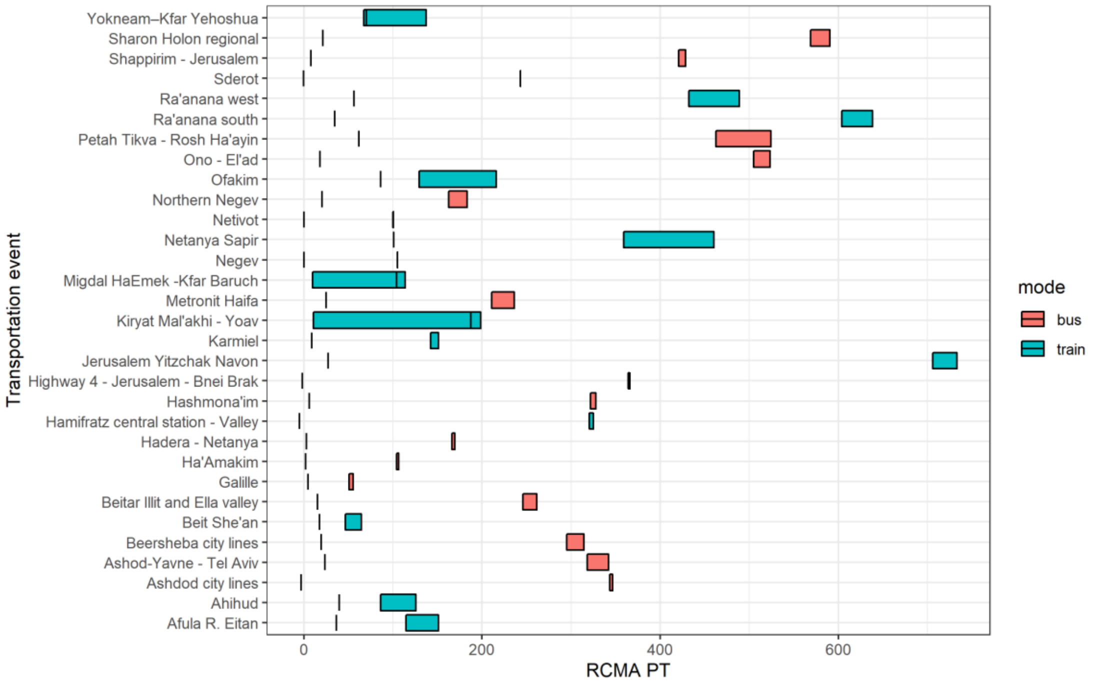


Figure A.3

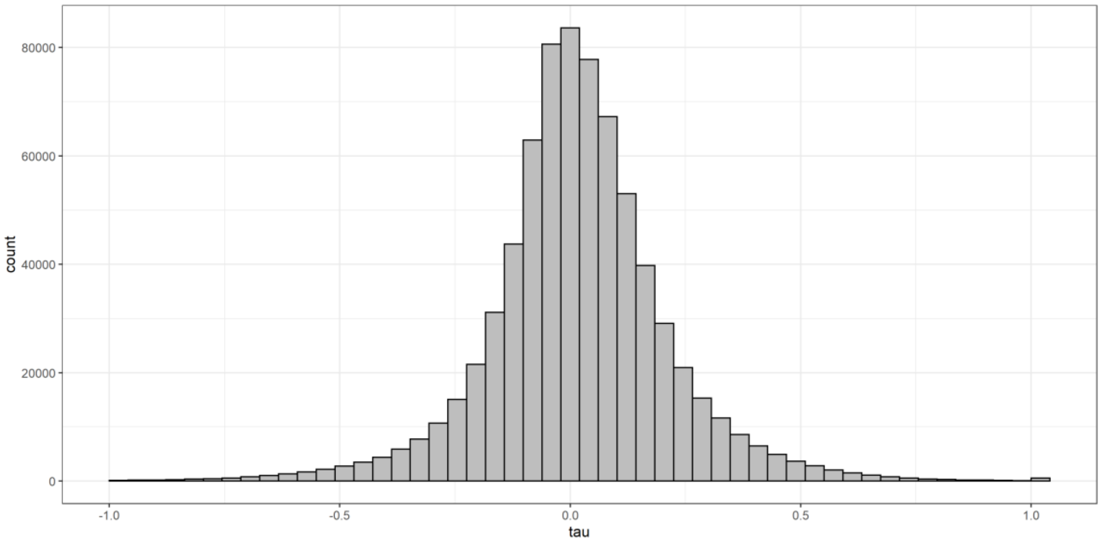
The change in $RCMA^{PT}$ following major transportation events



Note: The bars indicate the level of $RCMA^{PT}$ one year before and one year after the event. The thin black lines indicate the difference.

Figure A.4

Distribution of the estimated treatment effect



Note: For illustrative purposes, the displayed value is winsorized at an absolute value of 1.

Table A.1

Summary of data sets

Dataset	Source	Range	Relevant Variables
TRAIN_RIDES	Israel Railways Ltd.	2013-2019	Actual and planned time for each stop-at-station in each train ride
LIGHT_RAIL	Jerusalem Transport Master Plan Team	2013-2019	Actual time of the start and end of each light rail ride
BUS_RIDES	Israeli Ministry of Transportation	2016-2019	Actual time of the start and end of each bus ride
BUS_SCHEDULE	Israeli Ministry of Transportation	2013-2019	Planned time of the start and end of each bus ride
BUS_ROUTES	Israeli Ministry of Transportation	2013-2019	Complete description of each line's route: stations location, and road distance and planned travel time between stations. Received twice a year
ROADS_NETWORK	Survey of Israel (Mapi), part of the BENTAL dataset	2013-2019	GIS of all roads in Israel including number of lanes in each direction, received quarterly
RENTS	Private firm	2013-2019	Price, size, number of rooms, floor, number of floors in the building, number of toilet rooms. Dummies for renovation status and the existence of: air conditioner, lift in the building, parking, balcony, security room, new kitchen, barred windows.
ADDRESSES	Survey of Israel (Mapi)		Exact coordinates of addresses
OD_MAT	Israeli Ministry of Transportation	2018-2019	Period average by time of day of people making the journey (1250 polygons)
CBS_DATA	Israeli CBS	2013-2019	Annual statistical-area level data on Socio-Economic status and demographic variables

Table A.2

The effect of Residential Commuter Market Access on rents - First stage results

	IV	LASSO-IV
After Tender IV	0.012*** (0.001)	0.012*** (0.014)
R^2 (Within)	0.0103	0.0172
F test	1,175.10	1,182.20
Number of observations	731,548	

Table A.3

Summary statistics for the Causal Forest model

		CF Model
Results	Average Treatment Effect	0.017*** (0.006)
	Share with a positive effect	53.3%
Omnibus Calibration Test	Mean Forest Prediction	1.149*** (0.23)
	Differential Forest Prediction	1.018*** (0.028)
Data	Number of observations	731,548
	Number of unique addresses	107,875

Note: Standard errors clustered by address id shown in parentheses.

Table A.4

RCMA^{PT} coefficients with different specifications of time-geographic trends

Geo\Time	year	transportation period	month
Natural area	-0.000 (0.004)	-0.013*** (0.004)	-0.013*** (0.004)
Sub-district	0.003 (0.004)	-0.006* (0.004)	-0.006* (0.004)
District	0.004 (0.004)	-0.005 (0.004)	-0.006 (0.004)
none	-0.005 (0.004)	-0.016*** (0.004)	-0.017*** (0.004)

Note: Standard errors clustered by address id shown in parentheses

Appendix A: Calculation and definition of travel times

This appendix defines the travel times used in the paper and describes the data and procedures used to calculate them both by public transportation and private cars.

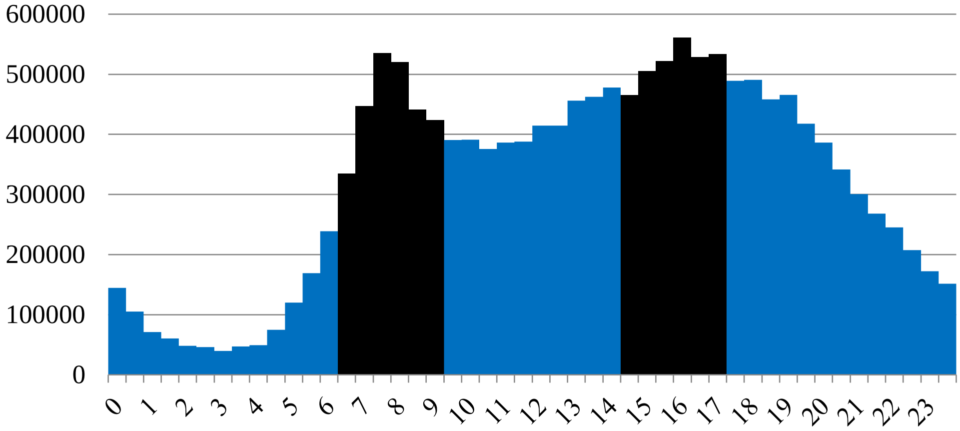
A.1. Definition of travel times

I aim to calculate the travel time of a typical commute; hence I define travel time between any points in space a and b as the roundtrip journey: the sum of total travel time from a to b in the morning commute, and from b to a in the afternoon commute.

$$(A1)\ \ Travel\ time_{ab} = Travel\ time_{ab}^{morning} + Travel\ time_{ba}^{afternoon}$$

I choose 6:30-9:30 as the relevant interval for the morning commute, and 14:30-17:30 as the relevant interval for the ride back based on the distribution of journeys throughout the day as observed in OD_MAT and presented in figure A.5.

Figure A.5
Average daily number of departures by time of day, 2018-2019



Note: Defined morning and evening rush hours are colored black.
Source: OD_MAT dataset, Israeli Ministry of Transportation

For some needs in the paper, I am required to define travel times between polygons (as opposed to travel times between points). For public transportation, I define total travel times between polygons o and d as:

$$(A2)\ \ t_{od} \equiv \underset{a,b}{\operatorname{argmin}}\{t_{ab}^{morning}\} + \underset{a,b}{\operatorname{argmin}}\{t_{ba}^{afternoon}\}, a \in area_o\ \&\ b \in area_d$$

That is, the sum of the minimal travel time between any stations in polygon o and any station in polygon d in the morning rush hour, and the minimal travel time in the opposite direction between any (possibly other) stations in these areas in the afternoon. For private cars, I define travel times between polygons as the travel times between the road intersections closest to the polygons' centroids.

Travel time between points in the morning or evening journeys is defined as the average of travel times in each half-hour interval during the peak weighted by the share of departures in the corresponding interval as observed in OD_MAT.

A.2. Travel times by public transportation

A.2.1 Data

<u>Buses and BRT</u>

The Israeli Ministry of Transportation provided the following datasets: (1) BUS_SCHEDULE which includes a detailed schedule for all bus lines in 2013-2019, (2) BUS_RIDES which records real complete ride travel time for the universe of regular bus rides in 2016-2019, and (3) BUS_ROUTES who contain data on routes, planned travel times and road distance between all stations in the route in each transportation period.[74] I translate travel times from the entire ride to travel times between stations by using the share of each edge in the planned travel time.

<u>Trains & Light Rail</u>

The TRAIN_RIDES dataset contains data from Israel Railways Ltd., covering the universe of all train rides between 2013 and 2019. The dataset contains, among other fields, planned and actual arrival and departure times for each station in each train ride during these years. The LIGHT_RAIL dataset, composed by the Jerusalem Transport Master Plan Team, contains data on the actual departure and arrival time of the universe of all the rides in the Jerusalem Light Rail throughout the research period. I divide the total ride's travel time into different segments using the real travel time and each segment's proportion in the planned travel time.

A.2.2. Imputation of bus travel times in the early period

Information about real bus travel times only covers the years 2016-2019, raising the need to impute travel times for the earlier period. I construct a new dataset in which

[74] The planning of the bus network is done separately and uniformly for each transportation period. I observe the data for the period between January 1st to the Jewish holiday Pesach, and from the end of Pesach until July 1st. I impute transportation data for the rest of the year as the average value of the two adjacent periods.

each observation represents a distinct bus line in each direction, year, transportation period, and time of departure.[75] For each observation I calculate characteristics including the average planned ride time in each half-hour interval, total distance travelled, the number of stops by activity,[76] all taken from BUS_ROUTES, and the median real travel time calculated from BUS_RIDES.[77] To further improve predictive ability, I divide each ride to its edges. I characterize each edge by length, planned speed, and importance in the network.[78] I divide each of these characteristics into eight bins, and the edge is classified into one of the categories resulting from the interactions between the bins. I then sum the distance each line travels in each of these categories.

The prediction itself is done using a Stochastic Gradient Boosting Machine algorithm, as implemented in R's XGBoost package.[79] The target variable is the difference between real and planned travel times. I use the difference instead of real travel times to maintain any line-specific knowledge known to the transportation planners but unknown to me. I train the model on data from the second transportation period of 2016 to the end of 2019 and test it on data from the first period of 2016. All model parameters are hyper-tuned using 5-fold cross-validation. Post estimation I sum the planned travel time with the predicted real-planned difference. Table A.5 presents goodness of fit measures on the test set both in minutes and in log terms.

Table A.5

The goodness of fit measures of bus times, imputation on the test set

	minutes	log(minutes)
Mean Absolute Error	2.82	0.0629
Root Mean Squared Error	4.27	0.0932
R^2	0.982	0.977
N - train set	262,306	
N - test set	30,076	

[75] By half hour intervals during rush hours, and three longer intervals containing the time before morning rush hour, between rush-hours and post afternoon rush hour.
[76] Drop-off only, Pick-up only, Both, and long refreshment stops.
[77] The median is calculated in two steps. I calculate it on the raw data, drop all observations whose ride time is either shorter than half, or longer than double the raw median. These observations contain obvious errors such as negative or close to zero ride times and unique events such as extreme congestion due to accidents or other extraordinary events. Finally, I calculate the median travel time of the subset of remaining observations. Lastly, I impose all median times to be in the 10-120 kmh interval.
[78] Defined as the share of all bus rides in the transportation period travelling in the same edge.
[79] Chen et al (2021)

A.2.3. Total travel times by public transportation

I calculate the minimal total direct travel time between stations every two minutes throughout morning and evening rush hours in every Tuesday[80] during the research period. Travel can occur by any mode of public transportation including walking.

I allow walking between every two points (apartment to station, or station to station) up to one kilometer away. Walking time includes a constant of 2 minutes and a function of the aerial distance: a walking speed of 4kmh in the first 400 meters, 3kmh in the 400-600 meters interval, 2kmh in the 600-800 meters interval, and 1 kmh in the 800-1000 meters interval. The maximal walking journey is one kilometer long, which takes 30 minutes to complete. The constant term is included to penalize complicated rides where the replacement occurs between close stations. The gradual slowdown represents the decreasing share of individuals willing to walk any distance, and penalizes, but doesn't rule out, accessibility which relies on long walks. This approach also diminishes the phenomena of sharp discontinuity of the accessibility measure between close locations.

Direct travel time between stations consists of both the waiting time (according to the planned schedule) and the time in ride. I define travel times for journeys starting within each half-hour interval as the average of travel times in the sampled time stamps within that interval, and the daily average (within the morning or evening commute) as a weighted average of the half-hour intervals as described above. For each transportation period, I define direct travel time as the median value of the daily times.

Lastly, I apply Dijkstra's algorithm[81] to obtain effective travel times between all stations in Israel.[82] I use direct travel times between each pair of stations as weights and apply the algorithm separately for each transportation period and separately in the morning and afternoon rush hours.

A.3 Travel times by private car

There is no direct data available on travel times by private car in Israel. Thus, I apply a two-staged procedure to compute travel times: (1) Estimation of travel speed in each road segment in Israel, and (2) Calculation of the shortest path between points. The data

[80] On Tuesdays only, according to a recommendation from the Israeli Ministry of Transportation. This is done to eliminate any unique day of the week effects. For example, a large part of the public transit system doesn't operate in weekends. Another example is increased service in some parts of the system that is targeted at getting soldiers to their base or back home on Sundays and Thursdays.
[81] Dijkstra (1959), as implemented in the R package CppRouting.
[82] 34,652 stations were active in at least one point of time during the research period.

on the road network comes from the ROADS_NETWORK dataset which is part of the standard BENTAL dataset produced by the Survey of Israel ("mapi"). It includes quarterly GIS data of the entire Israeli road network.

A.3.1 Estimation of travel speeds in road segments

I estimate road segment speeds using the travel speed of buses. Optimally I would have used buses travelling through the specific road segment, but parts of the road network are not used by buses, and my bus routes data contains information on the location and order of the stations for each bus line, but I have no direct knowledge regarding which road segment the bus travelled between those stations. I estimate the speed in each road segment using the following procedure:

1. Compute the maximal bus speed for each origin-destination station pair. The outcome is a 'ray' which represents the straight line between the two stations in the pair, and the travel speed in this ray.

1.A. For each bus line in each half-hour interval in each transportation period, I use direct travel time between stations as defined above, and the road distance from the BUS_ROUTES dataset to compute the speed in that edge.

1.B. Filter out extreme or problematic data: kmh lower than 10 or higher than 120.

1.E. For each possible half-hour interval-edge combination, assign the maximal speed.

1.F. For each edge in each transportation period and separately for morning and afternoon rush hours assign the final speed value: the weighted average of the speed in all half-hour intervals (as described above).

2. Match public transportation 'rays' to road segments.

2.A. For each road segment: find the closest 5 public transportation 'rays'.

The distance calculated is the distance between two lines: the road segment and the public transportation ray. The two prominent distance concepts between lines are the Frechet and Hausdorff distances. I prefer the Frechet distance due to its dependence on the direction one traverse on the line which is an important feature in this context.

2.B. For each road segment: assign travel speed: average of 5 closest 'rays'.

3. Calculate the cost for each road segment using travel speed and road distance.

The main assumption required to accept this procedure is that the ratio of public transportation travel speed and private car travel speed remains fairly constant across time and space. A constant ratio that is different from 1 poses no problem for the analysis since it is equivalent to a linear transformation of the travel cost, which makes no difference to the rest of the analysis. A violation of this assumption might distort the path choices in the Dijkstra algorithm and the estimations relying on this procedure.

The result of the procedure up to this point is a GIS database of all roads in Israel with the travel time in each direction and each road segment in the network for every transportation period and separately for morning and afternoon rush hours.

A.3.2. Total travel times by private cars

To find the shortest path between points I apply the following procedure separately for each transportation period and morning or afternoon rush hour.

4. prepare the dataset.

4.A. Transform roads network GIS object to a weighted graph: I perform this task using the weight_streetnet function from the dodgr package in R.[83]

4.B. For each transportation polygon (address) define the center as the point on the graph closest to its geometric centroid. This point will usually be an intersection of two roads or a turn within a road segment.

4.C. Simplify the graph (using the cpp_simplify function from the cppRouting R).[84]

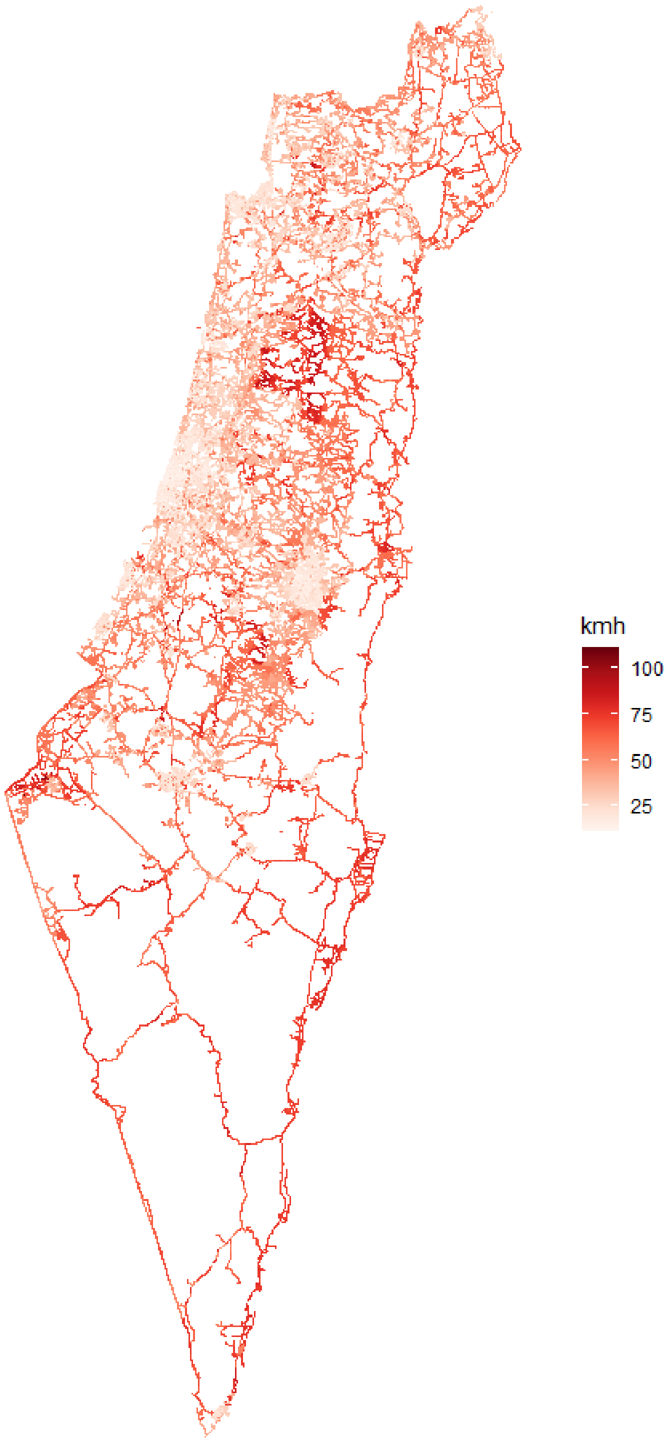
5. Apply Dijkstra's algorithm as implemented in the cppRouting package in R.

The estimated speed for each road segment in Israel is presented in figure A.6. One can note that, as expected, the estimated speed is high in peripheral areas and highways, and rapidly declines when approaching the large metropolis.

[83] Padgham (2019)
[84] Larmet (2019)

Figure A.6

Estimated road speeds in Israel, morning-peak 2019



Appendix B: Case-study analysis of the opening of new train stations

Both the Jerusalem Light Rail and Haifa's BRT system (Metronit) opened before or shortly after the beginning of my research period, not allowing direct estimation of the implied effect of their services in a classic case-study design. On contrary, 15 new train stations[85] opened during the research period, allowing direct estimation of the effect of proximity to train stations on rents. I examine this effect using a standard difference-in-differences hedonic model. Specifically, I limit the sample to apartments located up to 3 kilometers away from any of the 15 stations inaugurated during the research period and estimate:

$$(8)\quad \log(rent)_{ijrt} = \alpha + \rho * post_{rt} + \tau * \left[proximity_j * post_{rt}\right] + \mu_j + \lambda_t + \beta X_{ij} + \upsilon_{ijrt}$$

Where 'post' and 'proximity' are binary variables indicating whether the relevant station is already operational and whether the ad is in the inner or outer parts of the circle surrounding the station. Proximity gets the value 1 if the advertised apartment is located up to 1km away from any of the new train stations. X is the same vector of apartment-specific features used in the baseline model discussed in the main text,[86] and μ and λ address and year effects accordingly. This analysis relies on the difference between the before-after difference observed in apartments located close to the station and apartments located in the outer parts of the circle surrounding the station. The underlying identifying assumption is that absent the construction of the rail stations, the rents in different parts of that circle would have developed in a similar fashion. Note that this estimation does not rely on the Commuter Market Access concept guiding the rest of the analysis in this paper. Table A.6 presents the results.

There is a small positive effect, monotonically decreasing with the distance from the station. The only exception to the monotonicity is in the estimated effect for the closest proximity group, this might be the result of negative externalities in the immediate surrounding of a train station (as found in Haifa by Portnov et al, 2009), or a spurious result stemming from the small number of ads in this proximity group. The effect is

[85] Sderot, Netivot, Ofakim, Netanya (Sapir), Yokne'am-Kfar Yehoshua, Migdal Ha'Emek-Kfar Baruch, Afula (R. Eitan), Bet-She'an, Achihud, Karmiel, Ra'anana (West), Ra'anana South), Kiryat Mal'akhi – Yoav, Jerusalem (Yitzchak Navon), Mazkeret Batya.

[86] Including $log\left(RCMA_{jt}^{car}\right)$, population density, the number of floors in the building, the apartment's floor, number of rooms and toilet rooms, the apartment's size in square meters, the ratio of its size to the size of similar nearby apartments, and dummies for: a new kitchen, air conditioner, parking, barred windows, balcony, security room and renovation status.

always of an economically small magnitude, where in the most affected treatment group (apartments located 200-400 meters from the station) the effect is 0.022 log points. The reason this positive effect was not found for trains in table 5 is discussed in the main text.

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	0.012*** (0.004)	-0.006 (0.06)	0.022** (0.01)	0.014* (0.009)	0.011 (0.007)	0.009* (0.006)
R^2 (Within, adjusted)	0.603	0.603				
N – observations	47,837	47,837				
N – unique addresses	10,779	10,779				
N – observations in treatment group	10,006	62	1,076	1,833	3,044	3,991

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