Bank of Israel
Research Department

Who Drives the Fundamental Law of Road Congestion?

■ Discussion Papers Series ■

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May 2026

2026.03

Who Drives the Fundamental Law of Road Congestion?*

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Abstract

This paper examines the effect of road capacity on car usage. Previous work hypothesized a 'fundamental law of road congestion'—a one-for-one response of car usage to road capacity expansions. I use administrative microdata from Israel to document systematic variation in this effect, and explore the underlying mechanisms driving it. The effect is greater in more urban regions, is mainly due to the extensive margin, and is mostly driven by young families with low-medium income purchasing a second car for the household. These results align with a simple theoretical model introducing car ownership choice to the consumer's problem.

JEL classification: R41, R48
Keywords: Congestion, Fundamental Law, Roads, Urban transportation

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* I thank my advisors David Genesove and Naomi Hausman for their insights and guidance. I would also like to thank Michael Amior, Noam Ben Ze'ev, Shira Buzaglo-Baris, Yaakov Chen Zion, Nimrod Cohen, Elad Demal'ach, Alon Eizenberg, Stuart Gabriel, Matan Gdaliahu, Sarit Weisburd, Doron Zamir, and seminar and conference participants at the Alrov Institute for Real Estate Research at Tel Aviv University, the Bank of Israel's research department, The Israeli Economic Association, and IRSA annual conference for valuable advice. I thank Daniel Brodi (Survey of Israel) for allowing access and providing valuable advice on the roads network data, and the Israel Central Bureau of Statistics for providing access to the microdata used in the paper. This study was performed in the Israel Central Bureau of Statistics (ICBS) research room using de-identified Microdata (direct identifiers removed from data) in files prepared specifically for this project.

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מי מניע את הכלל היסודי של גודש בכבישים?

גל עמדי[1]

תקציר

מאמר זה בוחן את הקשר בין קיבולת רשת הכבישים לרמת השימוש ברכב פרטי. ספרות קודמת שיערה שקשר זה מקיים 'כלל יסודי של גודש בכבישים'- הגדלת קיבולת הרשת תביא לעלייה בשיעור דומה בשימוש ברכב פרטי, כך שסלילת כבישים לא תביא להקלה בגודש. מאמר זה משתמש בנתונים מנהליים ברמת הפרט על מנת לתעד שונות שיטתית בגודל הקשר, ולבחון מה הגורמים הקובעים את עוצמתו. הרחבת קיבולת רשת הכבישים תביא לעלייה גדולה יותר בשימוש ברכב פרטי באזורים יותר עירוניים. הקשר בין קיבולת לנסועה נובע ברובו מקניית רכבים חדשים, ולא מתוספת נסיעות של בעלי רכבים, ובעיקר מרכישת רכב שני למשק הבית על ידי משפחות צעירות ברמות הכנסה נמוכות-בינוניות. הדפוסים המתועדים במאמר תואמים את תוצאותיו של מודל תיאורטי המשלב החלטה על בעלות על רכב כחלק מבעיית הצרכן.

סיווג JEL: R41, R48

מילות מפתח: גודש, קיבולת רשת הכבישים, מדיניות תחבורה עירונית ביקוש מושרה.

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I. Introduction

The 'Fundamental Law of Road Congestion', first hypothesized by Downs (1962), states that increasing road capacity will lead to a proportional increase in vehicle kilometers traveled (VKT) such that in the new steady-state peak-hour travel speed will remain the same. Formally, denote the elasticity of VKT with respect to road capacity as ρ. If $\rho > 0$, there is 'induced demand': Increasing road capacity increases car travel, such that the intended relief in congestion is mitigated. If $\rho = 1$, the fundamental law holds and increased capacity would not affect congestion, and if $\rho > 1$ increasing capacity might even amplify congestion. Understanding the value of ρ is critical for policy makers considering urban development and transportation infrastructure investment decisions.

A series of papers inspired by Downs's hypothesis attempts to empirically estimate ρ by exploiting quasi-experimental variation in the city-level stock of roads and VKT in many different empirical contexts.[1] This literature consistently finds economically significant induced demand, including many studies that estimate $\rho \approx 1$, implying that the fundamental law hypothesis is empirically relevant in many contexts.

This paper uses linked individual-level administrative panel data from Israel to better understand what determines the road capacity-car usage relationship. I contribute three novel findings to the literature. Contrary to the hypothesized universality of the fundamental law of road congestion, ρ systematically increases with density. There is no effect of increased capacity on car usage in rural areas, and a large effect in urban regions. ρ also increases with density within urban regions, such that ρ in urban cores could be greater than 1, indicating that increasing capacity in high-density areas might even worsen congestion. This heterogeneity is mainly due to increased initial congestion and a lower motorization

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[1] Duranton and Turner (2011); Hsu and Zhang (2014); Chen and Klaiber (2020); Garcia-López, Pasidis and Viladecans-Marsal (2022); Ossokina, Van Ommeren and Van Mourik (2023); Chang, Indra and Maiti (2023).

rate in more urban areas.

I document that the effect is mostly driven by the extensive margin—improving road capacity induces residents to purchase more cars. Contrary to the mechanisms hypothesized but never empirically tested in previous work, there is at most a modest response in the intensive margin. Improving road capacity only moderately induces incumbent car owners to drive their cars more. This finding settles the apparent discrepancy between most empirical findings and the theoretical counter-argument recently made by Anas (2024) and further discussed below.

Lastly, I identify the population groups driving the aggregate effect, a type of result novel to the literature. I find that the aggregate effect is mainly driven by young low-to-middle-income families choosing to own a second car following capacity expansions. These results align with a simple theoretical model incorporating a car ownership choice to the agent's travel choice problem.

These findings improve current understanding of the mechanisms and determinants of the road capacity-car usage relationship, and suggest important policy implications regarding mobility and urban planning. Specifically, the results suggest that cities should not aspire to improve city-wide accessibility by both transit and private car concurrently.[2] The marginal capacity expansion could alleviate congestion only when car ownership rates are high. In such car-centric regions, transit would generally provide little added value to accessibility. In more transit-oriented high-density cities, where the ownership rate is low, roads could reduce the attractiveness of using transit both directly by improving the alternative, while worsening congestion for all road users, and indirectly through its effects on urban form.

Israel, the empirical context studied here, is characterized by an exceptionally rapid population growth rate alongside a low motorization rate compared to

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[2] The argument does not rule out specific investments in roads or transit projects, but questions the desirability of trying to achieve both well-developed transportation networks in the same city.

countries with similar income levels. Both these traits cast serious doubt on the possibility that continuing the trend of car-centric planning and road capacity expansions could alleviate congestion, which has been on the rise in recent years especially within urban centers. This suggests that the car-centric approach does not fit the Israeli context, and future transportation investments should be focused on transit infrastructure that should also be accompanied by transit-oriented development in new construction.

The remainder of this paper proceeds as follows: Section II reviews previous work examining the effect of road capacity on car usage; Section III develops a simple theoretical model rationalizing many of the patterns observed in the empirical part of the paper; Section IV describes the data used for the analysis; Section V describes the empirical context; Section VI presents empirical analyses on both the neighborhood level, corresponding to the type of elasticities estimated in previous work, and the household level, providing novel findings regarding the differential effect on different population groups; and Section VII discusses the main findings and their policy implications and concludes.

II. Literature

The 'Fundamental Law of Peak-hour Expressway Congestion' was first hypothesized by Downs (1962). The law refers specifically to peak-hour travel speed on expressways. The modern empirical literature, pioneered by the seminal Duranton and Turner (2011) paper, empirically verified a different version of the fundamental law. Since comprehensive travel speed data over long periods of time don't exist, the empirical exercise examines the elasticity of total annual VKT in a city with respect to its road capacity using variation over time in the city-level stock of roads and travel data, or instruments for road capacity in a cross-section of cities. Using this methodology and data on American metropolitan statistical areas, Duranton and Turner (2011) estimate $\rho \approx 1$. Road capacity expansions lead to a proportional increase in VKT on highways, as first hypothesized by Downs

(1962), as well as on other types of roads.

Similar results using this type of methodology and data have been found in various empirical contexts including national expressways in Japanese ‘Urban Employment Areas’ (Hsu and Zhang, 2014), all urban roads in Chinese cities (Chen and Klaiber, 2020), and expressways in European ‘Functional Urban Areas’ (Garcia-López, Pasidis and Viladecans-Marsal, 2022). Akbar et al. (2023*b*) and Akbar et al. (2023*a*) provide supporting evidence for the fundamental law by showing that the stock of major roads has no effect on congested travel speed in cross-sections of cities in India and around the world using a speed production function approach. Kim (2022) reports a similar result for the effect of road quality on speed. He finds that roadwork in California has a short-term effect on travel speed, which is quickly eliminated due to increased traffic volume.

Several recent studies challenge the universality of the fundamental law. Ossokina, Van Ommeren and Van Mourik (2023) finds an economically significant, but smaller than proportional, effect of intercity highway widenings in the Netherlands on the traffic volume on those highways and in their surroundings. Chang, Indra and Maiti (2023) estimate that the effect of road capacity on VKT is largely heterogeneous between different cities, using the same data as in Duranton and Turner (2011), though they also estimate an average effect of $\rho \approx 1$.[3]

Lastly, Anas (2024) argues that the $\rho = 1$ result found in many empirical settings is theoretically impossible. He argues, based on previous empirical literature, that individual demand for travel is quite inelastic (and strictly below 1) with respect to travel speed. Under any reasonable assumption of the capacity-travel speed relationship, the downward sloping demand curve for travel necessarily implies that $\rho < 1$ and there will be a relief in congestion.

Anas (2024) Further argues that the reason the empirical literature estimates

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[3] Chang, Indra and Maiti (2023) recognize that ρ can be affected by many city characteristics, but focus on its distribution along the initial congestion level gradient. In contrast to this study, they argue that ρ would decrease with initial congestion. This is due to allowing road capacity to shift the demand curve, an unusual assumption compared to most of the literature in which capacity only affects the cost curve, and several assumptions regarding relative sizes of different elasticities in their partial equilibrium model.

$\rho = 1$ is due to an inappropriate measure of congestion in the empirical exercise: a cost increasing with the ratio of aggregate VKT to the aggregate stock of roads (lane-kilometers), instead of a more traditional measure of delay in travel time. This basic idea is formalized in many variants of an urban traffic model, all resulting in $\rho < 1$. Importantly, none of these variants allow the agents to make a car-ownership decision, implicitly assuming that all agents are car owners, or alternatively that car-ownership bears no cost.

I contribute to this body of research by adding new evidence from large-scale administrative microdata regarding the differential effect in different types of regions and for different population groups. Obtaining this type of result is impossible with aggregate measures of car usage and road capacity, as used in all previous work surveyed here. I develop a theoretical model incorporating an extensive car-ownership margin into the agents' travel choice problem, rationalizing the estimated empirical results and settling the discrepancy between those results and the theoretical counter-argument made by Anas (2024).

III. Theory

Recent empirical literature found a large elasticity of car travel with respect to road capacity, but a formal analysis of the mechanism underlying this result is lacking. Specifically, the possibility of a proportional, or even greater than proportional, response, which was empirically documented in some contexts (Hsu and Zhang, 2014; Garcia-López, Pasidis and Viladecans-Marsal, 2022), is not thoroughly discussed in the empirical literature,[4] and is argued as theoretically impossible in recent work by Anas (2024). This section presents a simple model formally analyzing the expected response of different individuals to capacity expansions. The model can rationalize the empirical $\rho \geq 1$ result found in empirical

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[4] Hsu and Zhang (2014) argue that such a response is possible in cases where new expressways add coverage to the network, that is, they allow accessibility to destinations previously inaccessible by the highway network. This argument is less relevant when examining the entire road network rather than focusing specifically on national expressways.

work in contexts where the extensive margin is still relevant, and provides some predictions regarding the differential response of different population groups.

A. Baseline model

A region is inhabited by N residents, each endowed with income I, traveling on a road network with capacity R.[5] Individuals consume travel, X, and a composite consumption good C, both continuous and concave. These can be thought of as total annual travel and consumption. In order to travel, agents have to be car owners. To become a car owner, the agent must pay a positive fixed monetary cost of O. The price of C is normalized to 1. Hence, agents face the budget constraint: $I \leq O + C$. Conditional on owning a car, travel has no monetary cost, but does bear a nonmonetary disutility T. This disutility is intuitively largely determined by time spent on the road, but under this formulation it can include other factors as well. The individual's utility function is given as:

$$U = Wh\left(X\right) + m\left(C\right) - TX \tag{1}$$

where $(h', m') > 0, (h'', m'') < 0$, and W a constant.

The cost of travel is a function of R (road capacity), and $\overline{X}$ (aggregate travel): $T = f(\overline{X}/R)$ with $f' > 0, f'' > 0$. This general functional form nests the standard BPR congestion function (US Bureau of Public Roads. Office of Planning. Urban Planning Division, 1964), which is extensively used in urban planning and research, including the recent theoretical analysis by Anas (2024), and is also consistent with recent empirical evidence (Yang, Purevjav and Li, 2020).

Under this setup, and with derivations further detailed in Appendix B, whenever $0 < s < 1$, the marginal agent will be indifferent to ownership or nonowner-

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[5] The theoretical exercise presented here does not depend on any specific definition of road capacity. This measure can be thought of as representing all infrastructure affecting travel costs including road width, quality, lighting at night, and parking space, among other factors. In the empirical part of the paper I follow previous studies and define capacity using total lane-km.

ship, implying that in equilibrium each car owner will choose the same amount of travel: X^*. From first-order conditions of Equation (1) we get $T = Wh'(X^*)$. Since X^* is determined, we can conclude from first-order conditions that $T = f(\overline{X}/R)$ is constant, hence the ratio between aggregate travel and road capacity is constant, and ρ must equal 1.

Note that $\overline{X}$ can be written as the product of N, the exogenous number of residents, s, the share of car owners, and X, the amount of travel a household consumes. N is exogenous, and as long as $0 < s^* < 1$, X^* is constant, implying that under this setup, as long as the extensive margin is not exhausted, the total effect of road capacity on aggregate travel, ρ, stems only from the extensive margin—more agents will now buy cars. There is no effect on the intensive margin—car owners will not travel more following the capacity expansion.

In cases where ownership is universal, the size of the effect depends on the specific travel demand and travel technology functions, as well as exogenous model parameters, but, as in Anas (2024), is strictly smaller than 1. Specifically, one can obtain:

$$\rho = \frac{f'\left(\frac{X}{R}\right)}{f'\left(\frac{X}{R}\right) - WRh''(X)} \tag{2}$$

by totally differentiating the first order conditions with respect to R, while normalizing $N = 1$ (Appendix B). Since $f' > 0, h'' < 0$, one can conclude that $0 < \rho < 1$ and building more roads will alleviate congestion if car ownership is universal.

Equation (2) also implies that ρ is increasing with congestion. This is an intuitive result – building roads in congested areas would cause more induced demand relative to similar capacity expansions in noncongested areas where their effect on travel costs is smaller. This analysis implies a stronger anticipated effect in urban areas than in nonurban areas due to both higher congestion levels and lower ownership rates (Table 1), allowing a stronger effect in the extensive margin.

Previous work makes no distinction between the intensive and extensive margins, even though such a distinction evidently has important implications on the model's results. Anas (2024) implicitly assumes all agents are car owners (or equivalently that car ownership bears no cost), thus only allowing an intensive margin effect. Empirical work also implicitly makes a similar assumption when discussing mechanisms.

The empirical relevance of this modeling choice depends on the studied context. In many empirical contexts—including the United States in the period studied by Duranton and Turner (2011), most of Europe and the developing world (and Israel, which is studied in this paper)—car ownership is not universal, and many car-owning households choose to own only one car (see Appendix Figure A1). This type of empirical context implies an important extensive margin channel, which is expected to drive a response that might appear as a fundamental law of road congestion, even though there is nothing fundamental about it. In contexts where car ownership is near-universal one should expect a weaker effect. For example, in the United States today, car ownership is cheap relative to income, making it almost universal in most American cities. The high motorization rate implies that in those cities, the response would stem mainly from the intensive margin, and new road expansions do actually have the potential to alleviate congestion, in contrast with the influential results estimated by Duranton and Turner (2011).[6]

B. Adding heterogeneous income

As apparent from the baseline model, conditional on car ownership choice, an individual's income has no effect on the amount of travel consumed. This amount can be found by taking first-order conditions of Equation (1): $X^* = h'^{(-1)}\left(\frac{T}{W}\right)$.

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[6] The national US motorization rate was 658 in 1983 and 795 in 2003 (the first and last years in the data used by Duranton and Turner (2011)), and rose to 913 in 2023 - the most recent year for which data are available (National Center for Statistics and Analysis, 2025). This solid rise in the motorization rate over the years can explain the downward trend of ρ over the years in American cities as reported, but only briefly discussed, by Duranton and Turner (2011). It is reasonable to assume that due to this continued increase in the motorization rate, a similar analysis using more recent data would have resulted in an estimated $\rho < 1$ in American cities as well.

This expression does not depend on the individual's income. It does depend on the share of car owners in the population, which is affected by the distribution of income in the population. For each individual, income affects car ownership choice in the following way:

PROPOSITION 1: *For any choice of model parameters and income distribution, there is a certain level of income,* $\overline{I}$*, such that* $\forall I^- < \overline{I}$ *the agent would not choose to own a car and* $\forall I^+ > \overline{I}$ *the agent would choose to own a car.*

Proof: See Appendix B.

In this setup, the elasticity of car ownership with respect to the stock of roads depends on the distribution of income, and the intensive margin will adjust accordingly. Under this scenario the overall elasticity can be either smaller or greater than 1, depending on the model's parameters and the distribution of income. Also note that in this setup the elasticity of T with respect to R must not be constant. In scenarios where roads are more congested (T is high), the elasticity of T with respect to R is higher, and ceteris paribus, the effect on car usage would be higher.

C. Adding heterogeneous preferences for travel

I add heterogeneity in the demand for travel by allowing different values of W_i for different agents. This addition leads to a threshold result similar to the heterogeneous income case. There is a certain level of $\overline{W}$, such that all agents with $W_i^- < \overline{W}$ will not own a car, and all agents with $W_i^+ > \overline{W}$ will choose to own a car. (See proof in Appendix B.)

Unlike the heterogeneous income case, there are now important implications for the intensive margin as well. In equilibrium a car owner would travel $X_i^* = h'^{(-1)}\left(\frac{T}{W_i}\right)$. Agents with a higher level of W_i are more likely to become car owners, but will also choose to travel more conditional on car ownership. This implies a composition effect: Ceteris paribus, a higher share of car owners implies a lower average travel consumption. I examine and rule out the possibility that this type of effect drives the small intensive margin response found in the empirical section of the paper.

D. Predictions

I conclude this section by summarizing the main testable predictions regarding the effect of road capacity on car usage implied by the model:

1) The overall effect would stem mainly from the extensive margin.
2) The extensive margin effect would be particularly strong around a certain income threshold.
3) A stronger effect is expected in regions that were more congested or had a lower share of car-owners in the base period.

These predictions largely align with the empirical findings presented below.

IV. Data

To empirically examine the relationship between VKT and road capacity I rely on linked administrative individual-level balanced panel data covering 3.2 million adult individuals (Roughly two-thirds of the Israeli adult population) for the decade between 2010 and 2019.[7] Crucially, this precedes the lockdowns of the COVID-19 pandemic and the subsequent growth in working from home. I observe 10 years of data for any sampled individual, and can match between spouses, allowing me to examine household level results and decisions. The sample is largely representative of the adult Israeli population, as demonstrated in Appendix C.

I observe administrative data including place of residence, age, education, gender, number of children, year of birth for each child, and labor market outcomes including self-employment income and monthly employment status, annual wages,

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[7] The sample is composed of all respondents to CBS individual-level surveys in those years, a random sample of a third of all employees and self-employed, and spouses of all the above.

and a firm identifier and industry code for each position the individual holds. Information regarding the main target variables in this paper—car-ownership status and Vehicle Kilometers Travelled (VKT)—is obtained from administrative data sets providing information on ownership and VKT records for each vehicle collected during mandatory annual technical inspection. VKT information is available with universal coverage only since 2015.

Information regarding the treatment variable—road capacity—is obtained from GIS files of the complete road network extracted from the BENTAL dataset produced by the Survey of Israel (Mapi). In the main analysis I use lane kilometers in the 10 kilometer radius surrounding the centroid of the individual's residential neighborhood as the relevant road capacity measure.[8] Robustness to alternative capacity measures is discussed in Section VI. Lastly, I augment the data set with some important neighborhood (statistical area) level features: a proxy for residential and workers' density in the 3 km radius around the neighborhood's centroid using morning in and out commutes from detailed cellular location data (Cohen, 2021), and a measure of the level of transit services in the neighborhood as calculated in Amedi (2023).[9]

The data set has some important limitations, further discussed in Appendix C, which prevent one from credibly examining differences in both the treatment and outcome variables in high frequency. These limitations lead me to focus on the variation in a single, 2015-2019, first-difference to estimate the effect of road capacity on car usage.

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[8] Unlike the abstract measure used in the theoretical section, the empirical exercise requires a specific definition of capacity. This measure is consistent with previous empirical work, and can be easily compared across different contexts. I recognize its possible shortcomings as argued by Anas (2024), but use it due to the lack of a better available alternative measure and for consistency with prior research.

[9] This measure is based on highly granular nationwide data regarding travel times in public transportation in Israel throughout the period, which is aggregated to a theoretically grounded index of accessibility by transit in each region: the Residential Commuter Market Access measure developed by Tsivanidis (2019). A simpler alternative measure - the number of bus stops-at-station in the neighborhood, is used in a robustness check.

V. Empirical context

Figure 1 presents national-level trends in road capacity, total car usage, and its different margins as reported in the Israeli CBS annual statistical abstracts. Total VKT grew more than road capacity, mainly due to the increase in the motorization rate. A naive comparison of these trends might imply $\rho > 1$, but these long-term trends are largely affected by other confounding factors. Friedmann (2019) argues that the increase in motorization rate is mainly due to an increase in disposable income, tax policy, and an initially low motorization rate in addition to capacity expansions. Even after the presented increase in the number of vehicles, Israel's motorization rate is low relative to other developed economies with similar income levels (Appendix Figure A1).

The intensive margin (VKT per car) slowly decreases over the long term, but remains stable during the research period. The rapid growth in car ownership and usage, alongside the smaller increase in capacity lead to increased congestion, mainly in urban areas. There is no apparent deviation from any long-term trend during the research period.[10]

Figure 2 presents the distribution of the 2015–2019 log differences in road capacity and car usage variables across neighborhoods (CBS statistical areas) in Israel as calculated using the data in my sample. The figure only contains neighborhoods later included in the neighborhood-level analysis.[11] There is considerable variation in the allocation of new roads, though almost no region experienced a decline in road capacity during this period. Appendix Figure A2 presents this variation spatially at the commuting zone level.[12] Capacity increased more in peripheral and suburban commuting zones, but there are notable increases in some urban areas as well.

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[10] The downward tick in VKT and VKT per car in 2020 is due to the effects of the COVID-19 pandemic.

[11] The only inclusion criteria applied is observing at least 50 residents in the neighborhood both in 2015 and 2019.

[12] Commuting zones are based on the delineation proposed in Amedi and Porat Hirsh (2026), in the version grouping Judea & Samaria as a single, separate commuting zone.

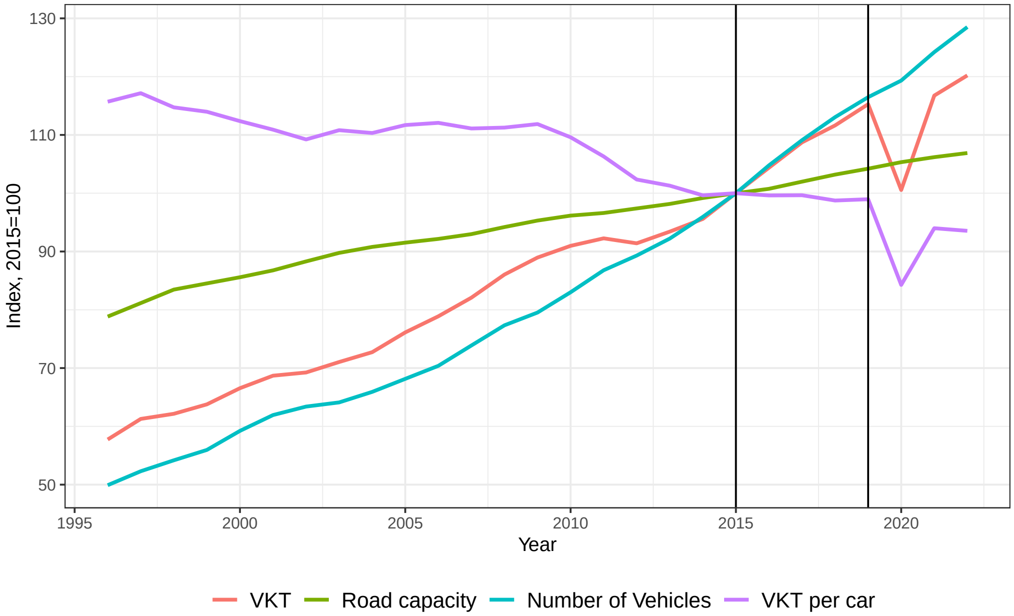

Figure 1. National trends in road capacity and car usage

Source: Israeli CBS annual statistical abstracts. This figure presents national trends in road capacity, total car usage, and its different margins. The vertical lines indicate the range of the research period.

Even though car usage increased on average during this period, there is considerable variation between neighborhoods in the 2015–2019 difference of both the extensive (number of cars) and intensive (VKT per car) margins of car usage, including several outliers. The main analysis includes all statistical areas for which I observe a sufficient number of residents in both periods, but I verify that the results are not significantly affected by those outliers, see a discussion of robustness to sample selection choices in Section VI.

Table 1 presents transportation statistics for urban and nonurban regions included in the sample. Urban regions are characterized by higher congestion levels than nonurban regions. This is caused by the higher residential density in those areas, and despite having a denser road network, lower average motorization rate and VKT per car.

The high congestion and low motorization rate support a higher elasticity of

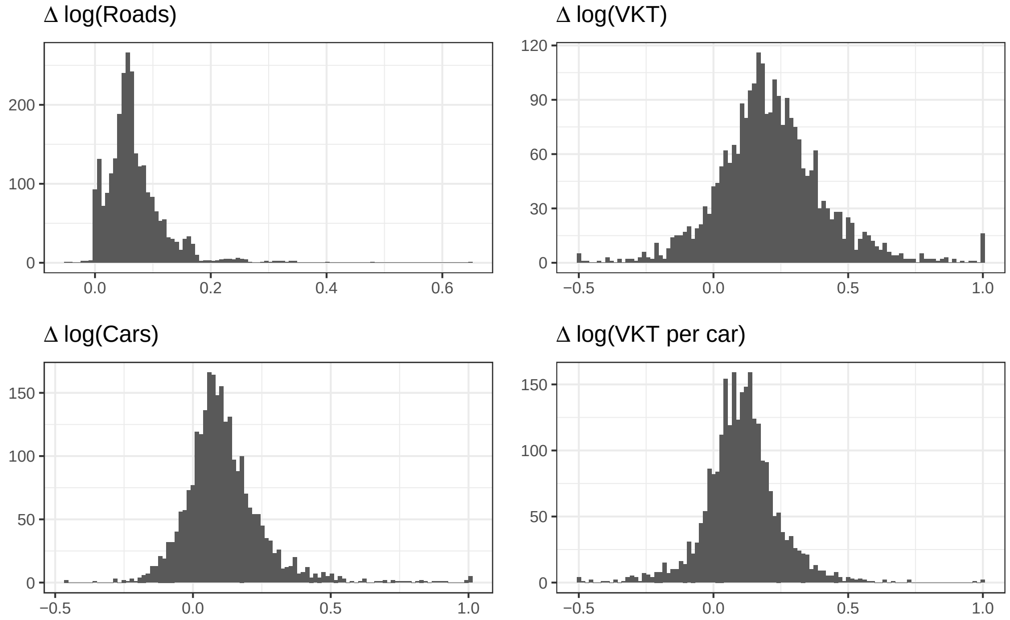

Figure 2. Distributions of the 2015-2019 log difference of road capacity and car usage

Note: This figure presents neighborhood-level distributions of the log difference of road capacity (as calculated using Survey of Israel GIS files) and the different margins of car usage (as calculated using my sample data) for all neighborhoods included in the analysis. For illustrative purposes, the presented distributions are winsorized between negative 0.5 and 1.

car usage with respect to road capacity as discussed in Section III. Figure 3 plots the relationship between the 2015–2019 log difference in road capacity and VKT in urban and nonurban regions, and only for $\Delta \log(Roads)$ values in the common support of both these types of regions. There is a clear positive log-linear relationship between these variables in urban regions, and no apparent trend is visible in nonurban regions. This simple correlation will be echoed and further explored in Section VI.

Table 1—Summary transportation statistics for urban and nonurban regions

	Urban regions	Nonurban regions
Road capacity (lane-kilometers)	440	184
Congestion	152	46
Motorization rate (vehicles per adult)	0.535	0.623
VKT per car	9,477	12,193
Density (residents per square kilometer)	6,866	830

Note: The table presents averages of transportation statistics in urban and nonurban regions. Urban areas are defined here as neighborhoods where the residential density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Road capacity is total lane-km in the 10-km radius around the neighborhood's centroid. Congestion is defined as total VKT by residents of neighborhoods in the 3 km radius around the neighborhood's centroid divided by road capacity. The motorization rate is the number of registered vehicles owned by residents of the neighborhood divided by the number of adults I observe (it's worth noting that the denominator does not include children as usually done in official statistics). All statistics refer to 2015, except for density which is computed using cellular location data from 2018-2019.

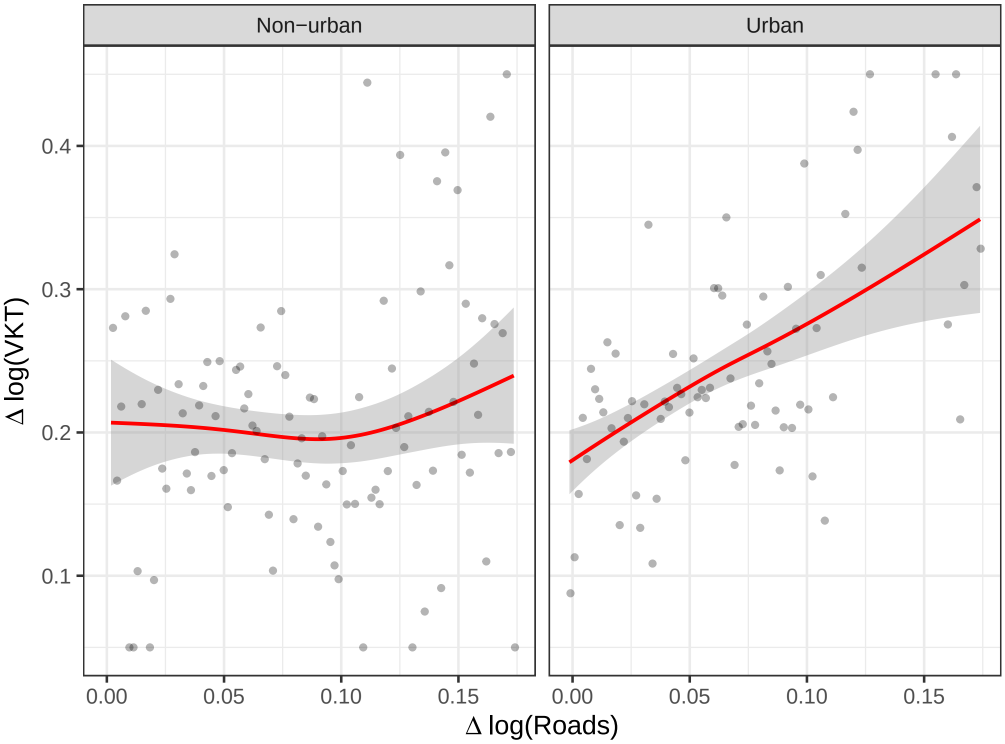

Figure 3. The relation between changes in capacity and VKT by urban status

Note: This figure presents a binned scatter plot, and an unconditional nonparametrically estimated smoothed relation between the 2015–2019 log differences of road capacity and VKT in urban and nonurban regions. The relation is only plotted for the common support of both groups of regions, covering roughly 95% of the regions (statistical areas) in the dataset. The estimation is performed using local polynomial regressions with default values from the `geom_smooth` function of the `ggplot2` package in `R`. For visualization purposes, bins with $\Delta \log(VKT)$ are winsorized in the plot to be within the $(0.05, 0.045)$ interval.

VI. Estimation

I estimate the effect of road capacity on car usage using a single first-difference between the years 2015 and 2019. This is due to limitations in the available data discussed in Section IV and Appendix C. I estimate elasticities of both the aggregate (neighborhood) level results, corresponding to results reported in previous studies, and household level results, which are novel to the literature and can shed new light on the types of individuals ‘driving’ induced demand.

A. *Neighborhood level analysis*

Methodology. — The unit of analysis in this section is a ‘statistical area’ as defined by the Israeli CBS. The average statistical area contained roughly 3,200 residents in 2018, and is largely comparable to a US census tract. I will use the terms ‘statistical area’ and ‘neighborhood’ interchangeably in this analysis. I examine the effect of increased road capacity on three measures of car usage: (1) Total Vehicle Kilometers Traveled (VKT) by residents of the region. This measure represents the overall effect of road capacity on car usage, conceptually corresponding to the effect of road capacity on Average Annual Daily Traffic (AADT) in a Metropolis, as examined in previous work. (2) The number of cars owned by residents of the region. This measure represents the extensive margin of the overall effect. (3) VKT per car which represents the intensive margin.

In the baseline analysis, the estimated models take the following form:

$$\Delta log\left(Y_j\right) = \sum_{\zeta} \left[\zeta_j + \rho^{\zeta} * \left(\Delta log\left(R_j\right) * \zeta_j\right)\right] + \beta X_j + \upsilon_j \tag{3}$$

where Y_j is one of three car usage variables described above in neighborhood j, R_j is the road capacity measure in the neighborhood, ζ_j an indicator for urban status, and X_j a vector of controls.[13] The main analysis divides the sample into

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[13] Specifically, X includes the neighborhood-level first difference of: log adult population, log number

two groups of urban and nonurban regions. Throughout the text I refer to the effect in urban and nonurban areas as ρ^{Urban} and $\rho^{Nonurban}$ accordingly.

The main threat to identification in this approach is nonrandom allocation of new roads.[14] If new road allocation, conditional on the included covariates, was positively correlated with higher car usage projections, ρ would be upward biased. I include the change in the quality of transit services in the area as a proxy for projected travel demand. This variable is especially relevant for concerns of nonrandom allocation, since any predicted change in travel demand inducing the planning authority to allocate more roads to a region is expected to cause the planning authority to respond by allocating more resources to transit as well.[15] I also include traffic preconditions and several covariates that should be predictive of the change in car usage by individuals due to changes in demography or economic conditions. The most notable are the change in population counts, income, employment rate, and the population share of groups for which a significantly greater effect was found in the household-level analysis described below.

I further account for possible selection on unobservables in the allocation of new roads by applying the 'unobservable selection and coefficient stability' method developed by Oster (2019). This method makes use of differences in the treatment effect coefficient (ρ^{Urban}) and the R^2 between a 'restricted' model, not including any controls[16], and an 'unrestricted' model including all possible controls included in the most detailed specification, to estimate a 'real' unbiased treatment effect.

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of children (0-18), share of households with children aged 0-5, log total income, share employed, share working in manufacturing, share academics, and the level of transit services, as computed in Amedi (2023). X also includes two variables summarizing the baseline traffic conditions: 2015 congestion level, and the 2013-2015 log-difference in the number of cars in the region. Lastly, X also includes the 2015 population shares of groups with a significantly stronger response to road capacity as estimated in the household level analysis: households where the average age of both spouses was between 30 and 35, households with income per adult between NIS 5000 and 7500, households with a single car in 2015, and households of married childless couples or couples with young children aged 0-5.

[14] I focus the discussion on factors and considerations relevant to planning authorities, though other sources of nonrandom allocation are possible. Time invariant factors are partialled-out in the first-differences approach, and other time-variant factors are of second-order importance or highly correlated to the planning authority's considerations, and therefore don't require a separate discussion.

[15] Controlling for the level of transit services is also important because transit is the main alternative to traveling by car.

[16] The restricted model can include additional variables, denoted m in Oster (2019), if the context demands it. In my estimation m includes ζ_j and the interaction term $\rho^{Nonurban} * \Delta log\left(R_j\right) * \zeta_j$, both included to allow a different effect between urban and nonurban regions.

Specifically, consider the following model:

$$\Delta log\left(Y_j\right) = \sum_{\zeta} \left[\zeta_j + \rho^{\zeta} * \left(\Delta log\left(R_j\right) * \zeta_j\right)\right] + \beta X_j + \Pi_j + \upsilon_j \tag{4}$$

This model is identical to the one I estimate in Equation (3), with the exception that now the index Π_j is included. This index contains all the information from variables unobservable to the researcher that are relevant to the problem. In my context, Π_j includes all information regarding expected changes in car usage or road allocation in neighborhood j resulting from factors unobservable to me, but observed by the planning authority. $\overset{\sim}{\rho}$ and $\overset{\sim}{R^2}$ denote, respectively, the treatment effect and R^2 obtained by estimating Equation (3), not including Π_j. ρ^* and R_{max} denote, respectively, the 'real', unbiased treatment effect and R^2 obtained from a hypothetical estimation of the unrestricted model described in Equation (4).

Oster (2019) demonstrates that the researcher can recover ρ^* by taking a stand regarding two parameters: (1) $\delta \equiv \frac{cov((\Pi|\beta X),R)/var(\Pi|\beta X)}{cov(\beta X,R)/var(\beta X)}$, which represents the degree of selection on unobservables compared to selection on observables. For example, a value of $\delta = 2$ would imply that the index of unobservables Π, after being stripped from the portion predicted by the vector of observables X, is twice as important as the included controls in explaining treatment allocation. (2) R_{max}, which is the hypothesized R^2 value from the unrestricted model described by Equation (4). Higher selected values of both δ and R_{max} would result in larger bias adjustments. Though parameter choice is context dependent, Oster (2019) suggests $\delta = 1$ and $R_{max} = \min\left(1.3\overset{\sim}{R^2}, 1\right)$ as conservative baseline values. As discussed below, in my context these values are usually excessively conservative. Thus, one can interpret the $\left(\rho^*, \overset{\sim}{\rho}\right)$ interval as bounding the real effect in the spirit of partial identification. I will apply this approach to the results reported below to demonstrate their robustness to possible confounders observed by the planning authority, but unobservable to me, determining road allocation and car usage, thus biasing estimates.

Results. — Table 2 presents ρ as estimated using the neighborhood-level first-differences approach specified in Equation (3) for urban and nonurban areas. I gradually add controls for groups of variables which one would a-priori believe to be less important confounders: 2015 population share of groups estimated to have a significantly stronger response to roads in the household analysis described below, first differences in log population, labor market outcomes, transit and traffic conditions, and demographic variables.

After controlling for the 2015 highly responsive population shares, population counts, and labor market outcomes, which are the three variable groups expected to have the strongest confounding effect, the estimated elasticity in urban areas stabilizes at $\rho^{Urban} \approx 0.75$. Controlling for more possible confounders has no effect on the estimated elasticity, nor does it significantly change the precision of the estimate or improve explanatory power. This stability remains when separately examining the extensive and intensive margins (Appendix Tables A1 and A2), with the extensive margin accounting for roughly three-quarters of the total effect. The effect in nonurban areas is always economically and statistically insignificant.

Unlike the findings for subways reported in Garcia-López, Pasidis and Viladecans-Marsal (2022), the difference in the level of transit services has little impact on the estimated effect. This can be the result of two opposing forces: the expected direct negative effect of transit on ρ as found in Garcia-López, Pasidis and Viladecans-Marsal (2022), and an upward bias resulting from the expected correlation of improved transit services and unobservable factors contributing to higher expected travel demand as discussed in the methodological section. This null effect can also be attributed to the low and decreasing share of transit commuters in Israel during the period.[17]

Table 3 collects estimates of the elasticity of different margins of car usage

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[17] I obtain a similar result when using a more traditional measure of transit—the number of bus-stops-in-station. See Appendix Table A3.

Table 2—The elasticity of VKT with respect to road capacity

	(1)	(2)	(3)	(4)	(5)	(6)
ρ^{Urban} : $(Urban * \Delta \log (R))$	1.000***	0.469**	0.661***	0.783***	0.725***	0.750***
	(0.351)	(0.177)	(0.137)	(0.131)	(0.115)	(0.124)
$\rho^{Nonurban}$: $(Nonurban * \Delta \log (R))$	0.281**	0.139*	0.118	0.121	0.119	0.122
	(0.104)	(0.070)	(0.085)	(0.096)	(0.088)	(0.089)
Urban	0.181***	0.262***	0.391***	0.352***	0.375***	0.390***
	(0.013)	(0.065)	(0.049)	(0.044)	(0.053)	(0.058)
Nonurban	0.001	0.000	0.054***	0.056***	0.047***	0.051***
	(0.019)	(0.012)	(0.010)	(0.010)	(0.009)	(0.011)
Married without kids or with kids aged 0–5		0.391***	-0.017	-0.037	-0.057	-0.075
(2015 share)		(0.065)	(0.050)	(0.057)	(0.055)	(0.083)
Single car owners		-0.582***	-0.699***	-0.638***	-0.648***	-0.655***
(2015 share)		(0.127)	(0.098)	(0.087)	(0.091)	(0.094)
Earning NIS 5,000–7,500 per adult		-1.654**	-2.336***	-2.125***	-2.024***	-1.981***
(2015 share)		(0.709)	(0.411)	(0.532)	(0.503)	(0.527)
Aged 30–35		0.318*	0.138	0.022	-0.019	-0.063
(2015 share)		(0.155)	(0.134)	(0.133)	(0.121)	(0.149)
$\Delta \log$ (Population)			1.088***	1.043***	0.972***	0.903***
			(0.046)	(0.045)	(0.069)	(0.079)
$\Delta \log$ (Total income)				0.217*	0.211*	0.207*
				(0.116)	(0.116)	(0.111)
Δ Employed				0.083	0.123	0.170
				(0.225)	(0.218)	(0.205)
Δ Share in manuf.				-0.281	-0.281	-0.274
				(0.204)	(0.206)	(0.204)
Δ Academics				0.371	0.365	0.277
				(0.252)	(0.241)	(0.267)
Δ Transit					0.000	0.000
					(0.000)	(0.000)
2015 Congestion level					0.000	0.000
					(0.000)	(0.000)
$\Delta_{2013,2015} \log (Cars)$					0.092**	0.092**
					(0.042)	(0.041)
$\Delta \log$ (Kids 0–18)						0.066
						(0.064)
Δ Share HH's with kids aged 0–5						-0.048
						(0.153)
Observations	2,568	2,568	2,568	2,568	2,568	2,568
R^2	0.016	0.174	0.455	0.466	0.470	0.471
Adj. R^2	0.015	0.171	0.454	0.464	0.467	0.468

Note: The table presents the estimated elasticity of VKT with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level and using the first-differences approach detailed in Equation (3). Urban areas are defined here as neighborhoods where the residential density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

with respect to road capacity using the same specification appearing in the last column of Table 2. Two results are apparent from this table. First, road capacity has a significant effect on car usage in urban areas, but no important effect in any of the margins in nonurban areas, corresponding to the simple correlations plotted in Figure 3. This is the expected result given that rural areas are generally not congested (see Table 1), meaning that increased capacity usually has no large effect on travel costs. Second, the overall effect is mainly the result of the extensive margin, that is, increased capacity has a relatively small effect on the intensity with which drivers use their cars, but has a large effect on the car-ownership choice residents make, matching theoretical predictions appearing in Section III.

Table 3—The elasticity of car usage with respect to road capacity, by margin

	$\Delta\log(VKT)$	$\Delta\log(Cars)$	$\Delta\log\left(\frac{VKT}{Car}\right)$
$\rho^{Urban} : (Urban * \Delta\log(R))$	0.750***	0.566***	0.184*
	(0.124)	(0.113)	(0.099)
$\rho^{Nonurban} : (Nonurban * \Delta\log(R))$	0.122	0.066*	0.056
	(0.089)	(0.036)	(0.096)
$\rho^*\left(\delta = 1, R_{max} = \min\left(1.3\widetilde{R}^2, 1\right)\right)$	0.656	0.515	0.140
$\delta^*\left(R_{max} = \min\left(1.3\widetilde{R}^2, 1\right)\right) \to \rho^* = 0$	5.813	7.329	3.562
Observations	2,568	2,568	2,568
R^2	0.471	0.760	0.058
Adj. R^2	0.468	0.758	0.052

Note: The table presents the estimated elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level and using the first-differences approach detailed in Equation (3). The specifications are identical to the last column in Table 2. Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

I control for possible nonrandom allocation of roads by conditioning on changes in population counts, demographic and labor market variables, population shares of the groups driving this effect (as estimated in the household-level analysis) and changes in transit, which can be viewed as a proxy for other unobservables affecting expected changes and unobservable to me. It is very unlikely that any unobservables remaining would include new information about selection, not predicted by the included controls, that would be more important than the information included in the observed controls. I Also note a very large R^2 in the extensive margin that is driving the aggregate outcome, leaving only a little variation to be explained.

The parameter values suggested by Oster (2019) in this specification ($\delta = 1$, $R_{max} = 0.99$) imply that new information contained in the unobservables has the same importance regarding selection as the included controls, and that $\Delta log\,(cars)$ would be almost perfectly predicted by the hypothetical complete regression described by Equation (4), not allowing for any notable measurement error, random variation, or idiosyncrasies to affect the outcome. These are undoubtedly excessively conservative assumptions, thus the ρ^* presented in Table 3 can be viewed as a lower bound on the real effect. For completeness, I also present δ^*, the level of δ that would imply $\rho^* = 0$ when assuming $R_{max} = \min\left(1.3\widetilde{R}^2, 1\right)$. Under these conservative assumptions, I can place a lower bound of $\underline{\rho} = 0.656$ in urban regions. One has to assume that selection on unobservables is almost six times more important than selection on observables to claim a possible zero effect due to omitted variable bias. Using the additive nature of the problem, $\Delta log\,(VKT) = \Delta log\,(cars) + \Delta log\left(\frac{VKT}{Car}\right)$, the extensive margin, overlooked in previous work, accounts for at least 69% of the aggregate effect.[18]

I further explore the findings reported in Table 3 using a more detailed partition of the sample based on the level of residential density in the neighborhood's surroundings, which is my preferred indicator for urbanism. The estimated regression is similar to the specification appearing in the last column in Table 2, except that the sample is now divided into four groups instead of two by their level of urbanism (measured by experienced residential density), with the least urban

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[18] This number is calculated by dividing 0.515, which can be viewed as a lower bound on the extensive margin effect, by the estimate for the total effect (0.75), which can be viewed as an upper bound to the overall effect if one assumes that no new information regarding positive selection of new road allocation is contained in the unobservables.

group corresponding to nonurban areas as defined in previous tables. Figure 4 presents the results.

Even within urban areas, a much greater effect is estimated in the most urban neighborhoods in the sample. Similar patterns emerge when using either locality population counts or metropolitan status as defined by the Israeli CBS as an indicator for urban status (see Appendix Figures A3 and A4). Recall that the car usage variables used in the analysis are based on place of residence, and not the region in which one drives his car. If one is willing to assume that suburban residents drive downtown more than urban residents drive to the suburbs, the actual gradient of the effect in terms of congestion is actually steeper than the one presented.

I estimate $\rho > 1$ in the most urban areas of Israel (metropolitan cores as defined by the CBS: Jerusalem, Tel Aviv, Haifa, and Be'er Sheva, see Appendix Figure A4), suggesting that new road allocation in urban cores might not only fail to relieve, but could actually worsen, congestion in these areas. The effect here is also due almost entirely to the extensive margin. New roads in urban cores encourage residents to become car owners, but usually have at most a minor and imprecisely measured effect on the intensity with which residents use their cars.

These estimates align with the theoretical model's predictions. More urban areas are characterized by both higher congestion and a lower motorization rate.[19] Higher congestion implies a higher elasticity of travel time with respect to new road allocation. Accordingly, I estimate a gradient of ρ increasing with congestion, which is driven by the extensive margin, as expected (Appendix Figure A5). Nonurban areas are less congested to begin with, hence increased capacity has a smaller effect on travel speed. A lower motorization rate in urban areas implies

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[19] In my sample, the average 2015 motorization rate (total number of cars divided by the number of adults residing in the region) in the four presented urban groups were: 62.3%, 56.4%, 55.3% and 48.6%. The lower number of cars in more urban areas is notable since urban areas are generally more wealthy. I define congestion as total VKT by residents of neighborhoods in the 3 km radius around the neighborhood's centroid, divided by road capacity. The average congestion in those four groups was: 46.4, 134.4, 165.4 and 160.3. Alternative congestion measures using different radii or computed at the commuting zone level display similar patterns, with some measures showing an increase in congestion in the most urban group as well.

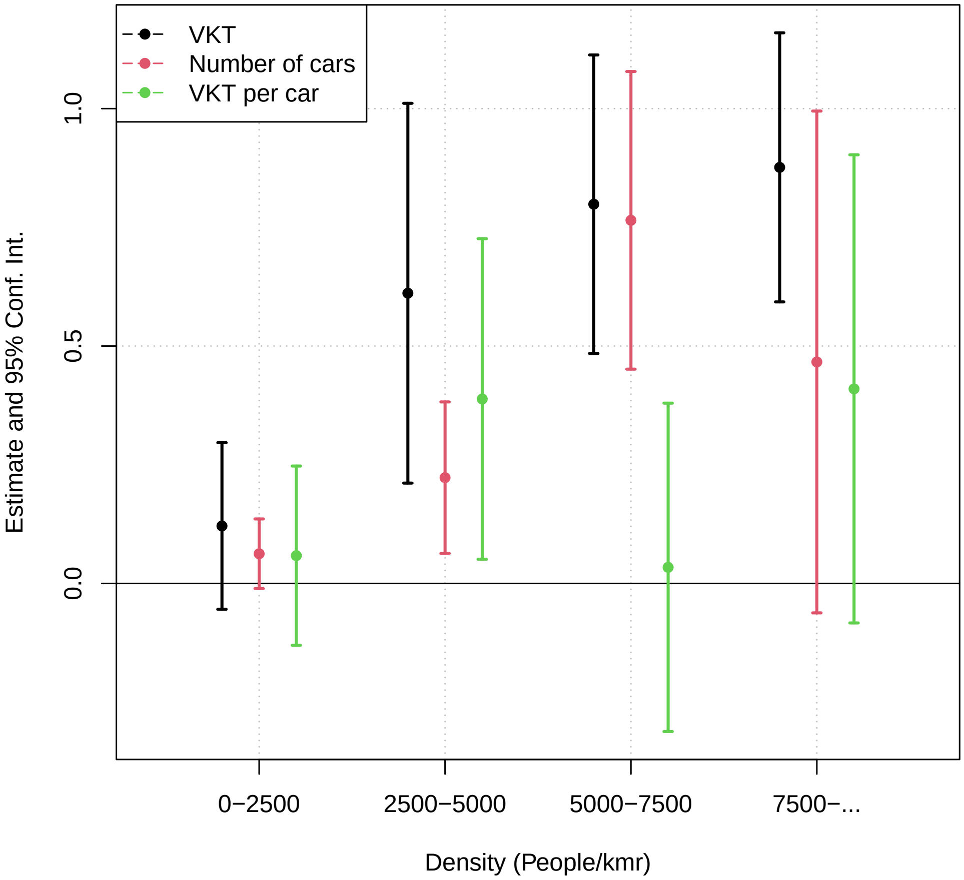

Figure 4. The elasticity of car usage with respect to road capacity, by residential density

Note: This figure presents the elasticity of the different margins of car usage with respect to road capacity by residential density groups, as estimated in the neighborhood level and using a first-differences approach detailed in Equation (3). The specifications include the same set of controls as in the last column of Table 2. Density is measured in the 3 km radius surrounding the centroid of the neighborhood. The 95% confidence intervals are based on standard errors clustered at the subdistrict level.

that more households are still able to respond to road allocation in the extensive margin, which I demonstrate both theoretically and empirically to be the dominant channel, also implying a higher effect.

I conclude the neighborhood-level analysis by examining the robustness of the finding that the intensive margin is not significant in determining the overall elasticity of VKT with respect to road capacity. As discussed in the theoretical section, new car owners might have a systematically lower propensity to travel compared to incumbent car-owning households, making them less likely to become owners in the first place. In that case, the estimated overall small intensive margin effect can be a mix of a positive effect on incumbent owners alongside a negative composition effect.

Table 4 presents the estimated effect of road capacity on VKT per car for the entire sample (similar to the specification reported in Table 3), the effect on total VKT in the same sample while controlling for log difference in the number of cars in the region, thus allowing a lower-than-proportional effect for new cars, and the effect on VKT per car in a group of incumbent car owners—households that didn't change their residence and the number of cars they own between both periods. I find no statistically or economically important effect on the intensive margin in these specifications. The effect is even smaller in the household-level analysis presented below, lending support to the notion that no large aggregate intensive margin channel is muted by a negative composition effect.

The rest of this section discusses different robustness checks for the main results. Findings are reported in the Appendix.

CONFOUNDING FACTORS. — The baseline estimation linearly controls for a large set of confounders, and the possible bias induced by missing confounders is gauged using the method developed in Oster (2019). I further attempt to examine robustness to confounding factors using two alternative estimation methods that allow a more flexible specification of confounders: (1) Double-selection LASSO (Belloni, Chernozhukov and Hansen, 2014) where the set of controls is augmented with all possible two-way interactions between them. This approach allows for more nuanced roles these confounding factors might have in the data generating process; (2) Nearest neighbor matching, which uses variation between observa-

Table 4—The elasticity of VKT with respect to road capacity: the intensive margin

Group	$\Delta\log\left(\frac{VKT}{Car}\right)$ All	$\Delta\log(VKT)$ All	$\Delta\log\left(\frac{VKT}{Car}\right)$ Incumbent owners
$\rho^{Urban} : (Urban * \Delta\log(R))$	0.184*	0.184*	-0.077
	(0.099)	(0.103)	(0.084)
$\rho^{Nonurban} : (Nonurban * \Delta\log(R))$	0.056	0.056	0.186
	(0.096)	(0.097)	(0.136)
$\Delta\log(Cars)$		0.999***	
		(0.057)	
Observations	2,568	2,568	1,988
R^2	0.058	0.588	0.131
Adj. R^2	0.052	0.585	0.124

Note: The table presents the estimated elasticity of the intensive margin of car usage with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level and using the first-differences approach detailed in Equation (3). All specifications include the same set of controls detailed in the last column of Table 2. Incumbent owners are households who owned at least one car in the base period, and did not change their marital status, residence and the number of cars they own between both periods. Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

tionally similar units to estimate the effect. Both methods provide results that are qualitatively and generally also quantitatively similar to those estimated using the baseline approach. Implementation details and results are reported in Appendix D.

Sample selection. — Baseline neighborhood-level results are based on all residents observed in my sample, and only include neighborhoods in which at least 50 residents are observed in both periods. I confirm that results are robust to this choice by repeating the baseline estimation with several alternative sample inclusion criteria.

I change the neighborhood inclusion criteria to observing at least 20 or 100 residents; I limit the sample to only include prime-age (25–64) residents[20]; I exclude residents with extreme car usage values from the sample; I estimate two

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[20] This check is conducted since I can better confirm that in those ages my sample is representative of the entire population (see discussion in Appendix C).

specifications in which I exclude neighborhoods where the change in either car usage or road capacity was in the top or bottom 2.5% of the distribution; and lastly, I repeat the baseline specification multiple times, where in each iteration I exclude one of the localities appearing in the sample to ensure that results are not largely affected by any single locality. The results, reported in Appendix Table A3 and Figure A6, demonstrate robustness to these alternative criteria.

ALTERNATIVE CAPACITY MEASURES. — I define road capacity as the sum of lane-kilometers in the 10 km radius surrounding the centroid of each neighborhood. I provide no specific evidence supporting the choice of this radius, so I estimate similar regressions using alternative capacity measures, including radii of 5 and 15 km surrounding the neighborhood's centroid. One could claim that the relevant area for travel is larger in rural regions than in urban regions. In response to such a concern, I also define two capacity measures for each neighborhood as the minimal circle around its centroid containing 100,000 residents or jobs (as proxied using cellular location data (Cohen, 2021)). All results, reported in Appendix Table A4, remain qualitatively similar to those presented in the main text, though the magnitude of the coefficients is smaller when the capacity measure is based on smaller radii around the centroid of the neighborhood, and greater when I allow a greater circle to be relevant.

ALTERNATIVE VINTAGES. — As discussed in Section IV, no single vintage of the roads network GIS file credibly describes the network as it is at a single point in time. In the baseline analysis I define the vintage relevant to 2015 as the one published in July 2015, and the vintage relevant to 2019 as the one published in December 2019. I reestimate all results presented in the main text using all the possible combinations of the current, previous, and next available vintages for each year (January 2014, July 2015, and May 2016 for 2015, and September 2019, December 2019, and June 2020 for 2019). The results, reported in Appendix Table A5, remain qualitatively and generally also quantitatively similar.

Inference. — I report standard errors clustered by subdistrict throughout the neighborhood-level analysis, and at the neighborhood level in the household-level analysis. In Appendix Table A6 I report standard errors clustered at different levels, and standard errors allowing for spatial correlation (Conley, 1999) for the main results to demonstrate that this choice has no important effect on statistical significance.

B. Household level analysis

I complement the neighborhood-level analysis presented above with an estimation of the heterogeneity in household-level responses to capacity expansions. This type of result is novel to the literature, and can shed light on the type of households driving the aggregate response function, providing empirical support to the mechanisms suggested above.

I examine the effect at the household level using two approaches: a standard first-difference similar to the neighborhood-level analysis to gauge the average incumbent household's response, and a second approach utilizing within-neighborhood variation to more credibly estimate heterogeneity in the response between different groups of households.[21]

First differences. — I estimate the average effect of capacity expansions on households' car usage by estimating a first-differences model similar to the one presented in the neighborhood analysis. I focus on the effect on incumbent households and exclude movers from the sample for easier interpretation of the results. Hence, predicted differential sorting into an area (which was a potential part of the mechanism in the neighborhood-level analysis above) does not affect the results at the household level. The examined car usage variables include total

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[21] I include in the sample households created or dissolved between both periods of the study by summing car usage for both spouses in the period when they were single. Omitting newly created households would leave very few observations of young families, which are an important segment of the population in my context.

household VKT, which represents the intensive margin for incumbent drivers, and the change in the number of cars in the household, which represents the extensive margin. I further explore the extensive margin by examining changes in a binary variable indicating ownership of any vehicle in the household. Specifically, I estimate variants of Equation (5):

$$\Delta Y_{ij} = \sum_{\zeta} \left[\zeta_j + \rho^{\zeta} * \left(\Delta log \left(R_j \right) * \zeta_j \right) \right] + \beta X_i + \upsilon_i \tag{5}$$

where ΔY_{ij} is the difference in the car usage measure of household i, which resides in neighborhood j, between 2015 and 2019, $\zeta_j \in (Urban, Nonurban)$ is the urban status of neighborhood j, ΔR_j is the road capacity measure in the region surrounding the individual's neighborhood of residence, and X_i is a vector of controls.[22]

This approach requires assuming that, conditional on included covariates, road allocation during the period was not correlated with the predicted future demand of the individuals residing in the area. Since the first-differences are taken at the household level, the assumption should also be interpreted at the household level. A possible violation of this assumption requires the planning authority to predict and respond in a timely manner to a change in the propensity of incumbent individuals in the region to use cars due to factors unobservable to me. As in the neighborhood-level analysis, I examine robustness to this assumption using the method and parameter values suggested by Oster (2019), though I acknowledge that the assumptions regarding R_{max} and δ are less conservative at the household level than in the neighborhood-level analysis presented above.

Table 5 presents the results from this estimation.[23] As in the neighborhood-

[22] Including a cubic in the average age of both spouses in the household, a binary variable for non-Jewish households, and the first-difference in the number of adults in the household, number of children, and a binary variable for children under 5 in the household, total household's income, and both spouses' months worked and level of education.

[23] It is important to note that magnitudes in the individual-level results need not directly correspond to neighborhood-level results. For example, this estimation puts an equal weight on each household instead of each region, and the sample now excludes households that changed residence between the periods and

level analysis, I find no important intensive margin, and a significant extensive margin effect in urban areas only. The estimated effect implies that doubling road capacity would lead to a 0.589 average increase in the number of cars a household owns (which is roughly a doubling of the baseline level in those areas, see Table 1). A doubling of the road capacity would also lead to a 19.6 percentage point increase in the share of car-owning households. The last two columns of Table 5 demonstrate that this effect is driven by both an effect on non-owners encouraging them to become owners, and an effect discouraging incumbent owners from selling their car. (These effects are estimated separately for the population of non-owners and owners accordingly.) The results are qualitatively robust when trying to account for possible nonrandom allocation of roads.

Table 5—The elasticity of household car usage with respect to road capacity

	(1)	(2)	(3)	(4)	(5)
	$\Delta\log(VKT)$	Δ Cars	Δ Owners	Δ New owners	Δ New non-owners
$\rho^{Urban}: (Urban * \Delta\log(R))$	-0.029	0.589***	0.196***	0.207*	-0.259***
	(0.111)	(0.057)	(0.031)	(0.107)	(0.039)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	-0.084	-0.038	-0.033*	-0.135**	0.031
	(0.079)	(0.034)	(0.018)	(0.055)	(0.028)
$\rho^{*}\left(\delta=1, R_{max}=\min\left(1.3\widetilde{R^2},1\right)\right)$	-0.1	0.509	0.131	0.166	-0.252
$\delta^{*}\left(R_{max}=\min\left(1.3\widetilde{R^2},1\right)\right)\rightarrow\rho^{*}=0$	-0.402	7.029	2.981	4.907	32.787
Observations	197,429	1,249,551	1,249,551	619,864	629,687
R^2	0.010	0.012	0.03	0.038	0.032
Adj. R^2	0.010	0.012	0.03	0.038	0.032

Note: The table presents the estimated elasticity of car usage with respect to road capacity in urban and nonurban areas, as estimated in the household level and using the first-differences approach detailed in Equation (5). Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Columns (4) and (5) are estimated using only the sub-sample of incumbent non-owners and owners accordingly). Standard errors clustered by neighborhood are reported in parentheses.

households with new cars not obliged to take an annual inspection test.

WITHIN-REGION DIFFERENCES. — The main advantage in using micro-level data in this analysis is that it enables one to understand which population groups are driving the aggregate result, providing empirical support for hypothesized mechanisms. I explore this heterogeneity by examining within-region variation in the response to increased capacity using Equation (6):

$$\Delta Y_{ij} = \alpha_j + \sum_{g \in G} \xi_i^g * \sum_{\zeta} \left[\zeta_j + \rho_g^{\zeta} * (\Delta log\,(R_j) * \zeta_j) \right] + \beta X_i + \upsilon_i \tag{6}$$

In this equation, α appears with a subscript j, indicating a distinct intercept for residents in each neighborhood. Since road allocation is defined at the neighborhood level, the effect is now estimated using only within-neighborhood variation. In addition, each group membership indicator, ξ_i^g, enters the regression as an indicator and as a multiplier on road capacity separately for urban and nonurban areas. Under this formulation, one cannot estimate an average treatment effect, but one can estimate heterogeneity in the effect between population groups relying on within-neighborhood variation in the response. The coefficient of interest, $\rho_g^{\zeta=Urban}$, estimates the excess effect in the specified group of interest g compared to the rest of the urban population if only a single group is examined (G is a set of size 1), and compared to a specified omitted base group when multiple exhaustive and mutually exclusive groups are examined.

This approach requires a significantly less restrictive assumption about the exogeneity of allocation. Specifically, one has to assume that even if the planning authority predicts and responds to a change in the average propensity to use cars in the region, allocation is not further influenced by the predicted differential change in travel demand of specific groups coinciding with the examined groups of interest. As in the first differences approach, I estimate this model without movers.

I focus the presentation on the extensive margin in urban regions only. A similar unreported analysis on the intensive margin showed no important or robust heterogeneity between groups. Even though both urban and nonurban regions are included in the sample, I focus on the estimated excess effect in urban regions only. A similar analysis for nonurban regions found no important heterogeneity in the effect in those areas.[24]

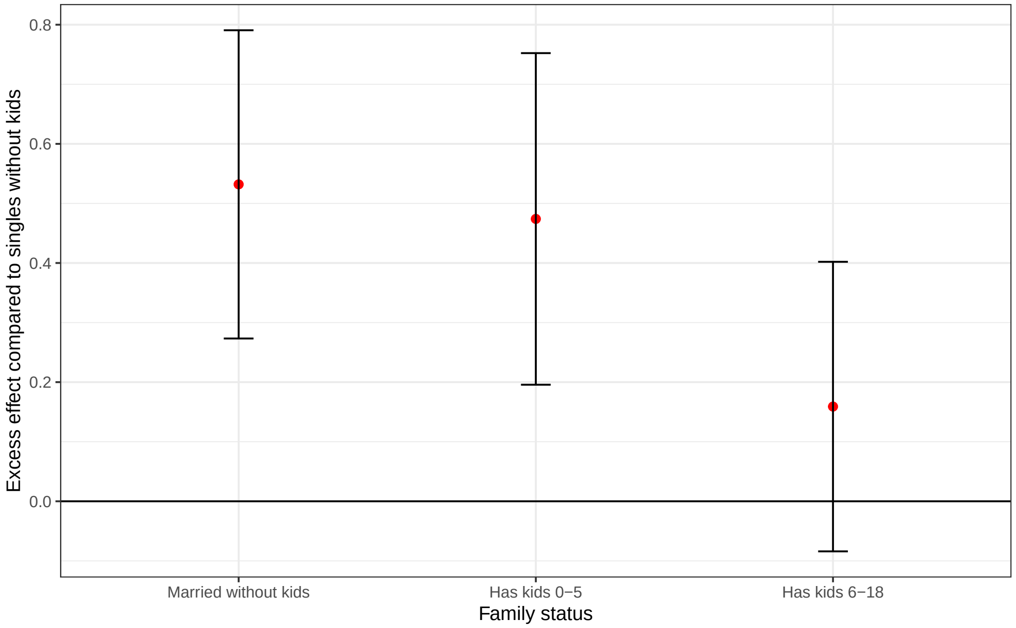

Figure 5. The excess effect of road capacity on the number of cars in the household, by family status

Note: This figure presents the excess effect of road capacity on the number of cars in the specified group of households in urban areas compared to childless singles. The excess effect is estimated using within-neighborhood variation as specified in Equation (6). Urban areas are defined here as neighborhoods where the density in the 3 km radius around the centroid is greater than 2,500 people per square kilometer. The 95% confidence intervals are based on standard errors clustered at the neighborhood level.

Figure 5 presents the excess effect road capacity has on the number of cars in the household for different types of households based on family status.[25] The defined groups are mutually exclusive and exhaustive, and the omitted base group includes childless singles. Hence, the estimated effect for each type of household is the excess effect for this type of household compared to the effect for childless

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[24] See Table 6 for a summary of results for nonurban areas.
[25] Family status is defined per the 2019 condition.

singles in urban areas. A large and statistically significant excess effect is found for families with children under 5, and for married childless couples. There is no significant excess effect for households with children above 5, indicating that one cannot reject the hypothesis that the effect of road capacity on car purchases for households with older children is similar to the effect it has on singles.

Figure 6 presents a similar exercise, with the sample now partitioned by the number of cars the household owned in the base period (2015). The omitted base group contains households without a car in 2015. I estimate a significantly greater effect for households with a single vehicle in the base period than for the rest of the sample. The excess effect is not significantly different from the omitted base group (non-owners in the base period) in households with two or more vehicles in the base period.

Figures 7 and 8 report the excess effect by age and income accordingly. The figures are based on multiple regressions where for each age or income bracket a separate regression is estimated in which this group is defined as the only group of interest in the regression (the set G in each regression is of Size 1). I find an excess effect in households where the spouses' average age is between 30 and 35, and income levels are low to medium. A significantly weaker effect is found for very low income levels and young ages.

The result regarding the level of income is similar to the one predicted by the theoretical model with heterogeneous income presented in Section III. Households with very low income cannot afford to purchase and maintain a car without sacrificing consumption that is more necessary to them. High-income households are less financially constrained, and usually owned their desired number of cars even before capacity expanded. The marginal households, which are most responsive to capacity expansions, are concentrated around a certain income threshold in which car ownership, or the purchase of a second car was made profitable in utility terms only after the expansion.

Overall, estimations using the within-regions differences approach indicate that

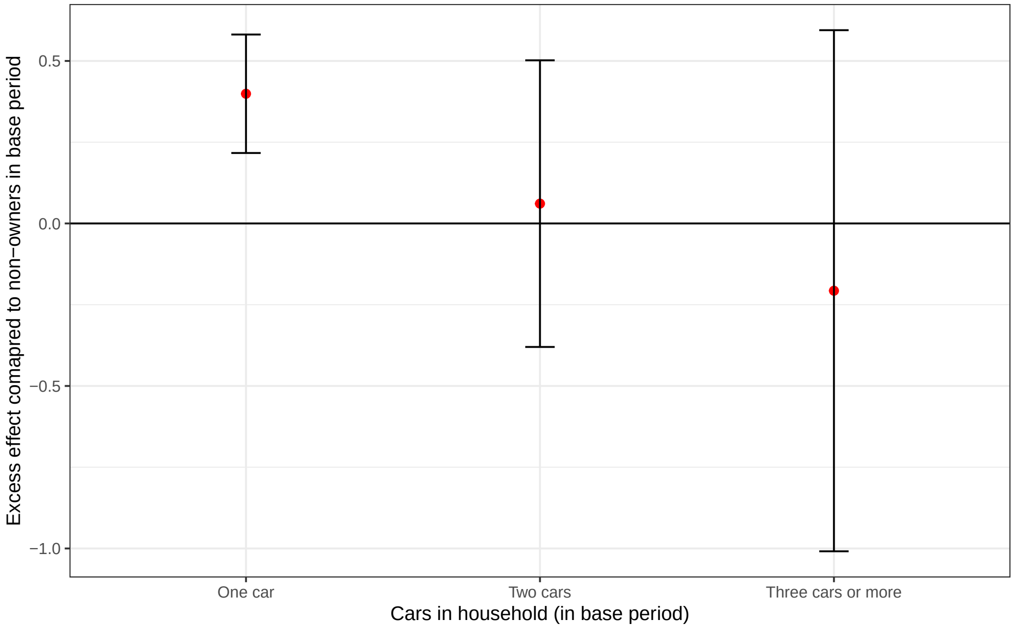

Figure 6. The excess effect of road capacity on the number of cars in the household, by number of cars in the base period

Note: This figure presents the excess effect of road capacity on the number of cars in the specified group of households in urban areas compared to households that were non-owners in the base period. The excess effect is estimated using within-neighborhood variation as specified in Equation (6). Urban areas are defined here as neighborhoods where the density in the 3 km radius around the centroid is greater than 2,500 people per square kilometer. The 95% confidence intervals are based on standard errors clustered at the neighborhood level.

the population group most responsive to road capacity were young families with low-medium income levels. The margin in which they responded most was the extensive margin, specifically choosing to own a second car in the household. A much weaker response was documented for singles, very young households and households with low income not owning a car in the base period.

There could be a significant overlap between the groups for which I estimate a significantly higher response. Table 6 displays estimates of the excess effect for each of these population groups in specifications with a single group of interest, and in a single specification where the effects of belonging to each of the population groups are jointly estimated. The inclusion of all groups in the same

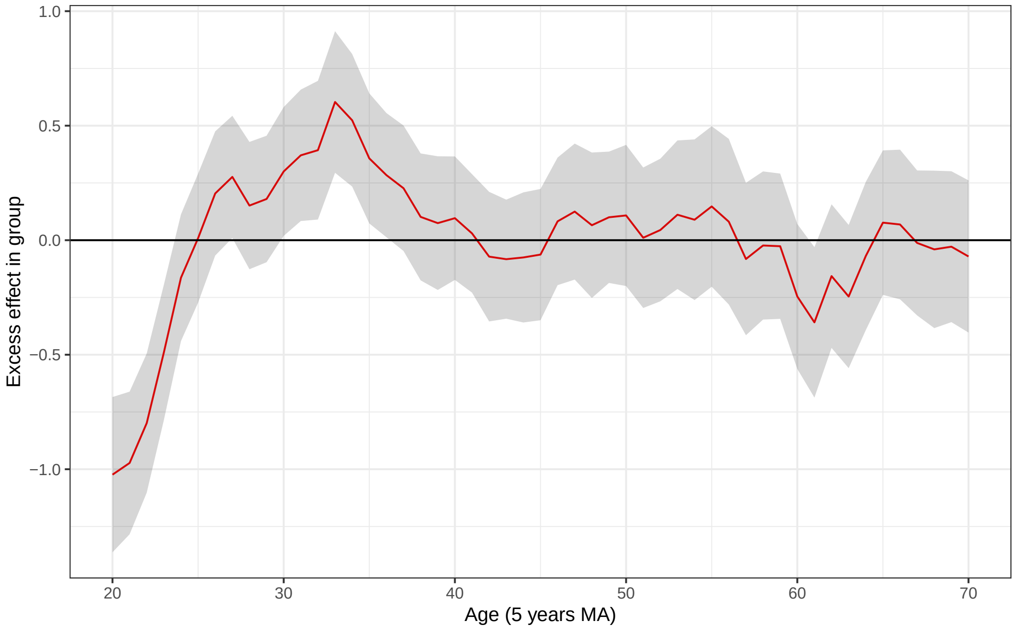

Figure 7. The excess effect of road capacity on the number of cars in the household, by age

Note: This figure presents the excess effect of road capacity on the number of cars owned by households in the specified age group compared to the rest of the sample in urban areas. The age of the household is defined as the average age of both spouses, and is estimated with a 5-year moving window. The excess effect is estimated using within-neighborhood variation as specified in Equation (6). Urban areas are defined here as neighborhoods where the density in the 3 km radius around the centroid is greater than 2,500 people per square kilometer. The 95% confidence intervals are based on standard errors clustered at the neighborhood level.

specification has only a small effect on the coefficients, demonstrating the unique contribution of each of these factors to the estimated excess effect.

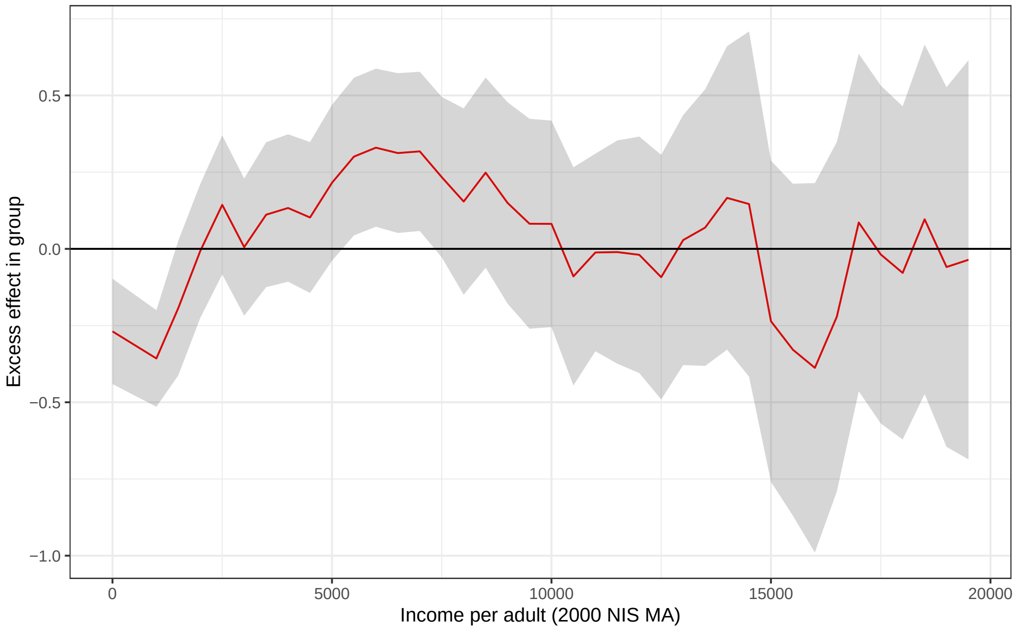

Figure 8. The excess effect of road capacity on the number of cars in the household, by household income

Note: This figure presents the excess effect of road capacity on the number of cars owned by a household in the specified income group compared to the rest of the sample in urban areas. Income is defined in a NIS 2,000 moving window. The excess effect is estimated using within-neighborhood variation as specified in Equation (6). Urban areas are defined here as neighborhoods where the density in the 3 km radius around the centroid is greater than 2,500 people per square kilometer. The 95% confidence intervals are based on standard errors clustered at the neighborhood level.

Table 6—The excess effect of road capacity on the number of cars a household owns

	(1)	(2)	(3)	(4)	(5)
Has one car $*\Delta\log(R)$	0.673***				0.625***
	(0.163)				(0.168)
Has one car $*\Delta\log(R)*NU$	0.101				0.106
	(0.108)				(0.113)
Income per adult 5000–7500 $*\Delta\log(R)$		0.294**			0.278**
		(0.119)			(0.119)
Income per adult 5000–7500 $*\Delta\log(R)*NU$		-0.024			-0.028
		(0.085)			(0.084)
Age 30–35 $*\Delta\log(R)$			0.486***		0.440***
			(0.146)		(0.146)
Age 30–35 $*\Delta\log(R)*NU$			-0.028		-0.022
			(0.09)		(0.089)
Married without kids or with kids aged 0–5 $*\Delta\log(R)$				0.331***	0.281***
				(0.098)	(0.103)
Married without kids or with kids aged 0–5 $*\Delta\log(R)*NU$				-0.036	-0.049
				(0.074)	(0.079)
Observations	1,249,551	1,249,551	1,249,551	1,249,551	1,249,551
R^2	0.015	0.015	0.015	0.015	0.015
Adj. R^2	0.013	0.013	0.013	0.013	0.014

Note: The table presents the estimated excess elasticity of the number of cars owned by the specified groups of households with respect to road capacity in urban and nonurban areas, compared to the rest of the sample. The excess effect is estimated using the within-region differences approach detailed in Equation (6). Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered at the neighborhood level are reported in parentheses.

VII. Discussion and concluding remarks

A. Main findings

Starting from the seminal work by Duranton and Turner (2011), papers in many empirical settings documented a version of the fundamental law of road congestion predicting a one-for-one response of VKT to road capacity, implying that expanding capacity would not affect congestion. A few recent papers tried to challenge the universality and theoretical plausibility of this law. This paper contributes to prior literature by first documenting systematic variation in the response of VKT to capacity expansions, and by using micro data to understand the different mechanisms driving this response. The empirical results align with predictions from a simple theoretical model incorporating a car ownership choice to the agent's travel choice problem.

Previous work assumed, either implicitly or explicitly, that the dominant margin determining the aggregate response is the intensive margin: capacity expansions would lead drivers to use their cars more. I show that the intensive margin's contribution to the overall response is marginal at best. The response is driven mostly by the extensive margin: more roads lead to people purchasing more cars. The dominant role the extensive margin plays in the overall response is predicted by the theoretical model described in Section III. I also show that enabling an extensive margin, which was missing in the theoretical argument made by Anas (2024), reconciles the apparent discrepancy between theory and previous empirical work.

I show that the effect of road capacity on congestion is not fundamentally constant. Road capacity has a systematically greater effect in more urban areas, such that the elasticity of VKT with respect to road capacity is approximately zero in rural regions, significant but less than one in suburbs, and greater than one in the most congested and urban regions in my sample (metropolitan cores as defined by the CBS), indicating that more roads would actually worsen congestion in these regions.[26] More urban areas are characterized by two attributes contributing to the stronger response: (1) a lower motorization rate than rural regions allows a stronger response in the dominant extensive margin; (2) congestion in these areas was worse in the first place, implying a high elasticity of travel times with respect to capacity expansions in them compared to this elasticity in nonurban regions.

I utilize the available micro data to identify the population groups driving the aggregate response. This type of result is novel to the literature. The effect stems from the extensive margin and is overwhelmingly stronger for young families in the lower to middle segments of the income distribution, mainly those households that owned a single car before the capacity expansion. The stronger extensive margin effect around a certain income threshold is predicted by the theoretical model with heterogeneous income developed in Section III. I find no important heterogeneity in the effect in the intensive margin or in nonurban areas between different population groups.

B. Policy implications

Modern urban life revolves around mobility. People work, study, consume products and services, and socialize in a variety of locations different from their residence. Thus, accessibility is a crucial component in determining the utility of living in different locations. However, in order to enjoy opportunities accessible only by travel, people have to pay a travel cost which consists mainly of time spent on the road. Planning authorities aspire to minimize travel costs with a variety of policy measures. Since congestion lowers speed, and thus increases travel costs for all road users, a popular policy measure to improve accessibility is the expansion of road capacity, allowing more cars to travel on the network at any point in time, thus hopefully reducing city-wide congestion and travel costs.

My findings imply that increasing capacity is not always a good policy instru-

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[26] Keeping in mind that I attribute car usage by place of residence, and assuming that suburban residents drive downtown more than the opposite direction, the urban gradient in terms of the effect on congestion is even steeper than implied by estimation results.

ment if one aims to mitigate congestion in urban regions. In fact, in my empirical setting, building more roads in metropolitan cores is more likely to worsen congestion than to relieve it.[27]

The main mechanism driving induced demand is the extensive margin: Building more roads will lead to people buying and driving more cars, which will eliminate the intended relief of congestion. As theory suggests, and according to my empirical findings, the intensive margin would not respond as strongly. Hence, in cities where car ownership is close to universal, we would expect $\rho < 1$, and building more roads would have the potential to relieve congestion, thus increasing accessibility. This description fits many modern-day American cities.

Transit-centric cities, like many cities in Europe and East Asia, provide residents with a high level of accessibility without the need to own a car. In this type of city, fewer residents own cars. This strengthens the potential response in the extensive margin, implying that, as in my empirical context, building more roads might worsen congestion. In places where transit is not provided with exclusive right of way, congestion would also directly impair accessibility by transit, encouraging even more residents to become car owners by making the alternative mode less competitive.[28]

The mechanisms explored here suggest a binary choice policy makers have to make when choosing the prominent mode of travel in the city, but this discussion only focuses on the effect of roads on accessibility, and is not a complete welfare analysis. Investing in private car infrastructure instead of transit has other important effects on the city not discussed here, including pollution, accidents, suburbanization and sprawl, and various equity effects, all favoring the choice of transit-oriented development.[29]

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[27] It is important to note that building more roads will still have the benefit of allowing more people to travel on the network, even though it will impair accessibility for incumbent owners through higher congestion.

[28] The urban form effects of car infrastructure reduce the attractiveness of transit to potential users indirectly as well. See the discussion by Amedi (2023).

[29] See Glaeser and Kahn (2004); Baum-Snow (2007); Currie and Walker (2011); Chen and Whalley (2012); Garcia-López, Holl and Viladecans-Marsal (2015); Gibson and Carnovale (2015); Knittel, Miller and Sanders (2016); Romem and Shurtz (2016); Garcia-López (2019); Lichtman-Sadot (2019); Alexander

Cities choosing transit as a prominent mode of travel would not benefit accessibility-wise from building more roads, and can improve accessibility only by using other policy measures: densification, and investments in transit or bike infrastructure or in making the city more walkable. Car-centric cities could mitigate congestion and provide accessibility to residents by expanding roads. However, this policy would only be effective if the road network was developed enough so that the motorization rate in the city was high in the first place, and will bear various other costs not discussed here. Cities trying to improve city-wide accessibility by both modes at once are doing themselves a disservice by both worsening congestion and reducing incentives to use transit while bearing an unnecessarily high monetary cost.

C. The case of Israel

Historically, Israeli cities were relatively transit-oriented, but they have become more car-centric in recent decades.[30] The motorization rate steeply increased over the years due to car-centric urban planning favoring wide roads and suburbanization instead of densification and revival of urban cores, and due to the increasing affordability of car ownership (see discussion at Friedmann (2019)). This process has the potential to continue, as the current motorization rate is still low relative to similarly developed economies (Appendix Figure A1). The increase in the motorization rate alongside Israel's exceptionally rapid population growth rate have led to a steep incline in the number of registered vehicles (Figure 1).

Although road capacity gradually increases as well, it seems unrealistic to expect it to catch up with such a steep increase in demand for car travel especially within urban areas, where increasing capacity is more complicated and bears higher costs both in monetary terms and in its effect on urban form. The widen-

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and Schwandt (2022); Fretz, Parchet and Robert-Nicoud (2022); Gendron-Carrier et al. (2022); Ostermeijer et al. (2022), for empirical evidence.

[30] For example, the national share of car-commuters was only 22.9 in the 1972 population census. This share rose steadily over the years to roughly two-thirds of all commuters according to recent CBS social surveys.

ing gap between the demand for car travel and the supply of roads leads to a pressing and worsening problem of traffic conditions across Israel, which is a concern of both public discourse and policy makers.

The potential for a continued increase in the number of vehicles, alongside current congestion levels, indicates that as a rule, Israeli cities should aspire to promote transit-oriented development while limiting resources dedicated to the private car. Such policies can include investment in urban mass transit systems, reducing the availability of curbside parking and parking requirements in new construction, the creation of dedicated bus lanes along all major urban roads, and urban densification.

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Appendix for

Who drives the Fundamental law of road congestion?

Gal Amedi, October 2025

Appendix A: Additional results

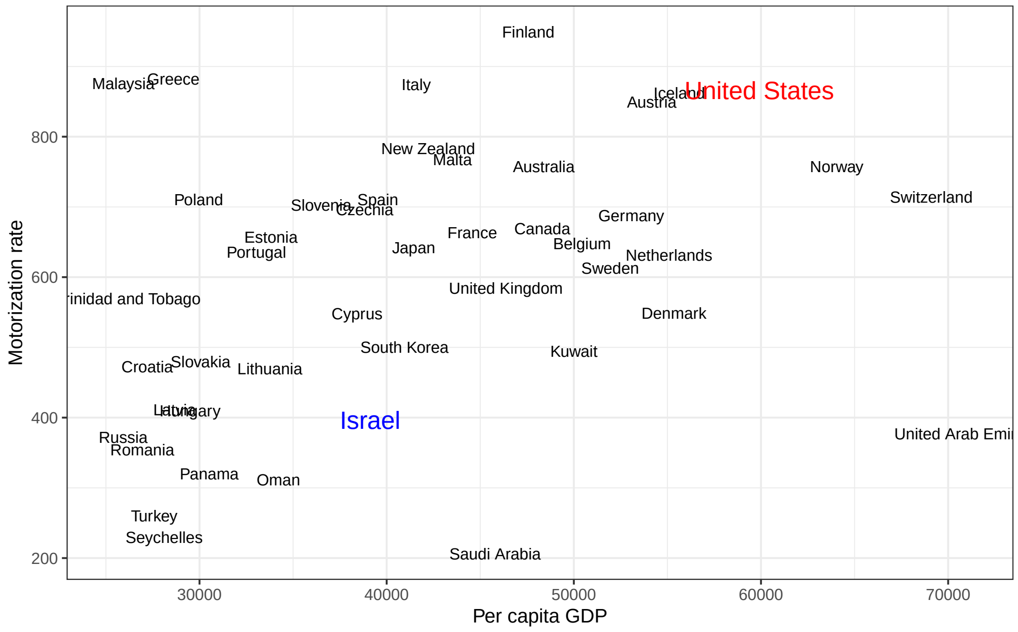

Figure A1. International comparison of motorization rates and per capita GDP, 2017

Source: World bank; WHO, Global Health Observatory (2022); United Nations. Population Division (2022). This figure presents an international comparison of motorization rates (registered vehicles per 1,000 people) and per capita GDP. Data is for 2017, or the closest year for which data was available. For visualization purposes, the figure only includes countries with a reported per capita GDP between 25,000 and 75,000 US dollars, and excludes San Marino for which an exceptionally high motorization rate was reported.

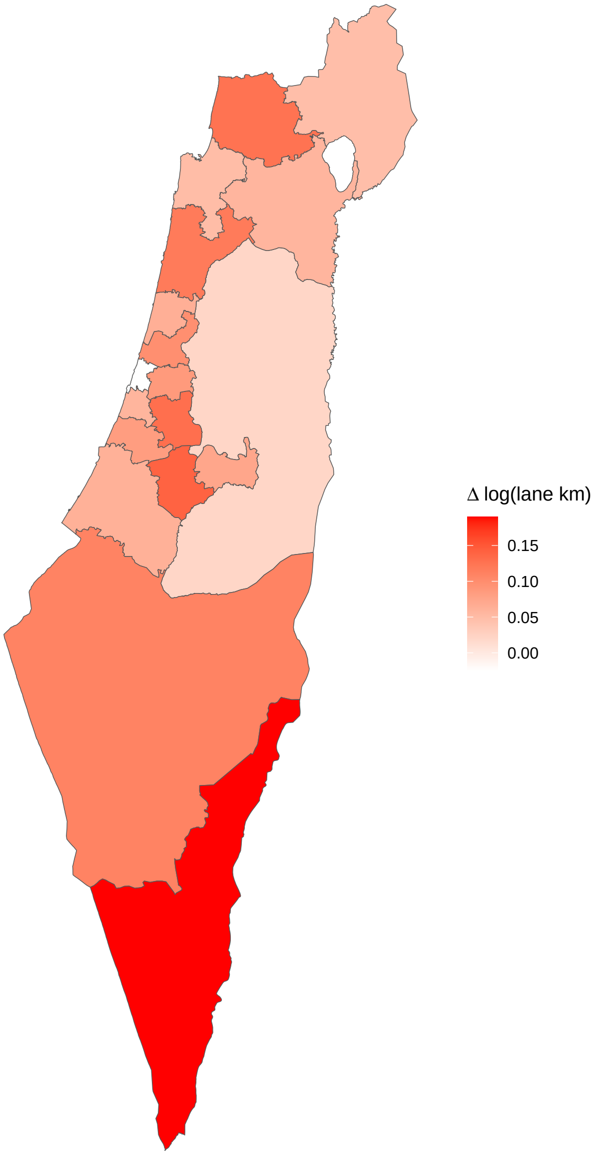

Figure A2. Capacity increases across Israel, 2015–2019

Note: The figure presents changes in log road capacity across commuting zones in Israel between 2015 and 2019. Commuting zone delineation is based on Amedi and Porat Hirsh (2026) in the version treating Judea & Samaria as a separate commuting zone.

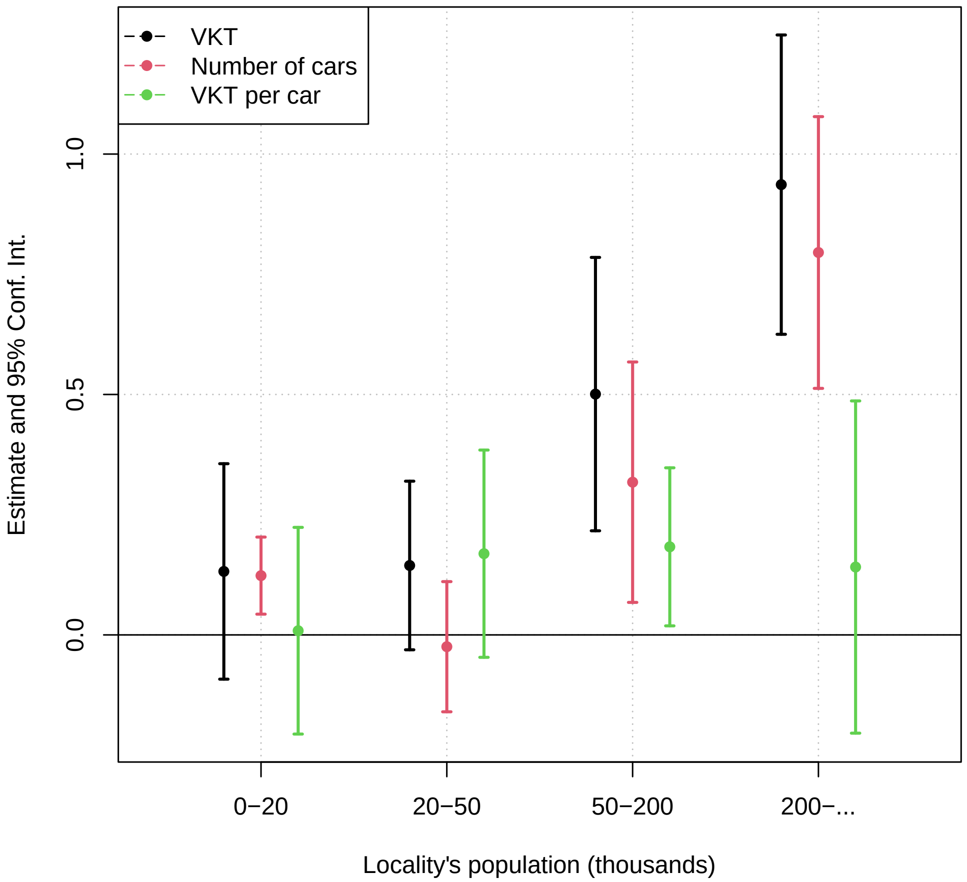

Figure A3. The elasticity of car usage with respect to road capacity, by locality's population

Note: This figure presents the elasticity of the different margins of car usage with respect to road capacity by locality population size, as estimated at the neighborhood level and using the first-differences approach detailed in Equation (3). The specifications include the same set of controls as in the last column of Table 2. The 95% confidence intervals are based on standard errors clustered at the subdistrict level.

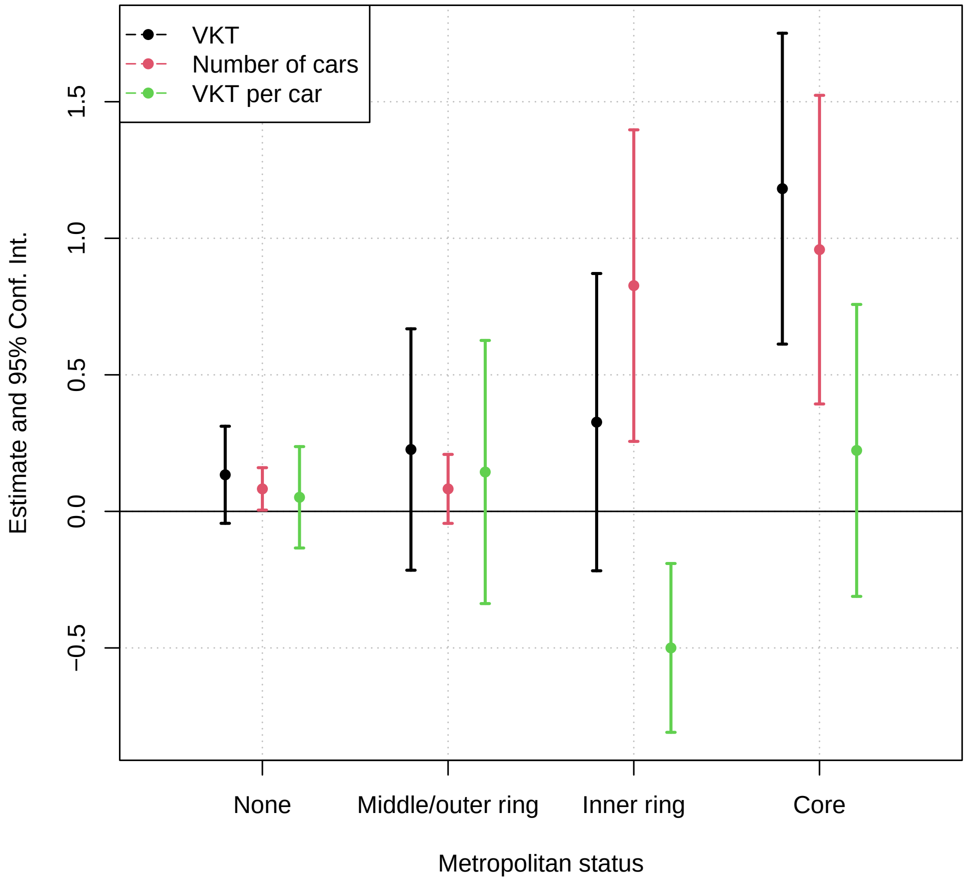

Figure A4. The elasticity of car usage with respect to road capacity, by metropolitan status

Note: This figure presents the elasticity of the different margins of car usage with respect to road capacity by metropolitan status, as estimated at the neighborhood level and using the first-differences approach detailed in Equation (3). The specifications include the same set of controls as in the last column of Table 2. The 95% confidence intervals are based on standard errors clustered at the subdistrict level.

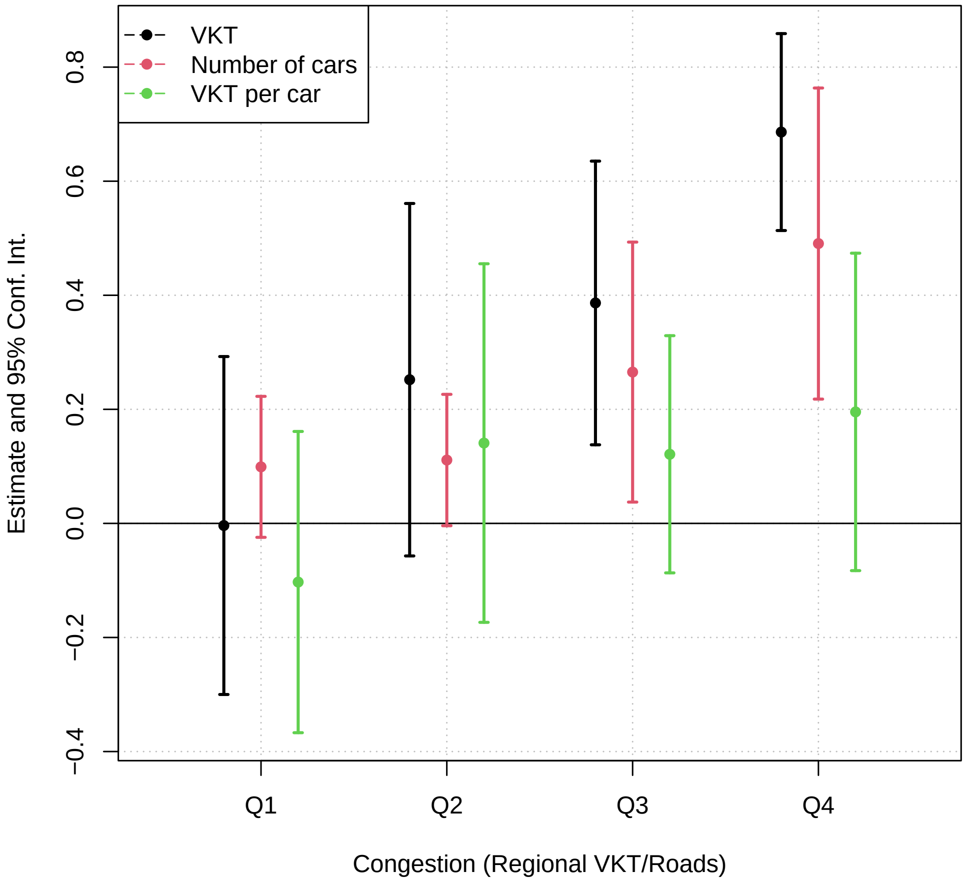

Figure A5. The elasticity of car usage with respect to road capacity, by base period congestion levels

Note: This figure presents the elasticity of the different margins of car usage with respect to road capacity by baseline congestion level in the region, as estimated at the neighborhood level and using the first-differences approach detailed in Equation (3). The specifications include the same set of controls as in the last column of Table 2. The 95% confidence intervals are based on standard errors clustered at the subdistrict level.

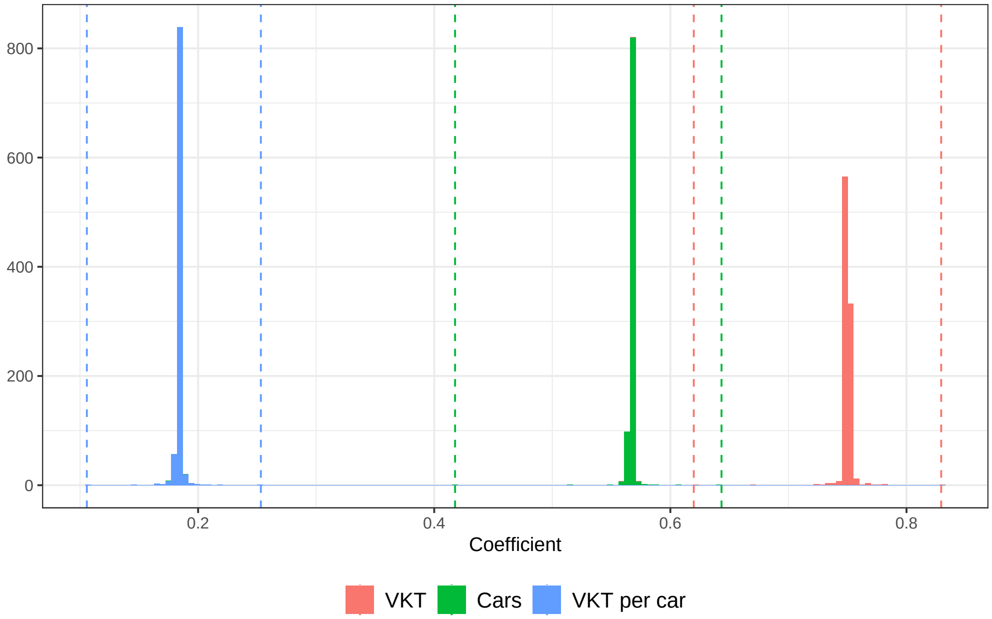

Figure A6. Coefficient distribution when excluding single localities

Note: The figure presents the distribution of coefficients for the elasticity of car usage with respect to road capacity in urban regions as estimated in 941 separate regressions for each outcome variable. Each regression excludes one of the 941 localities included in my sample. Dashed lines represent minimal and maximal values for each coefficient. The specification is detailed in Equation (3) and is the same as reported in Table 3.

Table A1—The elasticity of the number of cars with respect to road capacity

	(1)	(2)	(3)	(4)	(5)	(6)
$\rho^{Urban} : (Urban * \Delta \log (R))$	0.704***	0.308**	0.496***	0.579***	0.573***	0.566***
	(0.249)	(0.142)	(0.096)	(0.107)	(0.114)	(0.113)
$\rho^{Nonurban} : (Nonurban * \Delta \log (R))$	0.179**	0.077	0.056	0.056	0.060	0.066*
	(0.076)	(0.066)	(0.038)	(0.039)	(0.037)	(0.036)
Urban	0.085***	0.118**	0.245***	0.224***	0.222***	0.221***
	(0.011)	(0.044)	(0.026)	(0.023)	(0.020)	(0.025)
Nonurban	0.004	0.002	0.056***	0.058***	0.057***	0.057***
	(0.019)	(0.011)	(0.005)	(0.006)	(0.008)	(0.008)
Married without kids or with kids aged 0–5		0.356***	-0.044	-0.049	-0.037	-0.017
(2015 share)		(0.045)	(0.029)	(0.032)	(0.033)	(0.048)
Single car owners		-0.397***	-0.511***	-0.472***	-0.469***	-0.459***
(2015 share)		(0.081)	(0.043)	(0.041)	(0.038)	(0.043)
Earning NIS 5,000–7,500 per adult		-0.067	-0.737***	-0.603**	-0.579**	-0.548**
(2015 share)		(0.628)	(0.158)	(0.217)	(0.239)	(0.244)
Aged 30–35		0.191	0.014	-0.064	-0.052	-0.094
(2015 share)		(0.146)	(0.108)	(0.098)	(0.094)	(0.103)
$\Delta \log$ (Population)			1.068***	1.033***	1.059***	1.044***
			(0.033)	(0.029)	(0.044)	(0.032)
$\Delta \log$ (Total income)				0.098*	0.099*	0.100*
				(0.056)	(0.055)	(0.053)
Δ Employed				0.128	0.118	0.112*
				(0.076)	(0.079)	(0.061)
Δ Share in manuf.				-0.060	-0.063	-0.063
				(0.135)	(0.135)	(0.134)
Δ Academics				0.488***	0.483***	0.457***
				(0.095)	(0.091)	(0.101)
Δ Transit					0.000	0.000*
					(0.000)	(0.000)
2015 Congestion level					0.000	0.000
					(0.000)	(0.000)
$\Delta_{2013,2015} \log (Cars)$					-0.030	-0.029
					(0.023)	(0.023)
$\Delta \log$ (Kids 0–18)						0.005
						(0.037)
Δ Share HH's with Kids aged 0–5						0.077
						(0.100)
Observations	2,568	2,568	2,568	2,568	2,568	2,568
R^2	0.015	0.190	0.748	0.759	0.760	0.760
Adj. R^2	0.014	0.188	0.748	0.757	0.758	0.758

Note: The table presents the estimated elasticity of the number of cars owned by residents of the neighborhood with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level and using the first-differences approach detailed in Equation (3). Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

Table A2—The elasticity of VKT per car with respect to road capacity

	(1)	(2)	(3)	(4)	(5)	(6)
ρ^{Urban} : $(Urban * \Delta \log(R))$	0.296**	0.161	0.165	0.205**	0.152	0.184*
	(0.127)	(0.098)	(0.099)	(0.080)	(0.099)	(0.099)
$\rho^{Nonurban}$: $(Nonurban * \Delta \log(R))$	0.102	0.062	0.062	0.065	0.059	0.056
	(0.099)	(0.089)	(0.089)	(0.097)	(0.093)	(0.096)
Urban	0.096***	0.144***	0.146***	0.129***	0.154***	0.169***
	(0.003)	(0.035)	(0.035)	(0.033)	(0.046)	(0.049)
Nonurban	-0.003	-0.002	-0.001	-0.001	-0.009	-0.006
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)
Married without kids or with kids aged 0–5		0.035	0.027	0.012	-0.020	-0.058
(2015 share)		(0.029)	(0.033)	(0.035)	(0.034)	(0.050)
Single car owners		-0.185**	-0.187**	-0.166**	-0.178**	-0.195**
(2015 share)		(0.081)	(0.082)	(0.072)	(0.078)	(0.080)
Earning NIS 5,000–7,500 per adult		-1.586***	-1.599***	-1.522***	-1.445***	-1.434***
(2015 share)		(0.393)	(0.398)	(0.442)	(0.426)	(0.440)
Aged 30–35		0.127*	0.124*	0.086	0.033	0.030
(2015 share)		(0.067)	(0.066)	(0.078)	(0.078)	(0.089)
Δ log (Population)			0.020	0.011	-0.087*	-0.141**
			(0.026)	(0.031)	(0.047)	(0.065)
Δ log (Total income)				0.119	0.112	0.107
				(0.074)	(0.073)	(0.071)
Δ Employed				-0.045	0.005	0.058
				(0.194)	(0.186)	(0.184)
Δ Share in manuf.				-0.221	-0.218	-0.211
				(0.168)	(0.171)	(0.174)
Δ Academics				-0.117	-0.118	-0.180
				(0.217)	(0.195)	(0.208)
Δ Transit					0.000	0.000
					(0.000)	(0.000)
2015 Congestion level					0.000	0.000
					(0.000)	(0.000)
$\Delta_{2013,2015} \log(Cars)$					0.123***	0.121***
					(0.037)	(0.036)
Δ log (Kids 0–18)						0.061
						(0.038)
Δ Share HH's with Kids aged 0–5						-0.126
						(0.109)
Observations	2,568	2,568	2,568	2,568	2,568	2,568
R^2	0.004	0.036	0.036	0.041	0.057	0.058
Adj. R^2	0.003	0.033	0.033	0.037	0.051	0.052

Note: The table presents the estimated elasticity of VKT per car with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level and using the first-differences approach detailed in Equation (3). Urban areas are defined here as neighborhoods where the density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

Table A3—The elasticity of car usage with respect to road capacity: robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: $\Delta \log (VKT)$									
ρ^{Urban}	0.751***	0.840***	0.746***	0.698***	0.540***	0.695***	0.689***	0.779***	0.739***
	(0.124)	(0.151)	(0.12)	(0.151)	(0.066)	(0.122)	(0.148)	(0.132)	(0.124)
$\rho^{Nonurban}$	0.122	0.109	0.097	0.105	0.089	0.127*	0.05	0.117	0.020
	(0.089)	(0.086)	(0.081)	(0.086)	(0.099)	(0.069)	(0.142)	(0.091)	(0.127)
Panel B: $\Delta \log (Cars)$									
ρ^{Urban}	0.567***	0.630***	0.559***	0.582***	0.573***	0.553***	0.495***	0.588***	0.566***
	(0.112)	(0.138)	(0.112)	(0.139)	(0.114)	(0.104)	(0.11)	(0.121)	(0.060)
$\rho^{Nonurban}$	0.066*	0.034	0.075**	0.051	0.067*	0.067	0.02	0.062	0.072
	(0.036)	(0.052)	(0.035)	(0.044)	(0.037)	(0.039)	(0.06)	(0.037)	(0.068)
Panel C: $\Delta \log \left(\frac{VKT}{Car}\right)$									
ρ^{Urban}	0.184*	0.202*	0.187**	0.122	-0.033	0.158*	0.194*	0.191*	0.173
	(0.099)	(0.106)	(0.083)	(0.085)	(0.081)	(0.089)	(0.11)	(0.094)	(0.104)
$\rho^{Nonurban}$	0.056	0.05	0.022	0.049	0.022	0.145*	0.03	0.055	-0.052
	(0.096)	(0.091)	(0.102)	(0.088)	(0.106)	(0.075)	(0.158)	(0.096)	(0.161)

Note: The table reports the estimated elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as estimated in the neighborhood level. Column (1) presents the baseline results corresponding to the specifications reported in Table 3; Columns (2) and (3) repeats the same specification, but now includes all neighborhoods in which at least 20 or 100 residents are observed in each period accordingly; Column (4) repeats the same specification but only uses prime age (25-64) residents to compute neighborhood-level car usage statistics; Column (5) excludes households with extreme car usage values (over 100,000 annual VKT or owners of more than 10 cars) before computing aggregate values; Columns (6) and (7) excludes neighborhoods in which the aggregate change in the outcome variable or road capacity accordingly was in the top or bottom 2.5% of the distribution; Column (8) replaces the transit variable used in the baseline specification to a more simple measure - the first difference of the number of bus stops-in-station in the neighborhood; Column (9) replaces the congestion measure used in the baseline specification to a commuting-zone level measure which is defined as the ratio of total VKT to total road capacity in the commuting zone (commuting zones are based on Amedi and Porat Hirsh (2026) and are visualized in Appendix Figure A2.). Urban areas are defined here as neighborhoods where the residential density in the 3 km radius around their centroid is larger than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.

Table A4—Estimates of ρ using different capacity measures

	$\Delta \log(VKT)$	$\Delta \log(Cars)$	$\Delta \log\left(\frac{VKT}{Car}\right)$
Panel A: 5 kilometer radius			
$\rho^{Urban} : (Urban * \Delta \log(R))$	0.443***	0.333***	0.110**
	(0.095)	(0.086)	(0.05)
$\rho^{Nonurban} : (Nonurban * \Delta \log(R))$	0.154**	0.029	0.125**
	(0.06)	(0.035)	(0.047)
Panel B: 10 kilometer radius (Baseline)			
$\rho^{Urban} : (Urban * \Delta \log(R))$	0.750***	0.566***	0.184*
	(0.124)	(0.113)	(0.099)
$\rho^{Nonurban} : (Nonurban * \Delta \log(R))$	0.122	0.066*	0.056
	(0.089)	(0.036)	(0.096)
Panel C: 15 kilometer radius			
$\rho^{Urban} : (Urban * \Delta \log(R))$	0.944***	0.839***	0.106
	(0.135)	(0.144)	(0.131)
$\rho^{Nonurban} : (Nonurban * \Delta \log(R))$	0.148	0.105*	0.043
	(0.145)	(0.053)	(0.124)
Panel D: 100,000 closest residents			
$\rho^{Urban} : (Urban * \Delta \log(R))$	0.302***	0.244**	0.059
	(0.074)	(0.093)	(0.08)
$\rho^{Nonurban} : (Nonurban * \Delta \log(R))$	0.074	0.009	0.065
	(0.086)	(0.047)	(0.091)
Panel E: 100,000 closest workers			
$\rho^{Urban} : (Urban * \Delta \log(R))$	0.369***	0.318***	0.051
	(0.104)	(0.11)	(0.166)
$\rho^{Nonurban} : (Nonurban * \Delta \log(R))$	0.093	0.022	0.071
	(0.173)	(0.079)	(0.191)

Note: The table replicates estimation results of the elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as reported in Table 3 in the main text, using different capacity measures. Standard errors clustered by subdistrict are reported in parentheses.

Table A5—Estimates of ρ using different vintages of the road network file

	$\Delta\log(VKT)$	$\Delta\log(Cars)$	$\Delta\log\left(\frac{VKT}{Car}\right)$
Panel A: January 2014 - September 2019			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.560***	0.437***	0.123
	(0.106)	(0.105)	(0.081)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.192**	0.096*	0.096
	(0.086)	(0.052)	(0.08)
Panel B: January 2014 - December 2019			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.558***	0.437***	0.121
	(0.105)	(0.104)	(0.081)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.151*	0.065*	0.086
	(0.077)	(0.037)	(0.081)
Panel C: January 2014 - June 2020			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.553***	0.437***	0.116
	(0.077)	(0.074)	(0.076)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.098	0.052	0.045
	(0.068)	(0.041)	(0.072)
Panel D: July 2015 - September 2019			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.750***	0.564***	0.186*
	(0.125)	(0.114)	(0.099)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.164	0.097*	0.067
	(0.102)	(0.049)	(0.095)
Panel E: July 2015 - December 2019 (Baseline)			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.750***	0.566***	0.184*
	(0.124)	(0.113)	(0.099)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.122	0.066*	0.056
	(0.089)	(0.036)	(0.096)
Panel F: July 2015 - June 2020			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.684***	0.524***	0.159*
	(0.096)	(0.09)	(0.088)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.07	0.052	0.018
	(0.077)	(0.038)	(0.079)
Panel G: May 2016 - September 2019			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.756***	0.565***	0.191*
	(0.131)	(0.122)	(0.1)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.189	0.104**	0.085
	(0.111)	(0.05)	(0.104)
Panel H: May 2016 - December 2019			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.757***	0.568***	0.189*
	(0.13)	(0.121)	(0.099)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.143	0.070*	0.073
	(0.096)	(0.037)	(0.104)
Panel I: May 2016 - June 2020			
$\rho^{Urban}: (Urban * \Delta\log(R))$	0.687***	0.524***	0.163*
	(0.102)	(0.096)	(0.089)
$\rho^{Nonurban}: (Nonurban * \Delta\log(R))$	0.09	0.058	0.032
	(0.088)	(0.041)	(0.089)

Note: The table replicates estimation results of the elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as reported in Table 3 in the main text, using different vintages of the BENTAL road network file to define road capacity in both examined periods. Standard errors clustered by subdistrict are reported in parentheses.

Table A6—Inference for the neighborhood level effect of road capacity on car usage

	$\Delta \log(VKT)$	$\Delta \log(Cars)$	$\Delta \log\left(\frac{VKT}{Car}\right)$
Estimates	0.750	0.566	0.184
Observations	2,568	2,568	2,568
Standard errors:			
iid	(0.155)	(0.073)	(0.137)
Heteroskedasticity robust	(0.119)	(0.060)	(0.105)
Clustered by:			
Natural area	(0.120)	(0.094)	(0.107)
Subdistrict	(0.124)	(0.113)	(0.099)
District	(0.115)	(0.148)	(0.087)
Conley (10 km)	(0.119)	(0.123)	(0.085)
Conley (30 km)	(0.089)	(0.117)	(0.070)
Conley (50 km)	(0.098)	(0.071)	(0.076)

Note: The table replicates estimation results of the elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as reported in Table 3 in the main text, and reports a variety of standard errors for this specification.

Appendix B: Derivation of the theoretical model

This appendix supplies derivations and proofs omitted from the theoretical section in the main text.

B1. Baseline model

Differentiating the utility function described in Equation (1) with respect to travel, X, yields:

$$T = Wh'(X^*) \tag{B1}$$

Since all expressions in this equation are constant across agents, in equilibrium travel consumption, X^*, is identical for all car owners. To find an expression for X^* when $0 < s^* < 1$, note that in equilibrium the marginal agent would be indifferent between being a car owner or not. Using the expression derived above, the utility of car owners can be written as

$$U^{O+} = Wh(X^*) - X^*Wh'(X^*) + m(I - O) \tag{B2}$$

and the utility of nonowners can be written as:

$$U^{O-} = m(I) \tag{B3}$$

Equating these two utilities yields:

$$X^* = \frac{h(X^*) - (m(I) - m(I - O))/W}{h'(X^*)} \tag{B4}$$

This equality only holds when s^*, the share of car owners in the population, is between zero and one. If s^* is outside this range, all agents will strictly prefer one of the options, and Equation (B4) does not hold. With X^* determined, first order conditions imply that T is determined. Travel technology is defined as $T = f(\overline{X}/R)$, where $\overline{X}$ is aggregate travel consumption. Since T is determined, so is the ratio between $\overline{X}/R$, implying that ρ necessarily equals 1.

We continue by finding an expression directly relating $\overline{X^*}$ to R. One can write aggregate travel consumption as $\overline{X} = Ns^*X^*$. Plugging that expression and the expression for T from Equation (B1) into the travel technology function yields:

$$\overline{X} = s^*NX^* = Rf^{-1}\left(Wh'\left(X^*\right)\right) \tag{B5}$$

All the expressions in this equation are exogenous parameters and functions, except for the amount of travel an agent consumes in equilibrium, X^*, for which we found an expression earlier. Since X^* is constant when $s^* < 1$, this equation implies $\rho = 1$ when car ownership is not universal.

In cases where car ownership is universal ($s^* = 1$), the extensive margin is redundant and ρ is strictly smaller than 1. This can be verified by totally differentiating the first order conditions while normalizing $N = 1$:

$$\frac{d}{dR}\left[f\left(\frac{X}{R}\right)\right] = \frac{d}{dR}\left[Wh'\left(X^*\right)\right] \rightarrow \frac{\partial X}{\partial R} = \frac{f'\left(\frac{X}{R}\right)\frac{X}{R}}{f'\left(\frac{X}{R}\right) - WRh''\left(X\right)} \tag{B6}$$

Multiplying this derivative by X/R to obtain an expression for elasticity yields:

$$\rho = \frac{\partial X}{\partial R}\frac{R}{X} = \frac{f'\left(\frac{X}{R}\right)}{f'\left(\frac{X}{R}\right) - WRh''\left(X\right)} \tag{B7}$$

The first derivative of travel technology, $f'(X/R)$, is positive (travel costs increase with congestion), and the expression $Wh''\left(X\right)R$ is negative ($h\left(X\right)$ is concave). Hence, $0 < \rho < 1$, and building more roads will alleviate congestion when car ownership is universal.

B2. Adding heterogeneous income

We now turn to adding heterogeneous income, I_i, to the model. As apparent from the first order conditions, conditional on car ownership choice, income has no effect on the amount of travel consumed, $X^* = h'^{(-1)}\left(\frac{T}{W}\right)$, but there is an effect on car ownership choice.

PROPOSITION 2: *There is a certain level of income, $\overline{I}$, such that $\forall I^- < \overline{I}$ the agent would not choose to own a car and $\forall I^+ > \overline{I}$ the agent would choose to own a car.*

Proof: As shown in the baseline model, the utility from consuming travel is identical for all individuals and is given by $Wh(X^*) - TX^*$. Define the difference in utility from consuming I or $I-O$ units of $C : \Delta\left(I\right) \equiv m(I) - m(I-O)$. From concavity of $m(\cdot)$, $\Delta(I)$ is decreasing in I. Define $\overline{I}$ such that $\Delta(\overline{I}) = Wh(X^*) - TX^*$. $\forall I^- < \overline{I} : \Delta(I^-) < Wh(X^*) - TX^*$ so the agent would choose not to own a car, and $\forall I^+ > \overline{I} : \Delta(I^+) > Wh(X^*) - TX^*$ so the agent would choose to own a car.

The share of car owners now depends on the distribution of incomes. Specifically, $s^* = 1 - F(\overline{I})$ with $F(I)$ denoting the cumulative distribution of incomes. As long as the extensive margin is not exhausted, the overall effect (ρ) can now be smaller or greater than one, depending on the model's parameters and the income distribution.

B3. Adding heterogeneous travel preferences

Consider a setup where travel preferences differ between agents. Some agents enjoy travel more than others. I model this heterogeneity by enabling different values of W_i for agents. In this case, the first order conditions will be:

$$T = W_i h'\left(X^*\right) \tag{B8}$$

As intuition would suggest, and unlike the heterogeneous income case, conditional on car ownership, agents who enjoy travel more will consume more travel in equilibrium. The agent will choose to own a car if:

$$U^{O+} = W_i h\left(X^*\right) - X^* W_i h'\left(X^*\right) + m\left(I - O\right) > m(I) = U^{O-} \tag{B9}$$

This results in a proposition similar to the heterogeneous income case:

PROPOSITION 3: *There is a certain level of preference for travel, $\overline{W}$, such that $\forall W^- < \overline{I}$ the agent would not choose to own a car and $\forall W^+ > \overline{W}$ the agent would choose to own a car.*

Proof: The utility of nonowners, U^{O-}, is constant for all agents. The utility of owners increases monotonically in W. Denote the value for which $U^{O+}(\overline{W}) = U^{O-}$ as $\overline{W}$. $\forall W^- < \overline{W} : U^{O+}(W^-) < U^{O-}$ the agent would choose not to own a car, and $\forall W^+ > \overline{W} : U^{O+}(W^+) > U^{O-}$ the agent would choose to own a car.

In this case, both the extensive and intensive margins are affected by the preference for travel. This result differs from the heterogeneous income case by creating a composition effect when road capacity is expanded. Specifically, ceteris paribus, a higher share of car owners will result in a lower average travel consumption per agent. Also note that the optimal level of travel an agent chooses—$X^* = h'^{(-1)}\left(\frac{T}{W_i}\right)$—is convex in W, so given a reduction in travel costs ($\rho < 1$), agents with a stronger preference for travel would display a stronger response in the intensive margin. Again, ρ will depend on the empirical distribution and cannot be solved analytically.

Appendix C: Data Appendix

C1. Representativeness of the sample

One of the key findings of this paper is that the effect of road capacity expansions on car usage is heterogeneous with respect to both location and household characteristics. Since there is significant heterogeneity, the ability to extrapolate the estimated average treatment effects to the entire population depends on the representativeness of the sample. This Appendix examines how representative of the entire Israeli adult population the sample is.

The sample used in the main part of the paper is composed of all CBS survey respondents in the years 2010–2019, a random sample of one-third of all persons ever employed between 2010–2019, and spouses of all of the above. The sample covers roughly two-thirds of the entire Israeli adult population, and due to the way it was constructed, it is largely representative of the entire adult Israeli population.

There are two main possible sources of bias. First, I observe a 10-year balanced panel of the sampled population. This procedure under-samples persons in both extremes of the age distribution, as presented in Appendix Figure C1. I present summary statistics, and replicate the main results using only prime age (25–64) individuals as a robustness check since the sample age distribution in this range is more similar to the national distribution published by the CBS, as observed in the right panel of the figure.[31]

The second possible source of bias is possible under-sampling of unemployed individuals due to part of the sampling process relying on linked employee records. I find that the 2015 prime age (25–64) employment rate in my sample and official data was similar, leading me to believe that in practice this issue is not significant. Table C1 presents this and other statistics as computed in the sample and

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[31] The correlation between the number of individuals in each age in my sample and official publications in 0.93. This correlation rises to 0.98 within the 25–64 age range.

compared to the official published statistics.

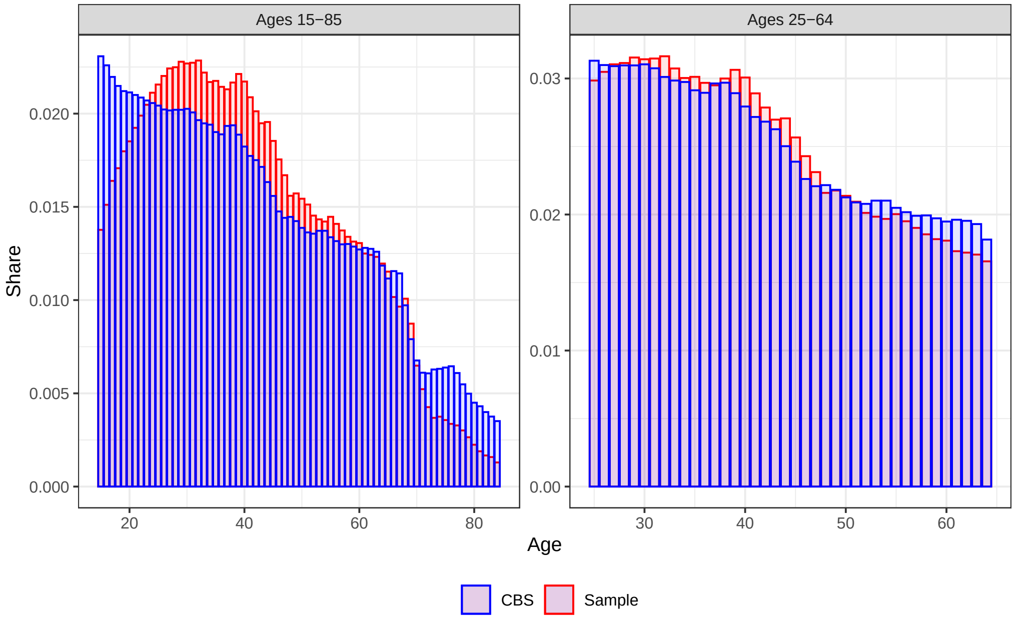

FIGURE C1. AGE DISTRIBUTION IN THE SAMPLE AND OFFICIAL STATISTICS, 2015

Note: The figure presents the 2015 age distribution in Israel as published in the CBS annual statistical abstract, and in the sample used in the paper.

TABLE C1—ADMINISTRATIVE AND SAMPLE SUMMARY STATISTICS

	Sample	Official publications
Employment rate (25–64)	76.2	76.1
Share academics (25–66)	30.0	32.0
Share males	50.0	49.6
Share minorities	20.8	18
Share with license (25–64)	76.6	80
Share married (25–64)	70.0	75.0
VKT per car	15.9	15.2

Note: The table presents sample summary statistics and compares them to official national-level statistics published by the Israeli Central Bureau of Statistics. All data refer to 2015, except for the share of academics, which refers to 2014 since no official data were available for 2015.

Table C2 presents the correlations between locality-level statistics as observed in my sample and in the official data. The correlation in population counts is computed on all Israeli localities. The correlation in car usage variables is computed on roughly 50 large localities for which such official data are published.

The sample is spatially representative, as can be observed in the locality-level correlation between the population counts in the sample and the official data. Total VKT and number of registered vehicles are also similar. There is a lower correlation between the sample and official data in VKT per car. When excluding individuals with very high VKT records (over 100,000 annual VKT) the correlation dramatically decreases. Excluding such individuals has no effect on the correlation of population counts, total VKT, or the number of cars. This leads me to believe that a large portion of the remaining difference in VKT per car between the sample and official publications is due to similar nonsampled individuals. I find no important differences in the results when including or excluding such individuals from the estimation (Appendix Table A3). As such, even though the correlation with the official data is not perfect, this difference should not have any major effect on the reported findings.

Table C2—Locality-level correlations between administrative and sample data

	Full sample	Excl. outliers
Population	0.98	0.98
VKT	0.96	0.96
Registered vehicles	0.98	0.98
VKT per car	0.64	0.41

Note: The table presents locality-level correlations between sample and official statistics published by the Israeli Central Bureau of Statistics. All data refer to 2015. VKT, VKT per car, and number of registered vehicles correlations are computed using a subset of roughly 50 large localities for which the CBS publishes official statistics. The 'Excl.outliers' column computes statistics after excluding individuals with very high car usage values: over 100,000 annual VKT or ownership of more than 10 cars.

C2. Data limitations

This section discusses some shortcomings of the car usage and road network data, which do not allow a higher frequency inspection of their variation.

Data regarding car ownership and usage originate from an administrative data set. In Israel every vehicle is legally obliged to pass an annual technical inspection at an authorized facility. Starting in 2010, Vehicle Kilometers Traveled (VKT) at the time of inspection are recorded and collected by the Israeli Ministry of Transportation, and are later aggregated to compose official statistics. I observe the annual inspection date and the difference between consecutive VKT readings for each vehicle owned by an individual in my sample starting in 2014, but coverage throughout 2014 was partial.

This data set allows me to infer car ownership status for every individual in the sample, and VKT for most of them. The data set does have some important limitations: (1) New cars are exempt from inspection in the first three years on the road, a VKT value for them is imputed by the CBS. I include these records when estimating aggregate VKT, but exclude them when I turn to the household-level analysis. (2) I have no proper method to divide the total annual VKT between households when a vehicle undergoes a change in ownership during the year. I omit such cases from the analysis. (3) Within a household, it is not clear that the registered owner is also the car's main driver, hence my micro-level analysis will always refer to household-level data. (4) There is no information regarding the distribution of VKT throughout the year for any vehicle. I aggregate all inspections conducted in a calendar year to define VKT in a region.

These limitations imply that one cannot analyze variation in car usage in years earlier than 2015, and complicate any aspiration to a higher frequency analysis. Shortcomings of the road network data further exacerbate these issues. Segments of the road network are updated only when new information about the region is made available and processed by the Survey of Israel. The annual calendar of flights conducted to obtain new orthophotos, and the considerable time it takes the Survey of Israel to process new sources of information imply that no single vintage of the road network file represents a complete snapshot of the road network as it is at a single point in time.[32]

I overcome these difficulties by examining the elasticity of car usage with respect to road capacity using a first-difference of a relatively long time interval. This long interval washes out most timing measurement errors of both the treatment and outcome variables. I also perform robustness checks using slightly different vintages for the same car usage period and obtain similar results.

Appendix D: Additional estimation methods

In the main analysis I partial-out confounders linearly by including them as controls in an ordinary regression. In this Appendix, I demonstrate the robustness of the main results to two alternative approaches that more flexibly partial-out confounders: Double-Selection LASSO and nearest neighbor matching.

Double Selection LASSO. — The Double Selection LASSO approach, first introduced in Belloni, Chernozhukov and Hansen (2014), is a statistical approach to automatic selection of controls. I give the model a set of controls composed of the set of controls included in the baseline estimation and augmented with all possible two-way interactions between those variables, and estimate the model using the `hdm` package in `R` (Chernozhukov, Hansen and Spindler, 2016). This approach allows for a more flexible specification considering interactions and quadratic terms while avoiding the curse of dimensionality, but relies on assumptions otherwise similar to the baseline estimation.

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[32] One could potentially have overcome this issue by combining information from different vintages to create a unified file representing a single point in time. This approach was proven infeasible in my context since in the past, documentation of the origins of each object in the network was not satisfactory. I thank Daniel Brodi, head of the Geographic Information System Department at the Survey of Israel (Mapi) for his participation and kind assistance in making such an attempt.

NEAREST NEIGHBOR MATCHING. — A second approach to partialling-out confounders is by comparing the outcome variable on a selected subset of the original sample in which treated and control units have similar observable characteristics. This method has some well-discussed shortcomings, but does have the advantage of explicitly comparing similar units when estimating the treatment effect, which is perceived by some as a more transparent research design, and does not require assumptions that are that strong regarding functional form, making it suitable as a robustness check to the main results.

In my context, treatment is continuous. To implement nearest neighbor matching I define treated and control units as those that were in the top and bottom quartiles of the $\Delta(R)$ distribution.[33] I run 1-nearest neighbor matching without replacement using Mahalanobis distance with the `MatchIt` package in `R` (Ho et al., 2011). I attempt to balance on the set of controls included in the baseline regression, the size of the locality (measured by total population), its peripherality level (as defined by the Israeli CBS), and the residential density around the neighborhood. I require exact matching on urban status, and don't allow neighborhoods in the same district to be matched.

Table D1 presents the matching process results. Treated units were generally smaller, less congested and more rural as discussed in the main text. The matching process greatly diminishes this discrepancy, and provides some improvement to the balance of other included covariates as well. In order to maintain consistency with the elasticity concept targeted in other parts of the paper, I estimate a linear regression on the matched sample using the same, continuous, treatment variable used in the main text. Since some significant differences in covariates remain, I include the full set of controls. Bin effects are also included, implying that the variation used is within matched treatment-control pairs.[34]

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[33] As Figure 2 shows, the control units generally received no or very little expansions. I omit the middle part of the distribution to avoid broadly similarly treated units being sorted to both treatment and control groups.

[34] Similar estimations without including controls, or without including bin effects, provide qualitatively similar results.

Table D1—Balance table: standardized mean difference between treated and control units

	Full sample	Matched sample	Balance improvement
Density	-4.32	-0.84	3.48
Locality-level population	-4.29	-0.61	3.68
Peripherality index	-2.00	-0.14	1.86
$\Delta \log$ (Population)	-0.12	0.05	0.06
$\Delta \log$ (Kids 0–18)	-0.55	-0.16	0.39
Δ Share HH's with Kids 0–5	-0.51	-0.24	0.26
$\Delta \log$ (Total income)	-0.02	0.28	-0.26
Δ Employed	0.29	0.38	-0.09
Δ Share in manuf.	0.07	0.11	-0.04
Δ Academics	-0.42	-0.14	0.28
Δ Transit	-0.15	0.15	0.00
2015 Congestion level	-1.03	-0.31	0.72
$\Delta_{2013,2015} \log (Cars)$	0.05	0.08	-0.03
2015 share:			
Married without kids or with kids aged 0–5	0.30	0.33	-0.03
Single car owners	0.00	-0.08	-0.08
Earning NIS 5,000–7,500 per adult	-0.35	-0.04	0.32
Aged 30–35	-0.29	0.08	0.21
Control	641	313	
Treated	642	313	
Total	1283	626	

Note: The table presents the standardized mean difference between treated and control units in the full sample (including all neighborhoods in the top and bottom quartiles of the road capacity difference distribution) and in the matched sample, and the balance improvement, which is defined as the difference between the absolute values of those columns.

Results. — Table D2 reports the estimation results. Both alternative methods provide results qualitatively and quantitatively similar to those reported in the main text. The Double-selection LASSO method doesn't improve the model's explanatory power, but does provide some improvement in terms of standard errors. The matching method, which is estimated on a subsample of the neighborhoods used in other methods, provides a noisier estimate, but improves explanatory power in this subsample. In both methods the extensive margin remains dominant, but its relative importance is somewhat diminished.

Table D2—The elasticity of car usage with respect to road capacity - alternative estimation methods

	Baseline	Double-selction LASSO	Matching
Panel A: $\Delta \log(VKT)$			
ρ^{Urban}	0.751***	0.604***	0.781***
	(0.124)	(0.114)	(0.262)
$\rho^{Nonurban}$	0.122	0.139	0.056
	(0.089)	(0.099)	(0.157)
Adj. R^2	0.468	0.464	0.483
Panel B: $\Delta \log(Cars)$			
ρ^{Urban}	0.567***	0.405***	0.418***
	(0.112)	(0.08)	(0.058)
$\rho^{Nonurban}$	0.066*	0.06	0.088
	(0.036)	(0.044)	(0.1)
Adj. R^2	0.758	0.761	0.765
Panel C: $\Delta \log\left(\frac{VKT}{Car}\right)$			
ρ^{Urban}	0.184*	0.179*	0.363
	(0.099)	(0.096)	(0.237)
$\rho^{Nonurban}$	0.056	0.061	-0.032
	(0.096)	(0.092)	(0.114)
Adj. R^2	0.052	0.05	0.146
Observations	2,568	2,568	626

Note: The table reports the estimated elasticity of the different margins of car usage with respect to road capacity in urban and nonurban areas, as estimated at the neighborhood level. Different methods are described in the text. Urban areas are defined here as neighborhoods where the residential density in the 3 km radius around the centroid is greater than 2,500 people per square kilometer. Standard errors clustered by subdistrict are reported in parentheses.