Subway Access and Life Satisfaction: Evidence from the Introduction of the Thessaloniki Subway *

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Abstract

The inauguration of the Thessaloniki subway in November 2024 introduced the first large-scale urban rail system to Greece's second-largest city. We exploit this event as a quasi-natural experiment to estimate the effect of improved public transport accessibility on subjective well-being. Using a balanced two-wave panel of 353 respondents surveyed before and one year after the subway's launch, we show that living within 10 minutes of a station increases life satisfaction by 0.23 standard deviations. This result is robust across cross-sectional, two-way fixed effects, and instrumental-variable specifications accounting for non-random transport exposure. Combining survey responses with over one billion geolocated traffic observations, we investigate the underlying channels. Based on our survey data, we find no evidence that the well-being gains operate through direct subway usage. Instead, benefits are driven by positive spatial externalities, with the largest increases in life satisfaction concentrated in neighborhoods with high baseline traffic congestion. These findings highlight substantial non-user welfare spillovers generated by major public transit investments.

Keywords: life satisfaction, subway, survey, well-being, transportation investments
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1 Introduction

Urban transportation systems play a central role in shaping the growth, accessibility, and livability of cities. Transportation infrastructure provides direct welfare benefits by reducing commuting (Severen, 2023) and shipping costs (Donaldson and Hornbeck, 2016), influencing urban form (Heblich et al., 2020), and mitigating environmental impacts (Saidi and Hammami, 2017; Gendron-Carrier et al., 2022). A key objective of such infrastructure is to alleviate traffic congestion (Gu et al., 2021), a persistent challenge in modern cities, while improving residents' well-being. This study examines how large public transport investments generate neighborhood well-being spillovers that extend beyond direct users.

Since 2015, the European Commission has emphasized that the Thessaloniki subway project aims to upgrade the city's public transport infrastructure and improve overall quality of life (European Commission, 2015), and more recently it has highlighted the launch of the subway in late 2024 as a major milestone in enhancing urban mobility in Greece's second-largest city (European Commission, 2026). Prior to its opening, the entire metropolitan area relied exclusively on buses. Daily mobility in Thessaloniki is substantial, with approximately 1.6 million car trips occurring each day. Of these, about 25% are directly linked to the city centre as either an origin or destination. The city's road network is frequently congested, with delays and illegal parking common during peak hours (Perra et al., 2017), a situation further exacerbated by its geography, as the center, home to around 320,000 residents, is located between the Thermaic Gulf and surrounding hills, creating natural transport bottlenecks (European Commission, 2026).

Against this backdrop, Thessaloniki provides a particularly clean empirical setting, as it is a mid-sized European city experiencing, for the first time, the introduction of a large-scale subway system. The opening of the subway therefore constitutes a plausibly exogenous change in urban mobility conditions, allowing for credible identification of the effect of improved public transport accessibility on life satisfaction. This setting differs from most previous studies, such as Sun and Du (2023) and Wu (2015), which primarily examine the expansion or improvement of already existing subway networks through additional lines or stations. To further strengthen identification, we additionally adopt the framework developed by Borusyak and Hull (2023), which exploits counterfactual transportation shocks while accounting for non-random exposure to treatment. This approach responds to longstanding concerns in the literature regarding causal identification in studies examining the relationship between transport accessibility and subjective well-being (Mokhtarian, 2018; Morris, 2011). Recent research has increasingly applied this framework in the context of transportation and spatial infrastructure (Chiopris, 2024; Costas-Fernández et al., 2026; Aboulkacem and Nedoncelle, 2022; Frye, 2024; Tsivanidis, 2023; Coşar et al., 2022; Hornbeck and Rotemberg, 2024), highlighting its suitability for evaluating the causal effects of

infrastructure investments.

We design a structured questionnaire and partner with a firm specializing in quantitative and qualitative market research to conduct the data collection. The first wave of responses was collected in November 2024, prior to the opening of the subway line, while the second wave was gathered one year later. Our final sample consists of 353 respondents, which is comparable to similar studies in the literature (Sun and Du, 2023). In contrast to previous studies (Wu, 2015; Li et al., 2018; Sun and Du, 2023), we combine self-reported survey measures with external geographic data through a geospatial matching exercise that enables us to approximate the neighborhood of each respondent. These spatial measures allow us to account more precisely for the urban environment surrounding respondents and to examine how localized accessibility, congestion conditions shape subjective well-being.

We find that living within 10 minutes of a subway station increases life satisfaction by 0.23 standard deviations. The estimate remains robust across a range of specifications, including cross-sectional regressions, two-way fixed effects models, and instrumental variable approaches. In addition, we account for several time-varying factors that may affect subjective well-being, including changes in bus routes, mental health conditions, and residential relocation. The estimated magnitude is substantial in policy terms. For example, Sun and Du (2023) report an effect of approximately 0.28 standard deviations on evaluative well-being among older individuals following subway introduction, whereas our estimates are based on the general population.

We examine two potential channels through which subway access may improve life satisfaction: increased subway usage (Stutzer and Frey, 2008) and changes in local traffic conditions (Emo et al., 2016). To our knowledge, this is the first study to jointly examine these channels in the context of subway infrastructure and subjective well-being using a quasi-experimental design. Unlike Sun and Du (2023), who consider subway usage without distinguishing trip purposes or accounting for neighborhood characteristics, we analyze both the extensive margin (whether respondents use the subway) and the intensive margin (the number of trips), as well as purpose-specific travel, including commuting and shopping. Across all specifications, we find no statistically significant evidence that improved subway accessibility increased self-reported subway usage. We then examine whether the effects of subway access vary with pre-existing neighborhood traffic conditions. Drawing on external traffic data from CERTH-HIT (2026), which combines billions of geolocated taxi speed observations, we construct measures of baseline neighborhood traffic conditions and interact them with subway accessibility. The results indicate that the life satisfaction gains from subway access are substantially larger in neighborhoods with greater baseline traffic congestion, whereas the effects are considerably weaker in areas where traffic conditions were already relatively favorable.

These findings suggest that the benefits of large public transport investments extend well beyond direct transit users. Rather than operating primarily through increased

subway ridership, the welfare gains appear to arise from improvements in the broader urban environment, particularly in neighborhoods burdened by severe traffic congestion. In doing so, our study connects the subjective well-being literature with theories of spatial congestion externalities (Zhang and Kockelman, 2016; Kreindler and Patekar, 2025) and transit-induced congestion relief (Anderson, 2014; Gu et al., 2021). More broadly, the results imply that conventional cost-benefit analyses focusing exclusively on user travel-time savings are likely to underestimate the full social welfare returns of major public transport investments, as they overlook important neighborhood-level spillover effects experienced by both riders and non-riders.

2 Literature Review

Our paper belongs to a growing literature that examines the impact of transportation access on well-being. Starting with Brereton et al. (2008), the authors examine the importance of space in the determination of well-being in Ireland. They include as a control proximity to rail station and find no significant results. Morris (2011) finds that economic development programs could be a powerful factor promoting well-being, and that fostering access to transportation resources is worthwhile. Yin et al. (2021) employ a case–control design in Xi'an, China, to examine the cross-sectional relationship between subway access and life satisfaction. Specifically, they compare individuals residing in neighborhoods with subway access to those without such access. Their findings indicate that living in areas served by the subway is positively associated with life satisfaction, primarily through improvements in transit service quality, walkability, accessibility, and overall travel satisfaction. Closer to our analysis are the studies by Wu (2015), Li et al. (2018) and Sun and Du (2023). Wu (2015) uses a unique large-scale microquality of life survey data set that was complied, consolidated and geo-coded by the Chinese Academy of Science. To match with rail access changes before and after the building of new rail transit lines, the author uses surveys that have been conducted in 2005 and 2009 respectively. The study explores the impact of rail improvements on happiness and finds that new rail transit infrastructure tends to significantly increase residents' happiness about their overall living environment and such impacts are not distributed evenly across different dimensions of the living environment. Subjective measures (happiness) may be consistent with economic valuation frameworks via capitalization into housing markets. Li et al. (2018) exploit a micro survey dataset of Shanghai in 2013, which tracks people who were born between the years 1980 and 1989. This dataset allows the author to track the households that bought their house 10 years earlier than the operation of their nearest subway station and those households living in non-market housing in Shanghai. Using these households the author finds that proximity to a subway station robustly promotes happiness at the individual level. Sun and Du (2023) investigates the impact of a new Subway line

on subjective well-being among older adults in Hong Kong. Using a sample of 449 individuals and a difference-in-differences approach, the authors find no direct effect of public transport infrastructure provision on improvements in subjective well-being. Instead, the relationship appears to be conditional on individuals' ability to adapt to the new Subway system. In particular, for older adults who sought to maintain or increase their reliance on bus services following the Subway intervention, the authors report a negative association between the intervention and subjective well-being.

Subway usage is considered by the literature as one of the most important mechanisms that can increase life satisfaction. Delbosc (2012) develops a conceptual framework in which transport influences life satisfaction both indirectly, by facilitating access to important life domains, and directly, through physical mobility and transport-related externalities. Similarly, Reardon and Abdallah (2013) discusses several mechanisms through which transport access may affect subjective well-being, including income, environmental quality, noise pollution, road safety, social relationships, and social exclusion. In addition, Mokhtarian (2018) highlights further pathways linking transportation access to well-being, such as experiences during travel, activities undertaken while traveling, participation in out-of-home activities, travel as an activity in itself, and individual motility. Only more recently have scholars begun to provide empirical evidence on the relationship between transportation access and subjective well-being. For example, Wang et al. (2021) examine the relationships among haze pollution, commuting behavior, and life satisfaction. With respect to commuting, they find that active commuters report higher levels of life satisfaction than transit commuters, while longer commuting times are associated with lower life satisfaction.

Furthermore, we contribute to the literature studying the effects of subway development on socio-economic outcomes. Lo and Hall (2006) explore the impact of Los Angeles strike in 2003 in public transit on highway congestion, The authors find that traffic speeds declined by as much as 20% during the strike, and the average length of the rush period increased by as much as 200%, even though increases in traffic were small, despite the fact that transit riders constitute a small fraction of the traveling population. In a second paper about Los Angeles strike in 2003 and highway congestion, Anderson (2014) find that average highway delay increases 47 percent when transit service ceases. Using data from Beijing, Li et al. (2016) document a positive and statistically significant impact of subway proximity on property values. Specifically, a 1-km reduction in the distance to a subway station increases property values by approximately 15 percent for properties located within 3 km of a station and by about 3.4 percent for those situated 3–5 km away. Regarding the property values Dewees (1976) finds that the opening of the subway impacts the in slope of the rent surface with distance from the subway stations, rather than changes in the slope along the subway line. In another study focusing on Beijing, Zhang et al. (2017) find that subway proximity reduces households' probability of owning a car and lowers subsequent fuel consumption. In a field experiment on Singapore's subways, Yang and

Long Lim (2018) find that temporary incentives can lead to lasting changes in people's daily routines. The authors make use of a public program implemented in Singapore in 2013 that provided a fare promotion with the goal to encourage commuters to travel prepeak to apply a difference-in-differences analysis. Findings suggest that the effect of the free-trip offer was modest but robust during the promotional period: on average, trips were 5.5% more likely to end before the morning peak time. Beyond housing and transportation choices, subway investments have also been shown to affect local labor markets. Bothe et al. (2018) analyze the impact of major urban transport investments on employment growth in Copenhagen and identify strong employment growth in Subway-served areas relative to non-Subway-served areas during the first ten years following the Subway's opening. Their results suggest that overall employment activity becomes concentrated around the Subway line, leading to a spatial restructuring of intra-urban employment patterns. Taking a global perspective, Gonzalez-Navarro and Turner (2018) examine 632 of the world's largest cities and find that, while large cities are more likely to have subways, subway systems have an economically insignificant effect on overall urban population growth. Nevertheless, they show that subways contribute to urban decentralization, although the magnitude of this effect is smaller than the previously documented effects of highways. Asahi and Pinto (2022) find that improved proximity to the subway system is associated with a reduction in educational disparities in Santiago. In the medium term (three years after the opening of new subway stations), the achievement gap between low- and high-performing students declines by approximately 5% of a standard deviation. The authors report that the underlying mechanism is the is class size. Because of the subway expansion, treated low-achievers-at-baseline had, on average, fewer classmates.

Finally, we contribute to a well-established literature examining the role of transportation infrastructure in shaping urban development. Urban transportation systems have been shown to influence city growth (Duranton and Turner, 2012), population suburbanization (Baum-Snow, 2007; Baum-Snow et al., 2017), employment decentralization (Baum-Snow, 2010, 2020), property values (Gibbons and Machin, 2005), and air pollution (Chen and Whalley, 2012), among other outcomes.

3 Public Transportation in Thessaloniki

The first public transportation network in Thessaloniki was the tram, which operated from 1893 to 1957. In 1957, under a decision by Prime Minister Konstantinos Karamanlis, the tram network was completely abolished (Makedonia Newspaper, 1957). In contrast to Athens, where trolleybuses were introduced, the Thessaloniki government granted monopoly power to the bus company OASTH (Organisation of Urban Transportation of Thessaloniki) instead of establishing a trolley system. Despite efforts made since 2000, the trolley network has never been restored. Following the opening

of the main line of the Thessaloniki Subway, bus routes were restructured to improve integration with the city's updated transportation network.

The first discussions about the creation of the subway system in Thessaloniki began in 1987 with the published a proposal for an extensive, multi-branch light Subway system by the Transport Engineering Laboratory of University of Thessaloniki. Construction began on the tunnel along Egnatia street until Aristotle University of Thessaloniki in 1989. The project ultimately failed due to funding issues and a lack of interest from the central government (To Vima, 2010). For the next decades, several political conflicts undermined the development of the subway network. In September 2003 the Ministry of the Environment, Urban Planning and Public Works decided to tender the Subway as a public work, co-financed by the Greek government, the European Union's Regional Development Fund, and loans from the European Investment Bank. Attiko Subway, the state-owned company which oversaw the construction of the Athens Subway, had its articles of association amended to enable it to oversee construction of the Thessaloniki Subway as well. A Greco-Italian consortium was appointed on 7 April 2006 and construction began in June of the same year (Buch, 2024). In 2018, Elliniko Subway S.A. was overseeing the construction of a two-line, twin-tunnel system composed of line 1 (the base project) and line 2 (the Kalamaria Extension).

Throughout the construction period, the project became synonymous with repeated delays. Successive governments announced opening dates that were later postponed because of archaeological discoveries (European Commission, 2026; Hill, 2026), engineering challenges, legal disputes, and funding issues. Consequently, many residents viewed official completion announcements with skepticism, and the subway's eventual inauguration on 30 November 2024 came as a genuine surprise after nearly two decades of construction. Figure 1 illustrates this pattern. Despite years of discussion and repeated promises of completion, public attention remained modest until the subway actually opened. Google Trends data show an unprecedented spike in searches precisely on the inauguration date, indicating that the opening constituted a major public event rather than the culmination of a widely anticipated schedule.

The base project consists 13 stations, spanning 9.2 kilometers (Hill, 2026) and serving more than 250,000 passengers per day. It became operational after nearly 20 years of construction and an investment exceeding 3 billion euros (Smith, 2024; European Commission, 2026; Hill, 2026). Figure 2 presents the subway line. The line crosses the municipality of Thessaloniki serving several important neighborhoods.

4 Data

4.1 Survey Data

We commissioned FFIND, a firm specializing in quantitative and qualitative market research, to conduct the data collection.[1] FFIND administered the survey interviews and managed the fieldwork. The first wave of data collection began on 19 November 2024 and concluded on 4 December 2024. Prior to the start of fieldwork, the questionnaire received approval from Copenhagen Business School in both its English and Greek versions.[2] FFIND was responsible for the Greek translation of the questionnaire. In addition, FFIND provided identifiers indicating which respondents were interviewed after the Subway became operational during the first wave, allowing us to exclude these individuals in a robustness check in the empirical analysis. The second wave of fieldwork was conducted between 17 October 2025 and 12 November 2025, prior to the temporary one-month closure of the Subway for testing related to the upcoming Kalamaria line expansion. The final dataset includes 400 respondents who participated in both survey waves. Of these, 45 respondents did not provide a valid postal code of residence and were therefore excluded from the analytical sample. Figure 3 presents the spatial dimension of our sample. As expected the majority of the respondents are from inside the city area. Nevertheless, we also have a good amount of respondents from the suburbs of Thessaloniki.

Dependent Variable: In this paper, we employ the life satisfaction scale originally developed by Diener et al. (1985), as it is one of the most widely validated and extensively used measures of global life satisfaction. The scale has been broadly adopted in the subjective well-being literature (Pavot and Diener, 2009) and has also been increasingly used in transport and mobility research (Friman et al., 2017). Following Diener et al. (1985), we use five items: "In most ways my life is close to my ideal," "I am satisfied with my life," "So far, I have achieved the important things I want in life," "The conditions of my life are excellent," and "If I could live my life over again, I would change almost nothing." Responses are recorded on a five-point Likert scale ranging from "Strongly disagree" (1) to "Strongly agree" (5).

The five-item scale exhibits satisfactory internal consistency, with a Cronbach's alpha of 0.785, thereby supporting the aggregation of the individual items into a single index (Nunnally and Bernstein, 1994). Consistent with the existing literature, we construct a composite life satisfaction index by summing the five items, where higher values indicate greater life satisfaction. Figure 4 presents the year-to-year percentage change in the life satisfaction index. The results reveal substantial variation over time: 120 respondents experienced an increase in life satisfaction, 88 reported a decrease,

[1] https://ffind.com

[2] Application to the CBS Ethics Council, case 24C1032. Stauts: successfully meets all the requirements.

and 145 remained at the same level.

Main independent Variable: To construct the main independent variable for this analysis, we rely on respondents' self-reported travel time to the nearest subway station. Travel time is measured across three modes: walking, by car, and by public transportation. We combine these three measures into a single index by taking the minimum value. This approach rests on the simplifying assumption that individuals choose the most time-efficient available mode to reach a subway station. We acknowledge that the literature identifies a range of heterogeneous factors influencing mode choice beyond travel time, including socio-economic characteristics, safety concerns, and comfort, among others (Ben-Akiva and Lerman, 1985; Ibrahim et al., 2024). This specification also helps minimize missing values, as some respondents may not have access to a car or may not typically walk to a subway station, particularly those living outside Thessaloniki.

In our analysis, we use as subway access a binary indicator equal to one if a respondent can reach a subway station within 10 minutes in 2025, once the subway line becomes operational (Marquet and Miralles-Guasch, 2014). Respondents within this threshold are classified as treated, while those farther away serve as the control group. In 2024, prior to the opening of the subway line, all respondents are coded as untreated. Figure 5 shows the distribution of responses: over 40% of respondents report a travel time of approximately 5 minutes to the nearest subway station, 62% require 10 minutes or less, and roughly 90% take under 30 minutes. As robustness checks, we also consider alternative definitions of treatment based on a 15-minute threshold, as well as traditional distance-based cut-offs of 1 km and 1.5 km (Glaeser et al., 2008).

Control Variables: Following existing literature, we include several key control variables in our analysis. These comprise demographic characteristics such as age (Hudomiet et al., 2021) and gender; health-related variables, including general health (Puvill et al., 2016), disability, and the perceived mobility necessities (PMN) index (Pagán-Rodríguez, 2010); and labor market indicators, such as self-employment, full-time employment, part-time employment, unemployment, and being out of the labor force (Georgellis et al., 2022). Family-related variables capture marital status (married, in a long-term relationship, single, divorced, or widowed) and the presence of children. To take into account sorting effects (Barwick et al., 2024) we include a dummy variable whether the respondent relocated in the year the subway began operations. We also include a measure of mental health (Puvill et al., 2016) and transportation-related variables, such as car usage and changes to bus routes resulting from the development of the subway network.

To construct the PMN index, we follow the methodology proposed by Haustein and Hunecke (2007) and subsequently applied by Thorhauge et al. (2020). We use the following items: "The organization of my everyday life requires a high level of mobility", "I have to be mobile all the time to meet my obligations" and "My work

requires a high level of mobility". The internal consistency of the items is satisfactory, with a Cronbach's alpha of 0.75. The index is computed as the mean of the individual items. For the mental health index, we rely on the validation framework developed by Ten Have et al. (2024). We included the following items: "How much of the time in the past four weeks did you. . . , 1) feel very nervous?, 2) feel so down in the dumps that nothing could cheer you up?, 3) feel calm and relaxed?, 4) feel depressed and sad? and 5) feel happy?". The corresponding items exhibit acceptable internal reliability (Cronbach's alpha = 0.70) (Nunnally and Bernstein, 1994). Consistent with the literature, the third and fifth items are reverse-coded before aggregating all items into a composite index. The resulting index is then rescaled to range from 0 to 100 as suggested by the literature. As an indicator of general health, we use the first item, "In general, would you say your health is:", of the SF-12 health survey (Ware et al., 1996). This item has been shown to perform well as a standalone measure of general health status (DeSalvo et al., 2005, 2009).

To examine the underlying channel, we use survey questions related to subway usage. The first question is a binary indicator (Yes/No) of whether the respondent uses the subway. If the answer is "Yes," we also collect information on the frequency of usage and the purpose of trips (Bohte and Maat, 2009). Respondents could select multiple purposes, including commuting to work, shopping, social activities, recreation, returning home, studying, or other reasons. The category "studying" did not receive a sufficient number of responses and was therefore excluded from the analysis.

In Table A.3, we compare the gender distribution and median age of our sample with the statistics reported by EUROSTAT for Thessaloniki (EL522) in 2024. The comparison indicates that our sample closely reflects the population characteristics of Thessaloniki, at least in terms of gender and age. Specifically, the gender composition shows only a 2% difference, with slightly more males responding to the questionnaire than in the overall population. The median age differs by approximately two years compared to the population of Thessaloniki. We also include comparisons between the survey values for age and gender and the ones reported by EUROSTAT for the year 2024 for Thessaloniki (NUTS code: EL522) using t-tests in Tables A.4 and A.5 and and we don't report significant differences.

4.2 Feasible Residential Areas

To fully leverage urban data and the IV methodology proposed by Borusyak and Hull (2023), we first construct an approximation of each respondent's residential neighborhood. This step introduces individual-level spatial variation in both the instrument and the heterogeneity analysis, which is crucial because, without such variation, postal-code fixed effects would absorb all relevant unobserved heterogeneity at the postal-code level, leaving no residual identifying variation. To reconstruct respondents' residential neighborhoods, we combine three sources of information: (i)

self-reported postal codes, (ii) self-reported distance to the nearest subway station, and (iii) a polygon shapefile of postal codes for Thessaloniki obtained from Greek Data.[3]

We compile a geocoded dataset of Thessaloniki subway stations and restrict the sample to stations operational during the study period, assigning each station a unique identifier to facilitate matching and subsequent analysis. Respondents are initially geocoded at the centroid of their reported postal code, serving as a baseline location. All spatial datasets, including subway stations, postcode polygons, and respondent locations, are projected into a common planar coordinate reference system measured in meters to ensure accurate distance calculations and geometric operations.

For each respondent, we identify the geographically closest operational subway station using Euclidean distance and designate it as the respondent's reference station. The self-reported distance to this station is converted into meters and interpreted as a radial constraint on feasible residential locations. Specifically, we construct a circular buffer centered on the reference station with a radius equal to the reported distance and intersect this buffer with the respondent's postcode polygon. The resulting intersection defines a feasible residential area that satisfies both administrative constraints (postcode boundaries) and behavioral information (self-reported distance to the subway).

This procedure was implemented in Python. It refines the spatial approximation of respondents' locations relative to simple postcode centroids while preserving anonymity and avoiding precise geolocation. Importantly, the method produces feasible areas rather than exact residences. Figure 6 illustrates an example of this procedure: for respondent 14 (left-hand subfigure), the algorithm makes a minor adjustment to the centroid, as most of the area falls within the computed radius based on the self-reported distance. In contrast, for respondent 26 (right-hand subfigure), the algorithm achieves a larger adjustment, yielding a more precise approximation of location.

4.3 Floating Car Data

Expect from subway usage we explore wheather changing conditions related to traffic affect the life satisfaction. For this reason, we employ the dataset of floating car data in Thessaloniki (fcd) in -almost- real time created by the Hellenic Institute of Transport (HIT) that is part of the Centre for Research and Technology Hellas (CERTH), a non-profit organization that directly reports to the General Secretariat for Research and Innovation (GSRI), of the Greek Ministry of Development (CERTH-HIT, 2026). The dataset provides historical floating car data from a taxi fleet in Thessaloniki, Greece, updated monthly on the CERTH-HIT OpenData Hub. The data includes timestamped, anonymous GPS positions (longitude, latitude), speed, altitude, and orientation.

We download the data from their server. We processed in Python over 1 billion recordings in total since December of 2023. We create a buffer radius area of 500

[3] https://github.com/lymperis-e/Greek-Data-QGIS-Plugin

meter around each respondent based on their feasible residential area.[4] We geolocate and isolate the recordings that fall within this buffer area. Then, based on these recordings we compute the average speed for the whole year. We consider the period from December 2023 until November 2024 since subway became operational the last day of November. The dataset also contains additional information on vehicle altitude and orientation at the time each speed measurement was recorded. To improve the precision and reliability of our estimates, we include these variables as controls in the regression models. Furthermore, we calculate the total number of recordings within the 500-meter buffer for each respondent and include this measure as an additional control variable to account for variation in the amount of recordings available across observations. For a small number of respondents (18 in total), no recordings are available within the 500-meter buffer area. To maintain consistency with the sample used in our other specifications, we assign these respondents a value of zero for average speed, orientation and altitude, and the variable capturing the number of recordings within the buffer area. In these cases, the recordings variable effectively functions as an indicator identifying observations with no available traffic data. As a robustness check, the Appendix A reports regression results excluding these 18 respondents entirely. The findings remain unchanged, indicating that the treatment of these observations does not affect the main conclusions.

As a final robustness check we also compute a version of the average speed based on Gu et al. (2021). In particular, we remove for both years the weekends and national holidays and we keep only morning rush hours between 7 AM and 9 AM and evening rush hours between 5 PM and 7 PM. We include the results in the Appendix A.

4.4 Other Urban Data

We collect additional data on population at a 100-meter spatial resolution for 2025 from Schiavina et al. (2023). This raster dataset provides estimates of the residential population, measured as the number of inhabitants per grid cell. The estimates are based on the Center for International Earth Science Information Network (CIESIN) GPWv4.11 dataset and are spatially disaggregated from census or administrative units to 100-meter grid cells using information on the distribution, volume, and classification of built-up areas derived from the Global Human Settlement Layer (GHSL) for the corresponding reference years.

In addition, we collect historical OSM (OpenStreetMap, 2025) data for the year 2024 that are retrieved through the Overpass API using the OSMnx Python package. To improve data retrieval reliability, queries are automatically rotated across multiple Overpass servers and repeated in the event of temporary server failures. All spatial data

[4] A 500-meter buffer is commonly adopted in the urban and environmental economics literature to measure neighborhood characterestics (Ostermeijer et al., 2022; Mittakola et al., 2025; Christodoulou et al., 2020; Gauderman et al., 2007).

are projected to the Greek Grid coordinate reference system (EPSG:2100), allowing distances to be measured in meters. Around each respondent's residence, circular buffers with radio of 500, and 1,000 meters are constructed. Spatial joins are then used to identify all amenities located within each buffer. For every respondent, buffer size, and survey year, we compute the number of restaurants, cafés, bars, and cinemas. Respondents with no amenities of a given category within a buffer are assigned a value of zero rather than being excluded from the sample.

5 Empirical Strategy

5.1 Cross Sectional Model

We begin by estimating a cross-sectional model that relates respondents' access to the nearest subway station to the percentage change in their life satisfaction index. The empirical specification is given by:

$$\text{PCLS}_i = \beta_0 + \beta_1 \text{Time}_i + \beta_2 \text{G}_i + \alpha_p + \varepsilon_i, \tag{1}$$

where PCLS denotes the percentage change in life satisfaction of respondent i between two consecutive years. Travel time (Time) is measured as the minimum travel time required for respondent i to reach the nearest subway station. The vector G_i includes a set of individual-level control variables: exposure to bus route changes induced by the subway opening, the percentage change in mental health, residential relocation in 2025, a transport vulnerability index, age and age squared, gender (male), parental status, employment status, marital status, general health, disability status, the PMN index, and car usage. The term α_p captures postal code fixed effects, and ε_i is the error term. We cluster the standard errors at the individual level.

5.2 Two Way Fixed Effect Model

Next, we exploit the panel structure of the data and estimate a two-way fixed effects model to identify the association between changes in subway access and life satisfaction over time. The empirical specification is given by:

$$\text{LS}_{it} = \beta_0 + \beta_1 \text{SA}_{it} + \beta_2 \text{K}_{it} + \alpha_{pt} + \gamma_i + \varepsilon_{it} \tag{2}$$

where LS denotes the life satisfaction of a respondent i in year t. Subway access (SA) is defined as a binary indicator that switches to one if respondent i resides within a ten-minute travel time threshold in year t. The vector K_{it} includes a set of time-varying individual-level control variables exhibiting meaningful variation across the two survey waves, namely: exposure to bus route changes induced by the subway, the mental health index and residential relocation. The term α_{pt} captures postal-code-by-year

fixed effects, absorbing all time-varying unobserved shocks at the local level, while γ_i denotes individual fixed effects, controlling for time-invariant individual heterogeneity. The error term is denoted by ε_{it}. Standard errors are clustered at the individual level.

5.3 Non-random Access to the Subway Network

Despite incorporating an extensive set of fixed effects and relevant individual-level controls, we cannot fully rule out the possibility that our estimates are affected by unobserved confounding factors. To further address potential endogeneity concerns, we adopt the identification strategy proposed by Borusyak and Hull (2023).

The intuition behind their methodology is that access to the subway network is jointly determined by two components: the spatial location of stations and the timing of their opening. While station placement is inevitably influenced by pre-existing patterns of population density, economic activity, and urban development, the timing of station openings can, under certain assumptions, be considered a plausibly exogenous source of variation. In particular, conditional on a set of geographically proximate stations, differences in opening dates may be interpreted as quasi-random if they are primarily driven by idiosyncratic construction delays rather than systematic differences in local characteristics.

For example, if construction delays are assumed to be as-good-as-random conditional on the planned network, counterfactual treatment assignments can be generated by randomly reallocating the order in which stations become operational. This creates alternative network configurations that preserve the spatial structure of the planned subway system while introducing variation in the timing of exposure.

The Thessaloniki subway provides an illustrative example of this type of variation through the Kalamaria extension. Initially, the extension was expected to become operational simultaneously with the main subway line. However, when the first phase of the network opened on 30 November 2024, the Kalamaria branch was not yet completed and was separated from the initial operating schedule. The extension was subsequently assigned several revised opening dates, initially expected in early 2025, later postponed to February 2026, and subsequently delayed further. These repeated postponements were primarily related to completion, testing, and system-integration requirements rather than changes in the underlying spatial demand for the extension. Such variation in the timing of operational availability illustrates the type of temporal uncertainty exploited by the methodology, where the realized exposure to subway access differs from the originally planned network structure .

This feature allows us to construct counterfactual subway access by considering stations that were planned but not yet operational at a given point in time. In our analysis, we define counterfactual stations as those located within 0.74 km, reflecting the average distance between stations.[5] We complement the 13 operational stations

[5]The total length of the network is 9.6 km, with 13 stations currently in operation. Dividing 9.6

with 8 planned stations, based on the official map from Thessaloniki's subway website.[6] Table A.6 contains the names of the subway stations in operation and planned that are used for this exercise. For the only operational stations that we couldn't find good counterfactuals are the first two stations of the line: the New Railway Station and Dimokratias. Following the methodology by Borusyak and Hull (2023) these two stations are always included in the counterfactuals.[7]

We randomly permute the opening year of comparable stations and repeat this procedure 1,000 times.[8] For each permutation, we recompute respondents' proximity to the subway network implied by the counterfactual opening schedule using two measures. First, we construct a binary indicator equal to one if a respondent resides within 1 km of the nearest station, based on straight-line distance.[9] Second, we define a binary indicator equal to one if a respondent resides within a 10-minute travel time of the nearest station, computed using least-cost path analysis. To implement the latter, we overlay a 100-meter grid and construct a least-cost surface using the 2025 road network and travel speed data from OpenStreetMap (2025). For each permutation, we then calculate the least-cost path from every respondent to the nearest station. An example is shown in Figure 7. We subsequently compute each respondent's average access across all counterfactual draws. This expected access captures the component of subway exposure driven by the spatial distribution of residences and economic activity, independently of the realized timing of station openings. In other words, it reflects respondents' predetermined exposure to the timing "shock." By permuting operational dates across planned/delayed stations (like Kalamaria), we construct a respondent's expected transit access based on spatial location alone.

Following Borusyak and Hull (2023), we construct the instruments by recentering treatment: we subtract expected treatment (average counterfactual access) from realized treatment (actual subway access), yielding the recentered treatment variables used as instruments. Subtracting expected access from actual access leaves only the exogenous shock of opening timing

We believe that the two instruments may exploit distinct sources of variation. The distance-based measure captures fine spatial discontinuities around stations, while the least-cost path measure incorporates network effects, accounting for respondents who may reside in more peripheral areas but can access stations via the road network (e.g., by car). The instruments are moderately correlated (Pearson correlation is approximately 0.57; see Table A.7 in the Appendix). We report estimates using each

by 13 yields an average distance of approximately 0.74 km between stations.

[6]The map is found under "Subway Thessalonikis, future expansions" and reports planned stations through 2040: https://www.thessmetro.gr/en/plan-for-2040/

[7]Borusyak and Hull (2023) always include the line Beijing to Shanghai because there isn't a good counterfactual line.

[8]In the Appendix we show that even if we increase the number of permutations to 2,000 and 5,000 nothing changes about our IV estimates.

[9]One kilometer corresponds to approximately 10–12 minutes of walking.

instrument separately and jointly.

We define the first stage equation as:

$$\mathrm{SA}_{it} = \beta_0 + \beta_1 \mathrm{RESA}_{it} + \beta_2 \mathrm{K}_{it} + \alpha_{pt} + \gamma_i + \varepsilon_{it} \tag{3}$$

where the variable RESA is the recentered expected subway access and then the second stage as:

$$\mathrm{LS}_{it} = \beta_0 + \beta_1 \widehat{\mathrm{SA}}_{it} + \beta_2 \mathrm{K}_{it} + \alpha_{pt} + \gamma_i + \varepsilon_{it} \tag{4}$$

The definition of the variables for both stages is the same as in in 6 as well as the controls. We cluster the standard errors at the individual level.

6 Results

In all the regressions tables the continues variables have been standardized as to have a mean equal to 0 and a standard deviation of 1. We present the summary statistics for all the variables used in the cross sectional regression analysis in Table A.1. Table A.2 includes the variables used in the two way fixed effects model. Possible variation in the number of observations reported across regression tables does not reflect differences in the underlying sample size but rather the exclusion of singleton groups, defined as groups containing only one observation. These singleton observations are dropped in high-dimensional fixed effects estimations because they do not contribute to the identification of fixed effects; their inclusion is not only computationally inefficient but may also lead to overstated statistical significance and biased inference (Correia, 2015).[10] In the Appendix A, we also include results preserving the singleton observations.

Cross Section: Table 1 presents cross-sectional estimates of the effects of travel time on percentage change of life satisfaction between the two consecutive years of our sample period. In column (1), we report the effect only with the inclusion of postcode fixed effects. We find that a one standard deviation reduction in travel time to the closest subway station is associated with a 0.18 standard deviation increase in the percentage change of life satisfaction. In column (2), we include important control variables from the survey. We report that once we take into account important controls variable the magnitude of our main independent variable increase while the standard error remains at the same level as in column (1). According to our estimates a one standard deviation reduction in travel time to the closest subway station is associated with a 0.23 standard deviation increase in the percentage change of life satisfaction. We also find a positive and statistically significant effect of changes in bus routes induced by the subway development. In contrast, mental health exhibits a negative

[10]Throughout the analysis, we use the Stata 17.0 commands "reghdfe" for linear regressions and "ivreghdfe" for the instrumental variable approach. The reghdfe command has since been incorporated as an official Stata command in version 19.0.

and significant association with life satisfaction, indicating that poorer mental health is linked to lower life satisfaction. These first correlational evidence suggest an effect of subway access and life satisfaction.

Balance Tests: Before proceeding to the two-way fixed effects analysis, we examine whether subway access is associated with predetermined neighborhood characteristics measured in 2024 in Table 2. Each row reports the results from a separate regression model, with all specifications including postal code fixed effects. Column (1) presents cross-sectional OLS estimates, while Column (2) reports instrumental variable (IV) estimates using the recentered LCP-Time treatment instrument. Overall, the OLS results provide little evidence of a systematic relationship between respondents' 2025 subway access and predetermined neighborhood characteristics measured before the subway became operational. The only exception is a positive and statistically significant association with the number of traffic recordings derived from the taxi dataset. In contrast, the IV estimates reveal no statistically significant relationship between subway access and any of the predetermined neighborhood characteristics, supporting the validity of the identification strategy.

Two Way Fixed Effects Model: Next, Table 3 presents the first-stage results from the IV two-way fixed effects model using the recentered LCP-Time exposure as an instrument. Column (1) reports the specification without additional controls, while column (2) introduces the relevant covariates. The estimated coefficient remains stable across specifications and exhibits a statistically significant positive relationship between the instrument and subway access. This positive first-stage relationship indicates that locations experiencing greater-than-expected exposure to the realized subway opening, relative to the counterfactual exposure distribution, were more likely to gain subway access. The first-stage F-statistic exceeds conventional thresholds, providing evidence that the instrument has sufficient predictive power and alleviating concerns regarding weak identification.

Table 4 reports the results from the two-way fixed effects models. Panel A contains the OLS results while panel B the IV. We begin with a baseline specification that includes only the main independent variable and fixed effects in column (1). Both OLS and IV results indicate that being within 10 minutes is associated with a 0.23 increase in life satisfaction. In column (2), we augment the model by including additional controls that exhibit substantial variation over time. The estimated coefficient of interest remains stable and comparable in magnitude to that reported in column (1), reinforcing the robustness of the main effect.

Table 5, explores the relationship between subway access and life satisfaction using all the possible instruments (based on time and distance). Panel A reports the first-stage results. The re-centered instruments performs well, exhibiting a positive and highly statistically significant effect on the endogenous variables. Table 5, Panel B presents the second-stage IV estimates. Across all specifications, the Kleibergen–Paap Wald rk F-statistic exceeds conventional thresholds, indicating that the instruments

are sufficiently strong (Lee et al., 2022). In column (1), we report the baseline finding subway access using the time-based instrument derived from the least cost path analysis as in Table 4. In column (2), we employ the distance-based instrument and obtain a similar effect. In column (3), both instruments are included simultaneously. The Hansen J-test does not reject the null hypothesis of instrument validity, suggesting that the instruments are jointly exogenous. The estimated effect remains close in magnitude to those reported in columns (1) and (2). The inclusion of additional control variables does not materially affect the estimated coefficients. The IV estimates are slightly larger than the corresponding OLS estimates reported in Table 4 when all the controls are included in the model.

Robustness Tests: We conduct a series of robustness checks for the two-way fixed effects models, reported in the Appendix. Table A.8 increases the number of permutations from 1,000 to 2,000 and 5,000 showing that the estimating effect is stable. Table A.9 presents results using alternative access thresholds. The estimated effects remain statistically significant when access is defined as within 15 minutes or 1 kilometer or within 1.5 kilometers. In Table A.10, we apply a double clustering at the individual and postal code level. We obtain statistically significant results. In Table A.11, we exclude from the sample respondents who were interviewed within two days after the subway network became operational. The estimated effects remain consistent with those of the baseline specification. In Table A.12, we include the full set of available control variables in the two-way fixed effects panel model, and the results remain unchanged. In Table A.13, we estimate the effect of Subway access on life satisfaction using a Poisson pseudo–maximum likelihood (PPML) model; the estimated effects remain positive and highly statistically significant. In Table A.14 we preserve the singleton observations in our regression sample and the results remain the same as in our baseline estimates. In Table A.15 we exclude from the sample the respondents that are more far away than 25 kilometers without affecting the results.

To evaluate the statistical precision of our empirical design, we implement an in-situ residual-based Monte Carlo power simulation based on 5,000 independent replications, tailored to the exact structure of our baseline two-way fixed effects (TWFE) specification. This exercise evaluates the ability of our empirical strategy to recover the treatment effect under repeated sampling while preserving the observed panel structure, treatment assignment share, fixed effects, and clustering structure. Assuming a true treatment effect of 0.232 standard deviations, the simulation indicates that our design rejects the null hypothesis at the 5% significance level in 97.4% of repeated samples. Figure B.1 in Appendix B presents the distribution of simulated treatment effects and the corresponding results of this power analysis.

7 Heterogeneous Treatment Effects

Next, we explore the heterogeneous treatment effects based on baseline exposure. As a first step we explore whether subway access is related to subway usage. We adopt the following specification:

$$\mathrm{SU}_{it} = \beta_0 + \beta_1 \mathrm{SA}_{it} + \beta_4 \mathrm{K}_{it} + \alpha_{pt} + \gamma_i + \varepsilon_{it} \tag{5}$$

where SU_{it} stands for subway usage. We consider both a binary indicator capturing whether an individual uses the subway (yes/no) and a frequency measure reflecting the intensity of use. We further examine specific purposes of subway use, including commuting to work and shopping activities among others, to better understand the channels through which subway access may operate. The remaining variables are defined as in the baseline specification, with SA_{it} denoting our main independent variable, subway access. In line with our previous specification we include the same controls and fixed effects and we cluster the standard errors at the individual level.

In addition, to this specification we explore whether the subway may improve subjective well-being is by alleviating the burden of road traffic. The introduction of a rapid public transportation alternative is expected to generate the largest benefits in neighborhoods where residents previously faced relatively congested road conditions. If reduced travel frictions constitute an important channel, the effect of subway access on life satisfaction should be stronger for individuals living in areas characterized by lower pre-opening traffic speeds.

To examine this hypothesis, we estimate a heterogeneous treatment effects specification by interacting subway access with a measure of local traffic conditions. Specifically, we use the average road speed within a 500-meter buffer around each respondent's residence, calculated from floating-car GPS data collected in 2024, prior to the opening of the Thessaloniki subway. This variable captures the traffic conditions in respondents' immediate residential environment and serves as an inverse proxy for local congestion, with lower average speeds indicating more congested roads. Because road speed is measured before the subway became operational, it is predetermined with respect to treatment and cannot itself be affected by the subway opening.

$$\mathrm{LS}_{it} = \beta_0 + \beta_1 \mathrm{SA}_{it} + \beta_2 \mathrm{SA}_{it} \, X \, \mathrm{NRS}_{i24} + \beta_3 \mathrm{K}_{it} + \beta_4 \mathrm{T}_{it} + \alpha_{pt} + \gamma_i + \varepsilon_{it} \tag{6}$$

The same variables are included as in equation (2). NRS_{i24} stands for neighborhood road speed. In addition, to the controls included in the baseline specification, we account for the number of local recordings within the respondent's 500-meter buffer area, as well as average altitude and vehicle orientation with T_{it}. We cluster the standard errors at the individual level.

7.1 Results

We next investigate whether the effect of subway access operates through changes in subway usage. Table 6 reports the results. Column (1) examines subway usage as a binary outcome, indicating whether the respondent uses the subway, while column (2) considers the frequency of subway use. Across both specifications, we find no statistically significant effect of subway access on subway usage for both OLS and IV models. In the Appendix A we also explore whether subway access affects the reasons for which individuals use the subway. Using the survey data, Table A.16 examines subway usage for commuting to work, shopping, social activities, recreation, returning home, and other purposes. The results reveal only limited evidence of an effect, with a weak positive association observed for shopping-related trips but this is effect does not hold for the corresponding IV estimation.

We provide additional descriptive evidence in Table 7 that complements the regression results. Of the 353 respondents in our panel, only 100 (approximately 28%) changed their dominant mode of transportation between the two survey waves. Among these respondents, 38% were previously car users, while the remaining 62% were bus users. This pattern is consistent with the existing literature, which shows that the introduction of a subway system initially attracts a larger share of public transport users than private car users, with substitution away from bus services intensifying over time and reaching its peak several years after subway operations begin (Chai et al., 2025). By contrast, shifts away from private car use tend to be more limited in the short run (Schafer and Victor, 2000). Importantly, these descriptive findings do not imply that the subway has little impact on traffic conditions. As argued by Anderson (2014), even a relatively small number of strategically located drivers switching from cars to public transit can generate substantial congestion relief because these commuters are typically those travelling on the most congested routes during peak periods. Consequently, improvements in neighborhood traffic conditions may arise even in the absence of widespread changes in individual travel behavior, providing a plausible explanation for the observed improvements in life satisfaction.

Next, we explore whether the main findings are consistent with a local congestion relief. Table 9 reports the results. Panel A presents estimates from the two-way fixed effects model, while Panel B reports the corresponding instrumental variables estimates. Across both specifications, subway access is associated with a positive and statistically significant increase in life satisfaction. More importantly, the interaction between subway access and neighborhood road speed is negative and statistically significant. The interaction coefficient equals -0.053 in the TWFE specification and -0.074 in the IV specification, with both estimates statistically significant at conventional levels.

The negative interaction implies that the well-being benefits of subway access are larger for respondents living in neighborhoods with lower pre-opening road speeds, corresponding to more congested traffic conditions. Conversely, the estimated gains

become smaller in areas where road traffic already flowed relatively freely before the subway opened. These findings are consistent with the hypothesis that improvements in local mobility and relief from traffic congestion constitute an important channel through which the subway enhances subjective well-being.

The main coefficient on subway access represents the treatment effect when the traffic variable equals zero and is therefore not economically meaningful on its own. Instead, the relevant quantity is the marginal effect of subway access, which varies with baseline neighborhood traffic conditions according to

Because the interaction coefficient is negative, the marginal effect declines as pre-opening neighborhood road speed increases. Thus, residents of neighborhoods characterized by heavier traffic congestion before the subway opened experienced the largest improvements in life satisfaction following the introduction of the subway. The similarity of the TWFE and IV estimates further suggests that this heterogeneous pattern is robust to accounting for the non-random spatial placement of subway infrastructure.

Figure 8 presents the IV marginal effects of subway access on life satisfaction across levels of neighborhood road speed, instrumenting for subway access and its interaction term. In heavily congested areas (-2 SD speed), subway access increases life satisfaction by approximately 0.40 standard deviations ($p < 0.05$). The marginal benefit monotonically declines as traffic conditions improve, becoming statistically indistinguishable from zero once road speed exceeds $+0.6$ standard deviations above the mean.

Tables A.17 present robustness checks for the traffic baseline results, accounting for time-of-day restrictions and holiday periods. Table A.18 reports the results after excluding respondents with no available traffic information for their residential area. Across both specifications, the estimated effects remain highly consistent with the baseline results reported in Table 9, supporting the robustness of the traffic relief effect. In Table A.19 we also explore whether neighborhood road speed could also be a mediator but we do not find supporting empirical evidence on that. Finally, in Table A.19 we present evidence that neighborhood road speed doesn't have a mediation relationship with subway access as the two channels are not related.

In Appendix C, we provide an exploratory analysis about alternative local channels, namely air pollution (Table C.1) and the availability of local amenities (Table C.2). For air pollution, we rely on the best publicly available source, the Copernicus Atmosphere Monitoring Service (CAMS) Atmosphere Data Store (Copernicus Atmosphere Monitoring Service, 2021). However, these data are available at a spatial resolution of approximately 10 km, implying limited within-city variation. To examine changes in neighborhood amenities, we extract historical Points of Interest from OpenStreetMap (OSM) (OpenStreetMap, 2025) for 2024 and 2025. We acknowledge that the 2024 data include observations from December, when the subway had already become operational, introducing a small degree of temporal overlap between the pre- and post-treatment

periods. Details on the construction of these variables and the corresponding empirical results are reported in Appendix C.

8 Conclusion

In this paper, we exploit the unique setting of Thessaloniki to examine the relationship between subway accessibility and life satisfaction. Using newly collected survey data and a recent econometric identification strategy, we provide consistent evidence that proximity to the subway has a positive and significant effect on life satisfaction. We employ a variety of econometric approaches, including a cross-sectional model, a two-way fixed effects model, and an IV strategy with two instruments, and our results remain robust across multiple specifications.

We also investigate potential channels underlying our baseline findings. First, we examine subway usage based on survey responses and we find no evidence that subway access increased self-reported subway usage. Next, we assess whether reductions in neighborhood traffic explain the observed impact. By geolocating and linking billions of external traffic recordings from Thessaloniki to our respondents, we show that the positive impact of subway access on life satisfaction is stronger in neighborhoods experiencing higher levels of traffic congestion, while the benefits are more limited in areas where traffic conditions are already relatively favorable. Our key finding is that large public transport investments generate neighborhood well-being spillovers that extend beyond direct users.

Overall, our results hold across a variety of econometric specifications, including cross-sectional, two-way fixed effects panel, and instrumental variable models, we provide consistent evidence that subway access positively affects life satisfaction. In terms of magnitude, proximity to the subway increases life satisfaction by approximately 0.23 an effect consistent across the different models and Monte Carlo simulations. The estimated effect size of 0.23 standard deviations is comparable to recent evidence from related quasi-experimental settings. For example, Sun and Du (2023) reports an effect of approximately 0.28 standard deviations on evaluative well-being among older individuals following subway introduction. Given that our analysis is based on the general population rather than a restricted sample of older individuals, the magnitude of our estimates is of a similar order and suggests that improved subway accessibility can generate economically meaningful gains in subjective well-being.

This highlights that transport investments generate benefits beyond immediate users, often overlooked in cost–benefit analysis. Policymakers can design projects knowing that even early adopters produce neighborhood-level benefits. This suggests that supporting complementary measures (e.g., bus route adjustments, pedestrian improvements) can amplify benefits while adoption grows. Overall, investments in new subway lines in cities without prior networks (like Thessaloniki) can generate large

marginal benefits per investment, especially in neighborhoods with high car traffic. This can guide equitable allocation of infrastructure to maximize life satisfaction improvements for residents most affected by congestion.

Of course, this study is subject to limitations. First, while our two-wave panel captures immediate pre- and post-launch dynamics, the absence of prior survey waves precludes a formal test of the parallel pre-trends assumption inherent to two-way fixed effects designs. Second, our evidence for the traffic relief channel reflects heterogeneous treatment effects anchored to pre-existing neighborhood road speeds, rather than a formal causal mediation chain tracking individual-level commuting changes. Third, although our analytical panel ($N = 353$) provides sufficient statistical power to identify the primary welfare effect, its size constrains our capacity to detect smaller individual behavioral shifts or subtle subgroup interactions. Finally, secondary environmental channels, specifically local air pollution and micro-amenity turnover, are constrained by coarse spatial resolution or limited pre-treatment longitudinal variation.

Future research could delve deeper into the specific factors driving subway usage with more granular data. Additionally, it could explore the evolving equilibrium between subway adoption and car usage. As new lines open and more citizens shift to public transit, reduced traffic congestion may generate larger positive externalities for remaining car users. Understanding the trade-off between private vehicle convenience and subway adoption could illuminate how urban mobility patterns stabilize over time and the broader implications for neighborhood well-being.

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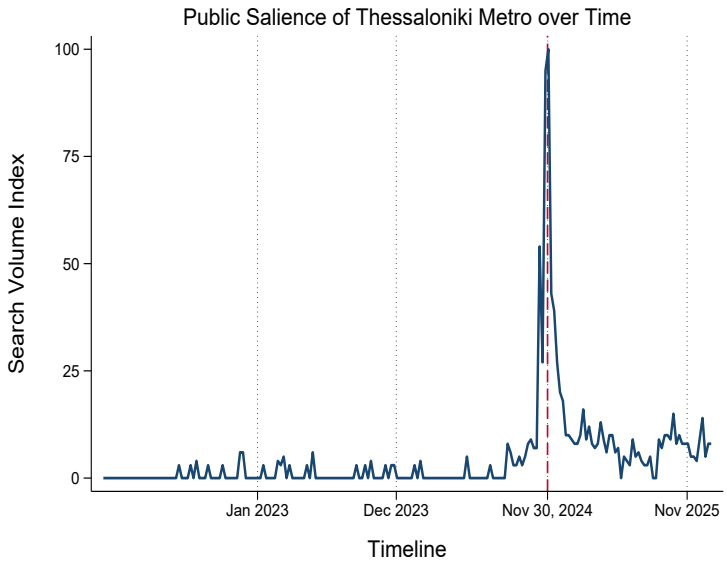
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9 Figures and Tables

Figure 1: Public Salience based on Google Trends



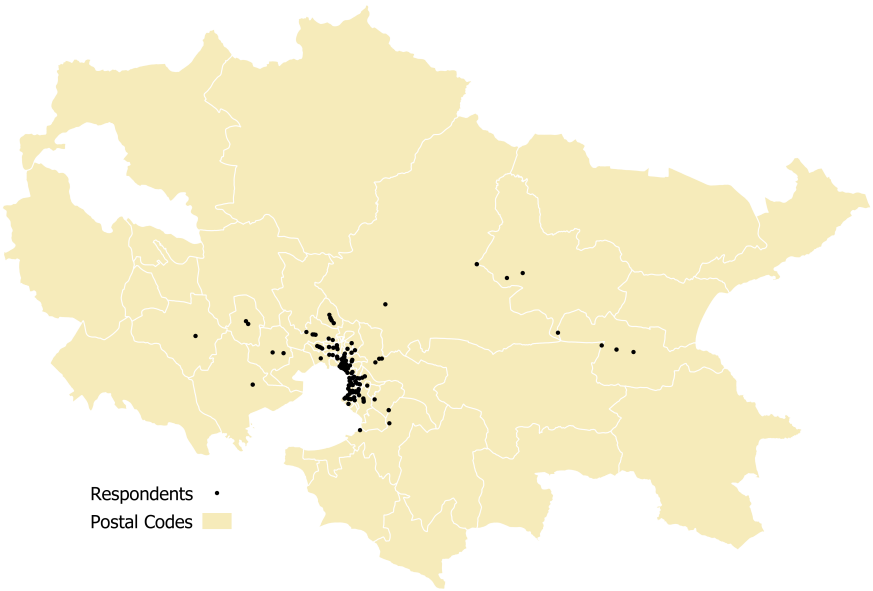
Notes: Source: Google Trends data (2023-2025). Dashed vertical line denotes the official opening (Nov 2024). We searched for the Greek terms metro (μετρό) and Thessalonikis (Θεσσαλονίκης).

Figure 2: Thessaloniki's Subway Line



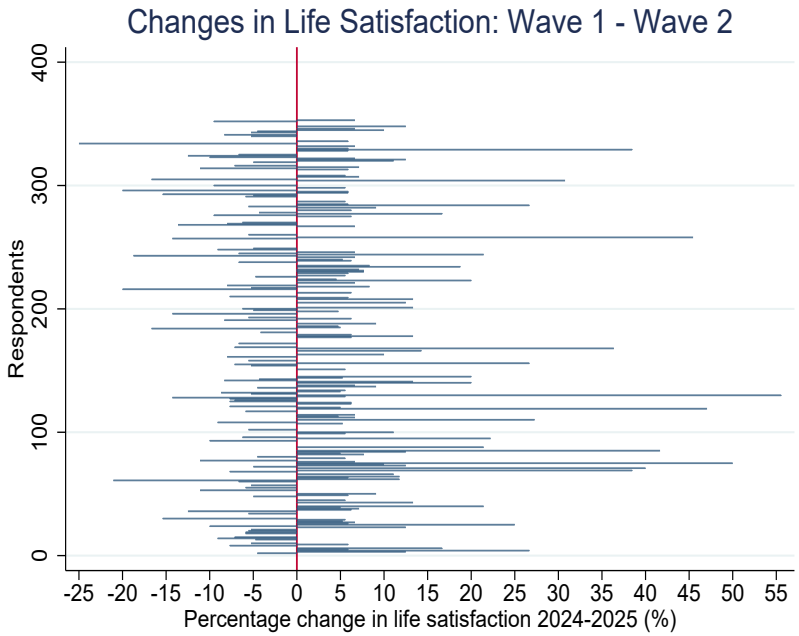
Notes: Authors' computations based on data from OSM, Eurostat and Copernicus

Figure 3: Spatial Distribution of the Respondents



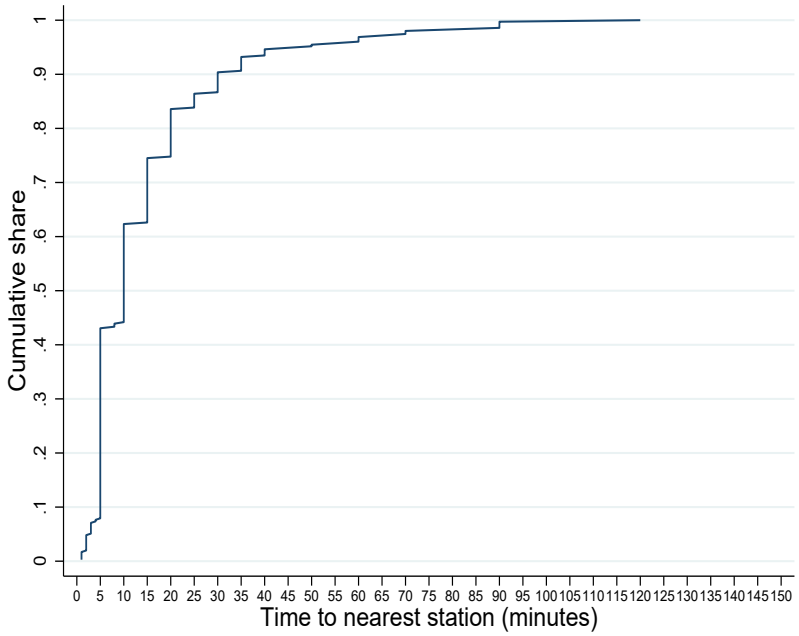
Notes: Authors' computations based on data from Eurostat and the survey

Figure 4: Changes in Life Satisfaction



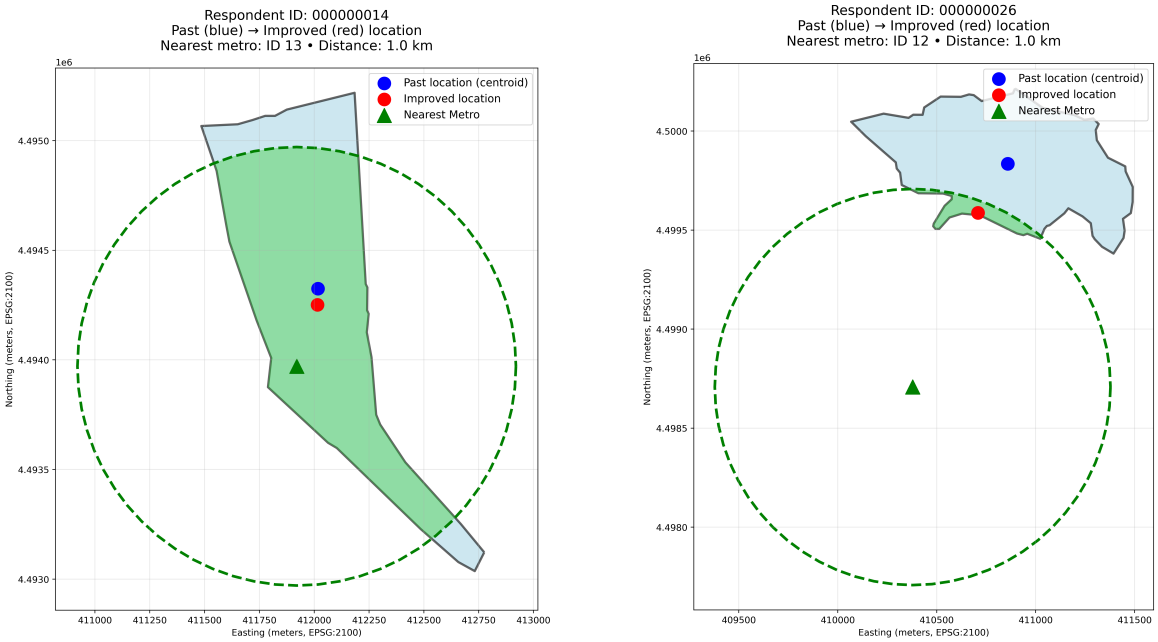
Notes: Authors' computations based on data from the survey.

Figure 5: Time to the Nearest Subway Station



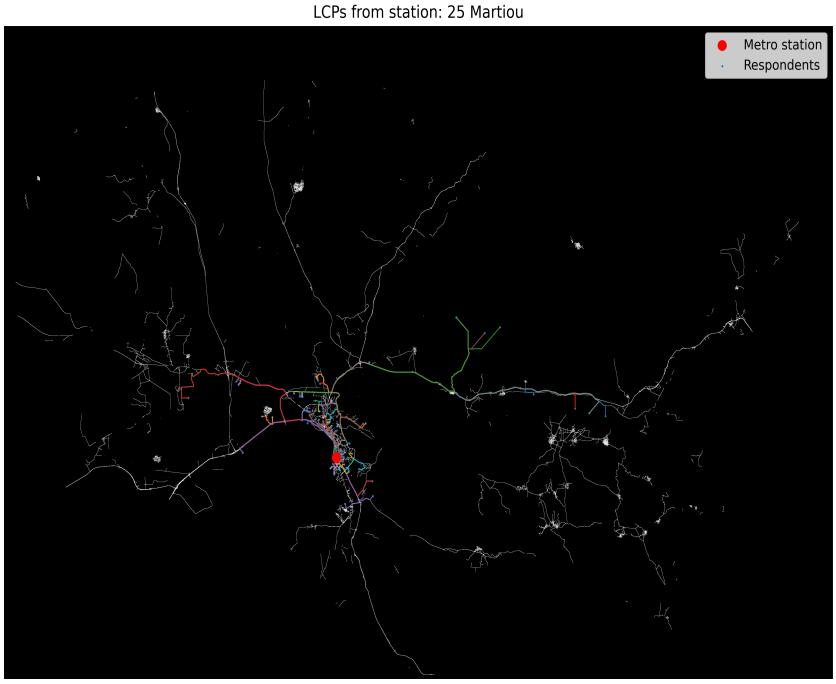
Notes: Authors' computations based on data from the survey.

Figure 6: Example of the Feasible Residential Areas



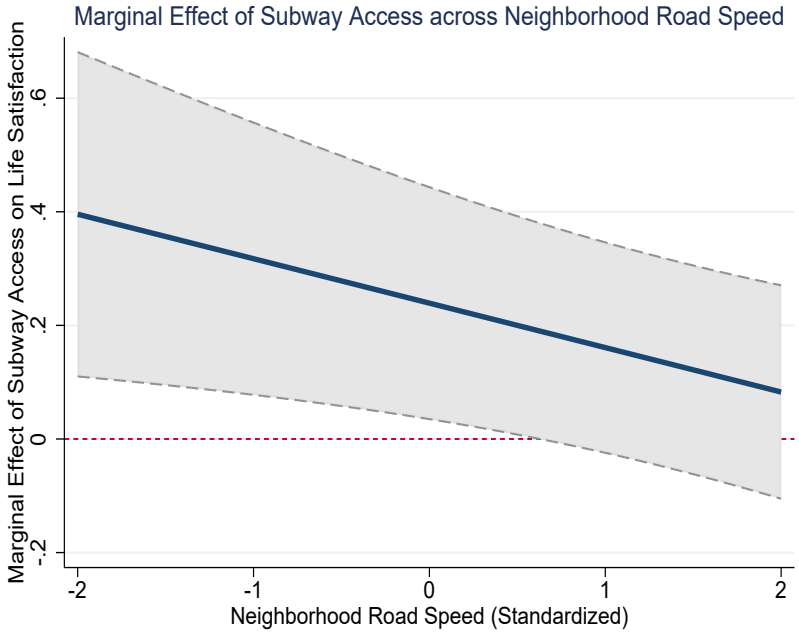
Notes: Authors' computations based on data from the Greek Data and the survey

Figure 7: Example of Least Cost Path for a Station



Notes: Authors' computations based on data from OSM, Eurostat and the survey.

Figure 8: Subway Access, Neighborhood Road Speed and Life Satisfaction



Notes: This figure shows the IV marginal effects of subway access on life satisfaction across levels of road speed, instrumenting for subway access and its interaction term.

Table 1: Cross Sectional OLS Model: Access to Subway and Life Satisfaction

	(1)	(2)
Panel A: Percentage Change of Life Satisfaction		
Travel Time	-0.180*	-0.234**
	[0.104]	[0.104]
Bus Routes Affected due to Metro		0.162**
		[0.067]
Percentage Change of Mental Health		-0.153**
		[0.069]
Relocated		0.035
		[0.062]
Transport Vulnerability		-0.149*
		[0.083]
Age		1.117**
		[0.470]
Age Squared		-1.209**
		[0.495]
Male		-0.043
		[0.074]
Children		-0.135*
		[0.074]
Full Time Employed		0.081
		[0.132]
Part Time Employed		0.018
		[0.079]
Unemployed		-0.072
		[0.044]
Self Employed		-0.078
		[0.067]
Long Term Relationship		0.068
		[0.048]
Single		-0.054
		[0.088]
Divorced		-0.073
		[0.052]
Widowed		0.080
		[0.081]
General Health		-0.107
		[0.086]
Disability		0.110
		[0.095]
PMN index		-0.028
		[0.127]
Car Usage		0.075
		[0.066]
R-squared	0.13	0.26
Sample Size	339	339
Postcode fixed effects	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 14 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 2: Balance Tests for Predetermined Neighborhood Characteristics (2024)

	(1) OLS	(2) IV
	Coefficient on Subway Access	
Road Speed	0.076	0.041
	(0.070)	(0.084)
Average Altitude	-0.013	-0.006
	(0.016)	(0.020)
Number of Traffic Recordings	0.087**	0.055
	(0.034)	(0.039)
Average Orientation	-0.121	0.021
	(0.108)	(0.125)
Log (Total Amenities + 1) in 500m	-0.073	0.066
	(0.064)	(0.086)
Log (Total Amenities + 1) in 1000m	-0.021	0.049
	(0.089)	(0.146)
Log (Population + 1) in 200m	-0.020	-0.058
	(0.153)	(0.206)
Log (Population + 1) in 300m	-0.098	-0.188
	(0.162)	(0.287)
Post Code fixed effects	Yes	Yes
Kleibergen-Paap Wald rk F statistic	-	262.51
Obs.	339	339

Notes: Each row reports a separate regression of the indicated 2024 location characteristic on Subway Access in 2025. Clustered standard errors at the individual level are reported in the parenthesis. Dropped 14 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 3: First Stage Results: Re-centered Instrument and Subway Access

	No Controls	Controls
	(1)	(2)
Panel A: Subway Access		
Recentered Treatment Time	0.758***	0.749***
	[0.0474]	[0.0474]
Bus Routes Affected due to Subway		-0.0197
		[0.0183]
Mental Health		-0.00851
		[0.0156]
Relocated		0.165**
		[0.0678]
Sample Size	674	674
Kleibergen-Paap Wald rk F statistic	256.22	250.60
Individual fixed effects	Yes	Yes
Postcode Year fixed effects	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 4: Two-way fixed effects panel model: Access to Subway and Life Satisfaction

	No Controls	Controls
	(1)	(2)
Panel A: Life Satisfaction - OLS		
Subway Access	0.231***	0.232***
	[0.084]	[0.085]
Bus Routes Affected due to Subway		0.157**
		[0.063]
Mental Health		-0.144***
		[0.053]
Relocated		0.048
		[0.177]
Panel B: Life Satisfaction - IV		
Subway Access	0.230**	0.233**
	[0.105]	[0.104]
Bus Routes Affected due to Subway		0.157**
		[0.063]
Mental Health		-0.144***
		[0.053]
Relocated		0.048
		[0.177]
Kleibergen-Paap Wald rk F statistic	256.22	250.60
Sample Size	678	678
Individual fixed effects	Yes	Yes
Postcode x Year fixed effects	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 5: IV panel model: Access to Subway and Life Satisfaction

	(1)	(2)	(3)	(4)
Panel A First Stage: Subway Access				
Recentered Treatment Time	0.758***		0.336***	0.331***
	[0.0474]		[0.0823]	[0.0805]
Recentered Treatment Distance		0.875***	0.562***	0.558***
		[0.0375]	[0.0901]	[0.0875]
Bus Routes Affected due to Subway				-0.0123
				[0.0150]
Mental Health				-0.0175
				[0.0180]
Relocated				0.128**
				[0.0590]
Panel B Second Stage: Life Satisfaction				
Subway Access	0.230**	0.249**	0.242**	0.255**
	[0.105]	[0.113]	[0.105]	[0.104]
Bus Routes Affected due to Subway				0.160**
				[0.064]
Mental Health				-0.142***
				[0.052]
Relocated				0.043
				[0.178]
Kleibergen-Paap Wald rk F statistic	256.22	544.34	454.00	449.83
Hansen P-value	-	-	0.75	0.56
Instrument	LCP-Time	Distance	Both	Both
Sample Size	678	678	678	678
Individual fixed effects	Yes	Yes	Yes	Yes
Postcode Year fixed effects	Yes	Yes	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 6: Access to Subway and Subway Usage

	Binary	Frequency
	(1)	(2)
Panel A: Metro Usage - OLS		
Subway Access	0.058	0.181
	[0.100]	[0.198]
Panel B: Metro Usage - IV		
Subway Access	0.050	0.301
	[0.117]	[0.255]
Kleibergen-Paap Wald rk F statistic	250.60	250.60
Sample Size	678	678
Individual fixed effects	Yes	Yes
Postcode x Year fixed effects	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 7: Switching to Subway in 2025 and Previous Dominant Mode

Switch to Subway	Frequency	Percent of Total	Previous Mode	Percent of Switchers
No	253	71.7	–	–
Yes	100	28.3	Car	38.0
			Bus	62.0
Total	353	100.0	–	–

Notes: Authors' descriptive statistics based on data from the survey.

Table 8: First Stage: Access to Subway and Traffic

	Subway Access	Subway Access x Neighborhood Road Speed
	(1)	(2)
Panel A: First Stage Results		
Recentered Treatment Time	0.752***	-0.0595
	[0.045]	[0.11]
Subway Access x Neighborhood Road Speed	-0.012	0.499***
	[0.011]	[0.051]
Kleibergen-Paap Wald rk F statistic	139.28	57.74
Sample Size	638	638
Individual fixed effects	Yes	Yes
Postcode Year fixed effects	Yes	Yes
Controls	Yes	Yes
Traffic Controls	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table 9: Access to Subway, Traffic and Life Satisfaction

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.237***
	[0.087]
Subway Access x Neighborhood Road Speed	-0.054**
	[0.026]
Panel B: Life Satisfaction - IV	
Subway Access	0.239**
	[0.104]
Subway Access x Neighborhood Road Speed	-0.078**
	[0.033]
Sample Size	638
Individual fixed effects	Yes
Postcode Year fixed effects	Yes
Controls	Yes
Traffic Controls	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Appendix A: Additional Findings

This Appendix section provides additional findings that confirm the benchmark analysis.

Table A.1: Summary statistics - Cross Sectional Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Percentage Change of Life Satisfaction Index	353	2.07	10.45	-25	55.56
Time in Minutes to the closest Metro Station	353	14.81	16.75	1	120
Percentage Change of Mental Health	353	-3.44	29.34	-100	200
Car Usage	353	2.16	1.59	0	4
Age	353	50.97	16.97	19	89
Age^2	353	2885.58	1709.97	361	7921
PMN index	353	3.63	1.01	1	5
General Health	353	3.29	1.07	1	5
Male	353	.49	.5	0	1
Disability	353	.12	.33	0	1
Bus Route Affected due to Metro	353	.42	.49	0	1
Has any Children	353	.7	.46	0	1
Self Employed	353	.16	.37	0	1
Full Time Employed	353	.56	.5	0	1
Part Time Employed	353	.08	.27	0	1
Unemployed	353	.02	.15	0	1
Not in the Labor Force	353	.34	.47	0	1
Married	353	.59	.49	0	1
Long Term Relationship	353	.01	.11	0	1
Single	353	.2	.4	0	1
Divorced	353	.1	.3	0	1
Widowed	353	.09	.29	0	1
Amenities 500m	353	28.96	46.59	0	253
Amenities 1000m	353	100.07	125.82	0	603
Population 200m	353	1989.69	1267.56	0	4191
Population 300m	353	4333.46	2717.2	0	9921

Table A.2: Summary statistics - Panel Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Life Satisfaction	706	17.06	3.17	7	25
Subway Access	706	.31	.46	0	1
Bus Routes Affected due to Subway	706	.21	.41	0	1
Mental Health	706	38.29	15.07	0	80
Relocated	706	.02	.13	0	1
Recentered Treatment Time	706	.03	.16	0	1
Recentered Treatment Distance	706	.07	.24	0	1
Subway Access interacted with Neighborhood Road Speed	706	6.59	11.04	0	66.7
Recentered Treatment Time interacted with Road Speed	706	.81	5.76	0	66.7
Number of Traffic Recordings	706	1.03e+07	1.04e+07	0	5.96e+07
Altitude	706	8.46	11.29	0	202.16
Orientation	706	181.3	49.59	0	328.25

Table A.3: Comparison between EUROSTAT demographic data and our survey

EUROSTAT: Year=2024	**Total**	**Males**	**Females**	**Median Age**
Value	1,086,927	517,564	569,363	55-59
Proportion (%)	100	47.62	52.38	-
Survey	**Total**	**Males**	**Females**	**Median Age**
Value	353	174	181	53
Proportion (%)	100	49.01	50.99	-

Notes: A comparison between the demographics reported by EUROSTAT for Thesssaloniki (EL522) for the year 2024 and our survey data. Source: EUROSTAT (demo_r_pjangrp3) and our own survey.

Table A.4: One-sample test: Gender

Statistic	Value
Number of observations (n)	353
Sample ($\hat{p}$)	0.4901
Standard error	0.0266
Hypothesized proportion (p_0)	0.4762
z-statistic	0.52
p-value (two-sided test)	0.601
95% confidence interval	[0.4380, 0.5422]

Notes: T-test between the proportion of male from EUROSTAT and the one reported by the survey.

Table A.5: One-sample test: Age

Statistic	Value
Number of observations (n)	353
Sample proportion ($\hat{p}$)	0.53
Standard error	0.0266
Hypothesized proportion (p_0)	0.57
z-statistic	-1.52
p-value (two-sided test)	0.1290
95% confidence interval	[0.4779, 0.5821]

Notes: T-test between the median age from EUROSTAT and the one reported by the survey.

Table A.6: Thessaloniki Subway Stations

Subway Station	**Status**	**Opening Year**
25 Martiou	working	2024
Agias Sofias	working	2024
Analipsi	working	2024
Dimokratias	working	2024
Efkleidis	working	2024
Fleming	working	2024
Nea Elvetia	working	2024
New Railway Station	working	2024
Panepistimio	working	2024
Papafi	working	2024
Sintrivani	working	2024
Venizelou	working	2024
Voulgari	working	2024
Nomarchia	planned	2026
Toumpa	planned	2040
Agia Kuriaki	planned	2040
Agiou Dimitriou	planned	2040
Aristotelous	planned	2040
Charilaou	planned	2040
Xanth	planned	2040

Notes: Operational and planned subway stations.

Table A.7: Correlation of the Instruments

	Recentered Treatment Time	Recentered Treatment Distance
Recentered Treatment Time	1.0000	
Recentered Treatment Distance	0.5727	1.0000

Notes: Correlation between the two instruments.

Table A.8: Access to Subway and Life Satisfaction: Additional Permutations

Dep. var. =	Life Satisfaction		
	(1) 1000 permutations	(2) 2000 permutations	(3) 5000 permutations
Panel A	Distance Instrument	Distance Instrument	Distance Instrument
Subway Access	0.249**	0.249**	0.249**
	[0.113]	[0.113]	[0.113]
Kleibergen-Paap Wald rk F statistic	544.34	540.86	535.87
Hansen P-val	-	-	-
Panel B	LCP Instrument	LCP Instrument	LCP Instrument
Subway Access	0.230**	0.230**	0.230**
	[0.105]	[0.105]	[0.105]
	[0.049]	[0.049]	[0.049]
Kleibergen-Paap Wald rk F statistic	256.22	256.22	256.22
Hansen P-val	-	-	-
Panel C	Both Instruments	Both Instruments	Both Instruments
Subway Access	0.242**	0.242**	0.241**
	[0.105]	[0.105]	[0.105]
Kleibergen-Paap Wald rk F statistic	454	452.70	450.92
Hansen P-val	0.75	0.76	0.76
Sample Size	678	678	678
Individual fixed effects	Yes	Yes	Yes
Postcode Year fixed effects	Yes	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.9: Access to Subway and Life Satisfaction: Higher thresholds

Dep. var. =	Life Satisfaction			
	(1)	(2)	(3)	(4)
Subway Access - Within 10 Minutes	0.232***			
	[0.085]			
Subway Access - Within 15 Minutes		0.203**		
		[0.089]		
Subway Access - Within 1 Kilometer			0.196**	
			[0.088]	
Subway Access - Within 1.5 Kilometer				0.197**
				[0.089]
Bus Routes Affected due to Subway	0.157**	0.143**	0.131**	0.128**
	[0.063]	[0.062]	[0.062]	[0.061]
Mental Health	-0.144***	-0.154***	-0.150***	-0.148***
	[0.053]	[0.054]	[0.054]	[0.054]
Relocated	0.048	0.101	0.118	0.086
	[0.178]	[0.165]	[0.156]	[0.157]
R-squared	0.95	0.95	0.95	0.95
Sample Size	674	674	674	674
Individual fixed effects	Yes	Yes	Yes	Yes
Postcode Year fixed effects	Yes	Yes	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 32 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.10: Access to Subway and Life Satisfaction: Double Clustering

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.232***
	[0.085]
Panel B: Life Satisfaction - IV	
Subway Access	0.233**
	[0.106]
Kleibergen-Paap Wald rk F statistic	105.53
Sample Size	678
Individual fixed effects	Yes
Postcode Year fixed effects	Yes
Controls	Yes
Clustering	Double Clustering

Notes: Double clustered standard errors at the individual and post-code level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.11: Access to Subway and Life Satisfaction: Around Opening Date

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.251***
	[0.093]
Panel B: Life Satisfaction - IV	
Subway Access	0.275**
	[0.114]
Kleibergen-Paap Wald rk F statistic	225.75
Sample Size	590
Individual fixed effects	Yes
Postcode Year fixed effects	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.12: Access to Subway and Life Satisfaction: Full set of controls

Dep. var. =	Life Satisfaction
	(1)
Subway Access	0.836***
	[0.282]
Bus Routes Affected due to Subway	0.490**
	[0.193]
Mental Health	-0.413***
	[0.154]
Relocated	0.204
	[0.491]
Transport Vulnerability	0.437*
	[0.258]
Age	-2.834
	[7.005]
Age^2	4.716
	[5.324]
Children	0.030
	[0.197]
Full Time Employed	-0.029
	[0.233]
Part Time Employed	-0.008
	[0.132]
Unemployed	0.004
	[0.084]
Self Employed	0.092
	[0.155]
Long Term Relationship	-0.177
	[0.125]
Single	-0.333
	[0.288]
Divorced	-0.007
	[0.151]
Widowed	0.298***
	[0.113]
General Health	-0.008
	[0.176]
Disability	-0.201
	[0.239]
PMN index	-0.193
	[0.256]
Car Usage	0.083
	[0.148]
R-squared	0.96
Sample Size	674
Individual fixed effects	Yes
Postcode Year fixed effects	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 32 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.13: Access to Subway and Life Satisfaction: PPML

Dep. var. =	Life Satisfaction
	(1)
Subway Access	0.046***
	[0.015]
Bus Routes Affected due to Subway	0.028***
	[0.011]
Mental Health	-0.027***
	[0.009]
Relocated	0.006
	[0.033]
Pseudo R-squared	0.11
Sample Size	678
Individual fixed effects	Yes
Postcode Year fixed effects	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.14: Access to Subway and Life Satisfaction: Singletons

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.232***
	[0.086]
Panel B: Life Satisfaction - IV	
Subway Access	0.233**
	[0.106]
Kleibergen-Paap Wald rk F statistic	241.52
Sample Size	706
Individual fixed effects	Yes
Postcode Year fixed effects	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.15: Access to Subway and Life Satisfaction: Less than 25 km

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.233***
	[0.085]
Panel B: Life Satisfaction - IV	
Subway Access	0.234**
	[0.105]
Kleibergen-Paap Wald rk F statistic	250.02
Sample Size	646
Individual fixed effects	Yes
Postcode Year fixed effects	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.16: Reasons to use Subway

	Work	Shopping	Social	Recreation	Home	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Subway Usage - OLS						
Subway Access	-0.082	0.141*	0.048	0.000	-0.026	0.017
	[0.067]	[0.085]	[0.084]	[0.093]	[0.081]	[0.089]
Panel B: Subway Usage - IV						
Subway Access	-0.109	0.152	0.039	-0.123	-0.067	-0.021
	[0.077]	[0.100]	[0.098]	[0.104]	[0.097]	[0.102]
Kleibergen-Paap Wald rk F statistic	250.60	250.60	250.60	250.60	250.60	250.60
Sample Size	678	678	678	678	678	678
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Postcode Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.17: Access to Subway, Traffic and Life Satisfaction - Robustness

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.236***
	[0.087]
Subway Access x Neighborhood Road Speed	-0.056**
	[0.026]
Panel B: Life Satisfaction - IV	
Subway Access	0.236**
	[0.103]
Subway Access x Neighborhood Road Speed	-0.083**
	[0.033]
Sample Size	638
Individual fixed effects	Yes
Postcode Year fixed effects	Yes
Controls	Yes
Traffic Controls	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.18: Access to Subway, Traffic and Life Satisfaction - No zeros

	Life Satisfaction
	(1)
Panel A: Life Satisfaction - OLS	
Subway Access	0.247***
	[0.089]
Subway Access × Neighborhood Road Speed	-0.053**
	[0.026]
Panel B: Life Satisfaction - IV	
Subway Access	0.248**
	[0.106]
Subway Access × Neighborhood Road Speed	-0.075**
	[0.033]
Sample Size	638
Individual fixed effects	Yes
Postcode Year fixed effects	Yes
Controls	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table A.19: Traffic as a Mediator

	Neighborhood Road Speed
	(1)
Panel A: Neighborhood Road Speed - OLS	
Subway Access	-0.008
	[0.008]
Panel B: Neighborhood Road Speed - IV	
Subway Access	-0.013
	[0.009]
Kleibergen-Paap Wald rk F statistic	247.43
Sample Size	678
Individual fixed effects	Yes
Postcode Year fixed effects	Yes
Controls	Yes
Traffic Controls	Yes

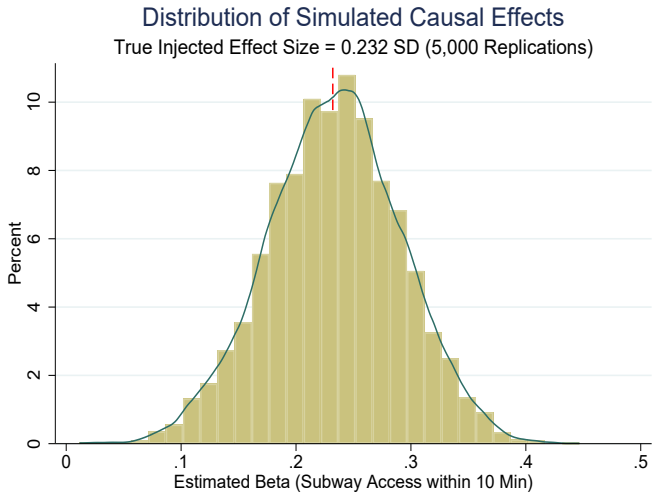
Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Appendix B: Monte Carlo Simulations

This Appendix section presents results from a Monte Carlo simulation exercise designed to evaluate the statistical precision of our empirical design. We implement an in-situ residual-based Monte Carlo power simulation based on 5,000 independent replications, tailored exactly to our baseline two-way fixed effects (TWFE) specification. Following standard simulation protocols, we construct a counterfactual no-treatment outcome by removing the estimated treatment effect from the observed outcome while preserving the original individual fixed effects, time effects, time-varying controls, and clustered error structure of the empirical sample.

In each replication, a pseudo-treatment indicator is randomly assigned to exactly 212 individuals in the 2025 wave, matching the treatment prevalence observed in the actual sample (approximately 62.5%). We then impose a treatment effect of 0.232 standard deviations on treated observations, corresponding to the estimated effect from our main specification. The simulation results provide strong evidence that our empirical design can reliably recover an effect of this magnitude. Across the 5,000 simulated samples, the mean estimated coefficient is 0.233, with a Monte Carlo standard error (MCSE) of 0.0008, indicating that the TWFE estimator recovers the imposed treatment effect with negligible bias under the simulated data-generating process. Moreover, the null hypothesis of no treatment effect is rejected at the 5% significance level in 4,870 replications, yielding an empirical power of 97.4%. Given the number of simulation draws, the Monte Carlo standard error of the power estimate is only 0.23 percentage points, corresponding to a 95% simulation-precision interval of [96.95%, 97.85%]. Figure B.1 presents the distribution of simulated treatment effects and the corresponding results of this exercise.

Figure B.1: Monte Carlo Simulations



Notes: Authors' computations.

Appendix C: Alternative Channels

This Appendix section provides findings about other potential Channels behind the baseline results.

Air Pollution Data

We extract the data about pollution from the Atmosphere Data Store of Copernicus (Copernicus Atmosphere Monitoring Service, 2021). CAMS European air quality reanalyses produces annual air quality reanalyses for the European domain at significantly higher spatial resolution (0.1 degrees, approx. 10km) than is available from the global reanalyses. The production is currently based on an ensemble of eleven air quality data assimilation systems across Europe. We make use of the essemple median model that is calculated from individual outputs, since ensemble products yield on average better performance than the individual model products. We choose the data at 0 meters above the surface. Then, we downloaded monthly files containing 1-hourly analyses since December of 2023. We follow the same strategy as the traffic data to compute the anual average values of air pollution. For 2024, we consider the period from December 2023 until November 2024 since subway became operational the last day of November. For 2025, we consider the period from December 2024 until November 2025.

We take into accout the literature and we consider as proxies for air pollution carbon monoxide and particulate matter 2.5 (Chen and Whalley, 2012; Zheng et al., 2019; Gendron-Carrier et al., 2022). In Table C.1, we examine whether subway access is associated with air pollution levels in respondents' neighborhoods. Although the estimated coefficient is negative, it is not statistically different from zero for both particulate matter and carbon monoxide. This suggests that subway access does not appear to have a meaningful effect on local air pollution and, therefore, air quality is unlikely to be the link through which subway access influences life satisfaction.

Local Amenities

To examine whether changes in neighborhood amenities constitute a potential channel through which the Thessaloniki subway affected life satisfaction, we construct respondent-level measures of local amenities using historical data from OpenStreetMap (OSM) (OpenStreetMap, 2025). Specifically, we extract Points of Interest (POIs) corresponding to four categories of amenities: restaurants, cafés, bars, and cinemas.

Historical OSM data are retrieved through the Overpass API using the OSMnx Python package. To ensure consistency with the timing of our survey, we query the OSM database at a fixed historical timestamp rather than using the current map. For the post-treatment period, amenities are extracted from the OSM snapshot corresponding to 2025. To improve data retrieval reliability, queries are automatically

rotated across multiple Overpass servers and repeated in the event of temporary server failures.

Because a small number of respondents changed residence between survey waves, we assign each individual to their most recent residential location. Respondents who did not move retain their original location, while respondents reporting a residential relocation are assigned their updated 2025 coordinates. This procedure ensures that the amenity measures correspond to the respondent's actual neighborhood during the post-treatment period.

All spatial data are projected to the Greek Grid coordinate reference system (EPSG:2100), allowing distances to be measured in meters. Around each respondent's residence, circular buffers with radio of 500, and 1,000 meters are constructed. Spatial joins are then used to identify all amenities located within each buffer. For every respondent, buffer size, and survey year, we compute the number of restaurants, cafés, bars, and cinemas. Respondents with no amenities of a given category within a buffer are assigned a value of zero rather than being excluded from the sample.

Finally, the newly constructed 2025 measures are combined with the previously generated 2024 amenity dataset to create a balanced respondent-year panel that is subsequently merged with the survey data for the empirical analysis.

Because historical OSM snapshots for 2024 are only available at discrete dates, the pre-treatment measure includes observations from December 2024, immediately following the inauguration of the Thessaloniki subway.

Table C.2 reports the relationship between subway access and the availability of local amenities. The dependent variable is the logarithm of the total number of amenities within 500-meter and 1,000-meter residential buffers. Across both OLS (Panel A) and IV (Panel B) specifications, the estimated coefficients are small and statistically insignificant. For example, the IV estimates imply increases of 3.8% and 4.1% in the number of nearby amenities within the 500-meter and 1,000-meter buffers, respectively, but neither estimate is statistically distinguishable from zero. The first-stage Kleibergen–Paap Wald rk F-statistic exceeds 250 in both specifications, indicating that the instrument is highly relevant. Overall, these findings provide no evidence that the improvement in life satisfaction following the subway opening operates through changes in the local stock of amenities.

Table C.1: Access to Subway and Air Pollution

	P 2.5	Carbon monoxide
	(1)	(2)
Panel A: Life Satisfaction - OLS		
Subway Access	-0.001	-0.002
	[0.005]	[0.006]
Panel B: Life Satisfaction - IV		
Subway Access	-0.001	-0.002
	[0.005]	[0.006]
Kleibergen-Paap Wald rk F statistic	250.60	250.60
Sample Size	678	678
Individual fixed effects	Yes	Yes
Postcode Year fixed effects	Yes	Yes
Controls	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Table C.2: Access to Subway and Amenities

	500 meter radius	1000 meter radius
	(1)	(2)
Panel A: Log (Total Amenities + 1) - OLS		
Subway Access - Within 10 Minutes	-0.048	0.022
	[0.032]	[0.041]
Panel B: Log (Total Amenities + 1) - IV		
Subway Access	0.038	0.041
	[0.037]	[0.044]
Kleibergen-Paap Wald rk F statistic	250.60	250.60
Sample Size	678	678
Individual fixed effects	Yes	Yes
Postcode Year fixed effects	Yes	Yes
Controls	Yes	Yes

Notes: Clustered standard errors at the individual level are reported in the parenthesis. Dropped 28 singleton observations. ***p< 0.01, **p< 0.05, *p< 0.1

Appendix C References

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