July 2026

Supplemental Information

Supplemental Information to:

Fearnley, N., & Veisten, K. (2026). A meta-analysis of the induced travel due to e-scooters

Content (Supplements)

S1 Material (meta-data)

50 study references with 192 outcomes

The following table lists the 192 outcomes from 50 studies, the 42 non-confidential references (studies), with the 8 confidential studies aggregated at the bottom line.

Table S1.1. References covering 192 survey-based e-scooter induced-travel outcomes, from 50 studies in Europe, North America and Oceania (95 different case areas)

Reference	No. of outcomes	Case area(s)
Agence de la Mobilité de la Ville de Paris, 2022. Étude sur les usages et usagers de la micromobilité à Paris. Mai 2022, Ville de Paris (https://eu.ftp.opendatasoft.com/parisdata-dvd/AM/Micromobilite.pdf, accessed 22 Aug 2024)	1	Paris
Ali, T.A.H.M., 2021. Analysis of traveler's behavior using electric scooters based on surveys. Master degree thesis, KTH Royal Institute of Technology, Stockholm (https://www.diva-portal.org/smash/get/diva2:1591199/FULLTEXT01.pdf, accessed 24 Aug 2024)	1	Stockholm
Arup/NatCen, 2022. (Operator data, 32 trials) National evaluation of e-scooter trials - technical report. Dec 2022, Arup / NatCen Social Research, London (https://assets.publishing.service.gov.uk/media/63b53f488fa8f56b17ac2196/national-evaluation-of-e-scooter-trials-technical-report.pdf, accessed 22 Aug 2024)	16[a]	Bournemouth, Cambridge, Cheltenham, Great Yarmouth, High Wycombe, London, Milton Keynes, Newcastle upon Tyne, Norwich, Nottingham, Oxford, Salford, Slough, Sunderland, Whitehaven, York
Arup/NatCen, 2022. (User survey, 10 trials) National evaluation of e-scooter trials - findings report. Dec 2022, Arup / NatCen Social Research, London (https://assets.publishing.service.gov.uk/media/64e4a5de3309b7000d1c9c41/national-evaluation-of-e-scooter-trials-findings-report.pdf, accessed 22 Aug 2024)	7[b]	Bristol, Cambridge, Liverpool, London, Milton Keynes, Newcastle upon Tyne, York
Auckland Council, 2019. Rental e-scooter trial 2.0 - Results, evaluation and recommendations. Report, Auckland Council (https://www.aucklandcouncil.govt.nz/licences-regulations/report/rental-e-scooter-trial-2.0-evaluation-report.pdf, accessed 24 Aug 2024)	1	Auckland
Chatterjee, K., Parkin, J., Bozovic, T., Flower, J., 2023. West of England e-scooter trial: Evaluation final report. May 2023, Centre for Transport & Society, UWE Bristol (https://www.westofengland-ca.gov.uk/wp-content/uploads/2022/07/West-of-England-E-scooter-Trial-Evaluation-Final-Report-v3.6.pdf, accessed 28 Aug 2024)	4	Bath, Bristol
Christoforou, Z., de Bortoli, A., Gioldasis, C., Seidowsky, R., 2021. Who is using e-scooters and how? Evidence from Paris. *Transportation Research Part D*, 92: 102708, https://doi.org/10.1016/j.trd.2021.102708	1	Paris
City and County of Denver, 2021. Dockless mobility vehicle permit pilot program. Final report, March 2021, Dep. of Transportation & Infrastructure, City and County of Denver (https://denver.prelive.opencities.com/files/assets/public/v/2/doti/documents/programsservices/dockless-mobility/dockless-mobility-pilot-final-report.pdf, accessed 25 Aug 2024) (not including appendices b and c)	1	Denver CO
City of Alexandria, 2019. Alexandria dockless mobility pilot evaluation. Report Nov 2019, City of Alexandria (https://media.alexandriava.gov/docs-archives/tes/info/evaluationreportreducedsize.pdf, accessed 22 Aug 2024)	1	Alexandria VA
City of Atlanta, 2020. Atlanta E-scooter survey - results 2019. City of Atlanta, Dep of Transportation (https://www.atlantaga.gov/home/showpublisheddocument/49802/637474395805300000, accessed 22 Aug 2024)	1	Atlanta GA
City of Calgary, 2020. Electric scooter share pilot. Report Oct 2020, City of Calgary (https://engage.calgary.ca/scootershare, accessed 24 Aug 2024)	1	Calgary
City of Hobart, 2023. E-scooter survey - Statement of results. Feb 2023, City of Hobart (https://ehq-production-australia.s3.ap-southeast-2.amazonaws.com/c974ffee968497a64e0b2310ea1520682cb0934b/original/1676936307/64700253b7fdb0a74d3803a8913444e2_Community_Survey_Statement_of_Results.pdf?X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIA4KKNQAKIOR7VAOP4%2F20240831%2Fap-southeast-2%2Fs3%2Faws4_request&X-Amz-Date=20240831T102043Z&X-Amz-Expires=300&X-Amz-SignedHeaders=host&X-Amz-Signature=82fb3dac0b0788240390bf31d5fd7ab342c16ac6a833166b45c41ed1c19c12fd, accessed 31 Aug 2024)	1	Hobart
City of Hoboken, 2019. Hoboken shared E-scooter program end-of-pilot survey. Nov 12 2019 (https://assets.website-files.com/58407e2ebca0e34c30a2d39c/5dd570e833006067e38907ca_e-scooter%20survey.pdf, accessed 31 Aug 2024)	1	Hoboken NJ
City of San Antonio, 2019. Dockless vehicle community engagement report. May 15, 2019, City of San Antonio (https://www.sanantonio.gov/Portals/0/Files/CCDO/Dockless%20Vehicle%20Community%20Engagement%20Report%20-%20May%202019.pdf?ver=2019-05-23-141425-113, accessed 26 Aug 2024)	1	San Antonio TX
Dowdall-Masters, L., 2020. E-scooter survey results (wave 1 and 2). Report, April 2020, Wellington City Council (unavailable online, copy available from authors)	3	Wellington
Fearnley, N., Berge, S.H., Johnsson, E., 2020. Delte elsparkesykler i Oslo - En tidlig kartlegging. TØI Report 1748, Institute of Transport Economics, Oslo (https://www.toi.no/getfile.php?mmfileid=52254, accessed 28 Aug 2024)	1	Oslo
Fitt, H., Curl, A., 2019. E-scooter use in New Zealand: Insights around some frequently asked questions. Report from University of Canterbury (https://ir.canterbury.ac.nz/handle/10092/16336, accessed 23 Aug 2024)	1	Christchurch

Reference	No. of outcomes	Case area(s)
Guo, Y., Zhang, Y., 2021. Understanding factors influencing shared e-scooter usage and its impact on auto mode substitution. *Transportation Research Part D*, 99: 102991, https://doi.org/10.1016/j.trd.2021.102991.	1	Tampa FL
Hollingsworth, J., Copeland, B., Johnson, J.X., 2019. Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. *Environmental Research Letters*, 14(8): 084031, https://iopscience.iop.org/article/10.1088/1748-9326/ab2da8.	1	Raleigh NC
Institute of Transport Economics, 2022a. Unpublished analysis of user survey. Institute of Transport Economics, Oslo	4	Bergen, Oslo, Stavanger, Trondheim
Institute of Transport Economics, 2022b. Unpublished analysis of general survey – sub sample e-scooter users. Institute of Transport Economics, Oslo	1	Oslo
Institute of Transport Economics, 2022c. MikroReg user survey 2022. Unpublished data analysis results. Institute of Transport Economics, Oslo	3	Bergen, Oslo, Trondheim
James, O., Swiderski, J.I., Hicks, J., Teoman, D., Buehler, R., 2019. Pedestrians and E-scooters. An initial look at E-scooter parking and perceptions by riders and non-riders. *Sustainability*, 11(20): 5591, https://doi.org/10.3390/su11205591 + (the same results are reported in) Chowdhury, A., Hicks, J., James, O., Swiderski, J. I., Wilkerson, A., Buehler, R., 2019. Shared mobility devices in Arlington. Working draft report, Spring 2019, Virginia Tech Urban Affairs and Planning Studio (https://ralphbu.wordpress.com/wp-content/uploads/2019/05/working-draft-report_051419-1.pdf , accessed 24 Aug 2024	1	Arlington VA
Krauss, K., Doll, C., Thigpen, C., 2022. The net sustainability impact of shared micromobility in six global cities. Fraunhofer Institute for Systems and Innovation Research ISI, Karlsruhe / Lime (https://www.isi.fraunhofer.de/content/dam/isi/dokumente/ccn/2022/the_net_sustainability_impact_of_shared_micromobility_in_six_global_cities.pdf, accessed 26 Aug 2024)	6	Berlin, Düsseldorf, Melbourne, Paris, Seattle WA, Stockholm
Krier, C., Chrétien, J., Lagadic, M., Louvet, N., 2021. How do shared dockless E-scooter services affect mobility practices in Paris? A survey-based estimation of modal shift. *Transportation Research Record*, 2675(11), 291-304, https://doi.org/10.1177/03611981211017.	2	Paris
Lime, 2018a. The data-backed case for Lime-S electric scooters in San Francisco. June 20 2018 (https://www.li.me/blog/data-backed-case-lime-electric-scooters-in-san-francisco, accessed 26 Aug 2024)	1	San Francisco CA
Lime, 2019. Lime for a sustainable Paris. + Krier et al., 2021. How do shared dockless E-scooter services affect mobility practices in Paris?	1	Paris
Lovett, N., 2019. Christchurch E-scooter trial. Presentation, Christchurch City Council (https://az659834.vo.msecnd.net/eventsairaueprod/production-harding-public/ad07791301af427f8c53e0fcff0ecc3a, accessed 23 Aug 2024)	1	Christchurch
Meroux, D., Broaddus, A., Telenko, C., Chan, H.W., 2023. How should vehicle miles traveled displaced by E-scooter trips be calculated? *Transportation Research Record*, 2677(1), 356-368, https://doi.org/10.1177/03611981221099506	4	Portland OR, San Francisco CA, Tampa FL, Washington DC
Miller, M., 2020. Dockless electric scooters and the sustainable mobility transistion in Stockholm. Master degree project, KTH Royal Institute og Technology (https://kth.diva-portal.org/smash/get/diva2:1521070/FULLTEXT01.pdf, accessed 23 Aug 2024).	1	Stockholm
Mobility Lab, 2019. Arlington County shared mobility devices (SMD) - Pilot evaluation report. Sep 2019, Arlington County Commuter Services (ACCS) (unavailable online, copy available from authors)	1	Arlington VA
Murphy, C., Curtis, T., Costagliola, E., Clewlow, R., Seki, S., Xu, R., 2021. Transit and Micromobility. National Academies of Sciences, Engineering, and Medicine (https://doi.org/10.17226/26386)	1	San Jose CA
Neuron, 2021. Responses to UK E-scooter preferences survey. May 2021, Neuron data (Excel spreadsheet).	3	Newcastle upon Tyne, Slough, Sunderland
OakDOT, 2020. The year in review 2019 OakDOT shared mobility snapshot. City of Oakland Dep. of Transportation (OakDOT) (https://medium.com/oakdot/the-year-in-review-2019-oakdot-shared-mobility-snapshot-64f519aeeb60, accessed 22 Aug 2024) + Reinhardt, K., Deakin, E., 2020. Best practices for the public management of electric scooters. Report No.: UC-ITS-2020-25, Institute of Transportation Studies, UC Berkeley (https://escholarship.org/uc/item/8x67x360, accessed 22 Aug 2024)	1	Oakland CA
PBOT, 2019. 2018 E-scooter findings report. Portland Bureau of Transportation (PBOT), City of Portland (https://www.portland.gov/transportation/escooterpdx/2018-e-scooter-findings-report, accessed 23 Aug 2024)	1	Portland OR
PBOT, 2020. 2019 E-scooter findings report. Sep 2019, Portland Bureau of Transportation (PBOT), City of Portland (https://www.portland.gov/sites/default/files/2020/pbot_e-scooter_report_final.pdf, accessed 23 Aug 2024)	1	Portland OR
Populus, 2019. Brookline, MA - Scooter pilot program April 1st - November 15th 2019. Brookline Results (https://www.brooklinema.gov/DocumentCenter/View/35201/Populus---Brookline-E-Scooter-Pilot-Results?bidId=, accessed 31 Aug 2024)	1	Brookline MA
SDOT, 2022. E-scooter share pilot evaluation. March 2022, Seattle Department of Transportation (SDOT) (https://www.seattle.gov/documents/Departments/SDOT/NewMobilityProgram/ScooterShare_Pilot_Report_Final.pdf, accessed 26 Aug 2024)	1	Seattle WA
SFMTA, 2023. Powered scooter evaluation report. San Francisco Municipal Transportation Agency (SFMTA) (https://www.sfmta.com/media/37148/download?inline, accessed 25 Aug 2024)	1	San Francisco CA
TIER, 2022. TIER Nordics. TIER Mobility (unavailable online, copy available from authors)	1	Oslo
Transport for London, 2024. London e-scooter rental trial: Phase 1 report findings - Data collected from June 2021 to September 2023. Feb 2024, Mayor of London / London Councils / Transport for London (https://content.tfl.gov.uk/london-e-scooter-rental-trial-phase-1-report-june-2021-to-september-2023.pdf, accessed 28 Aug 2024)	1	London
Vallamsundar, S., Jaikumar, R., Venugopal, M., 2022. Exploring the spatial-temporal dynamics of travel patterns and air pollution exposure of E-scooters. Journal of Transport Geography, 105, https://doi.org/10.1016/j.jtrangeo.2022.103477	1	Austin TX

Reference	No. of outcomes	Case area(s)
Confidential studies/data (2020-2023)	108	Aachen, Aalborg, Aarhus, Augsburg, Basel, Bath, Bergen, Berlin, Bern, Bordeaux, Bremen, Bristol, Brussels, Cambridge, Cologne, Copenhagen, Corby, Coventry, Düsseldorf, Frankfurt, Gothenburg, Hamburg, Helsingborg, Helsinki, Karlsruhe, Kettering, Lillestrøm, Liverpool, Lübeck, Malmö, Marseille, Milan, Munich, Norrköping, Northampton, Nuremberg, Oslo, Oxford, Peterborough, Portsmouth, Rome, Rushden, Southampton, Stockholm, Stuttgart, Tampere, Trondheim, Turku, Uppsala, Västerås, West Bromwich, Winterthur, Zürich

This is a subset of a larger set of meta-data described by Fearnley and Veisten (2025), a subset of the surveys that presented proportions of those stating that the last trip by e-scooter would not have been carried out if an e-scooter were not available (which is applied directly as an estimate of the induced travel due to e-scooter availability).

The 95 case-areas where the 192 outcomes are estimated

The following table lists the 95 case areas where the 192 outcomes were estimated. Several case area characteristics (area size, population size, transport) were not generally available from the studies but added into the meta-data for the meta-analysis.

Table S1.2. The 95 case areas (of the 192 outcomes), in Europe, North America and Oceania

Country of study data	Location/city of study data	Population in (study data) built-up area	Built-up land area (sq.km)	Population density (pop./sq.km)	Tram / light rail in area	Km tram / light rail in area	Metro / subway in area	Km metro / subway in area	City bike scheme in area	Proportion commuting by private 2 or 4-wheeled motorised vehicle (PMV)	Proportion commuting by public transport (PT)	Proportion commuting by bicycle or on foot (AT)
Germany	Aachen	248 878	161	1 547	0	0	0	0	1	0,60	0,14	0,26
Germany	Augsburg	295 830	147	2 014	1	45	0	0	1	0,67	0,16	0,17
Germany	Berlin	3 664 088	891	4 112	1	190	1	148	1	0,26	0,27	0,48
Germany	Bremen	566 573	327	1 734	1	115	0	0	1	0,36	0,16	0,48
Germany	Cologne	1 083 500	405	2 675	1	246	0	0	1	0,50	0,28	0,22
Germany	Düsseldorf	619 000	217	2 853	1	78	1	69	1	0,40	0,19	0,41
Germany	Frankfurt	764 104	248	3 077	1	73	1	86	1	0,44	0,30	0,26
Germany	Hamburg	1 852 478	755	2 453	0	0	1	106	1	0,36	0,22	0,42
Germany	Karlsruhe	308 436	173	1 779	1	334	0	0	1	0,34	0,17	0,49
Germany	Lübeck	215 846	214	1 008	0	0	0	0	0	0,44	0,15	0,41
Germany	Munich	2 008 000	482	4 166	1	79	1	95	0	0,34	0,24	0,42
Germany	Nuremberg	515 543	186	2 765	1	33	1	38	1	0,39	0,23	0,38
Germany	Stuttgart	1 357 000	477	2 845	1	128	0	0	0	0,45	0,24	0,31
France	Bordeaux	994 920	1 292	770	1	77	0	0	0	0,51	0,12	0,37
France	Marseille	1 400 000	689	2 032	1	12	1	22	1	0,54	0,11	0,35
France	Paris	2 175 601	105	20 720	1	105	1	225	1	0,20	0,60	0,20
Norway	Bergen	265 470	90	2 940	1	20	0	0	1	0,46	0,30	0,23
Norway	Oslo	1 043 168	270	3 857	1	131	1	85	1	0,34	0,30	0,35
Norway	Trondheim	191 771	59	3 272	1	9	0	0	1	0,42	0,19	0,38
Norway	Stavanger	229 911	80	2 871	0	0	0	0	1	0,59	0,15	0,26
Norway	Lillestrøm	94 000	410	229	0	0	0	0	1	0,55	0,38	0,07
Sweden	Gothenburg	607 882	231	2 632	1	161	0	0	1	0,53	0,21	0,26
Sweden	Helsingborg	113 828	41	2 780	0	0	0	0	1	0,59	0,19	0,23
Sweden	Malmö	325 069	78	4 150	0	0	0	0	1	0,51	0,18	0,31
Sweden	Norrköping	98 088	38	2 612	1	21	0	0	0	0,58	0,14	0,28
Sweden	Örebro	126 604	55	2 301	0	0	0	0	0	0,57	0,08	0,35
Sweden	Stockholm	1 617 407	422	3 829	1	40	1	108	1	0,34	0,44	0,22
Sweden	Uppsala	166 698	43	3 856	0	0	0	0	1	0,38	0,13	0,48
Sweden	Västerås	128 660	50	2 551	0	0	0	0	1	0,66	0,09	0,25

Country of study data	Location/city of study data	Population in (study data) built-up area	Built-up land area (sq.km)	Population density (pop./sq.km)	Tram / light rail in area	Km tram / light rail in area	Metro / subway in area	Km metro / subway in area	City bike scheme in area	Proportion commuting by private 2 or 4-wheeled motorised vehicle (PMV)	Proportion commuting by public transport (PT)	Proportion commuting by bicycle or on foot (AT)
Denmark	Aalborg	142 937	61	2 351	0	0	0	0	1	0,55	0,09	0,36
Denmark	Aarhus	285 273	100	2 854	1	110	0	0	1	0,45	0,20	0,35
Denmark	Copenhagen	1 336 982	293	4 571	0	0	1	38	1	0,25	0,35	0,39
Denmark	Odense	180 760	79	2 279	0	0	0	0	1	0,49	0,04	0,46
Finland	Helsinki	1 200 000	515	2 330	1	96	1	35	1	0,22	0,30	0,47
Finland	Tampere	334 112	259	1 292	1	16	0	0	1	0,56	0,09	0,35
Finland	Turku	254 671	255	1 000	0	0	0	0	1	0,61	0,07	0,32
Belgium	Brussels	1 208 542	162	7 442	1	139	1	40	0	0,43	0,28	0,28
Switzerland	Basel	532 000	199	2 673	1	66	0	0	0	0,22	0,27	0,51
Switzerland	Bern	134 000	52	2 596	1	33	0	0	1	0,22	0,32	0,45
Switzerland	Winterthur	111 840	68	1 643	0	0	0	0	0	0,35	0,20	0,44
Switzerland	Zürich	922 000	243	3 794	1	73	0	0	0	0,21	0,33	0,46
Italy	Milan	1 400 000	182	7 702	1	182	1	97	1	0,30	0,42	0,29
Italy	Rome	2 872 021	1 285	2 235	1	39	1	60	1	0,54	0,29	0,17
UK	Bath	88 859	29	3 064	0	0	0	0	0	0,79	0,02	0,19
UK	Birmingham	2 624 000	598	4 388	1	20	0	0	0	0,74	0,14	0,11
UK	Bournemouth	547 539	276	1 984	0	0	0	0	1	0,79	0,08	0,13
UK	Bristol	687 000	145	4 738	0	0	0	0	0	0,59	0,13	0,29
UK	Bristol (agglom.)	847 260	190	4 459	0	0	0	0	0	0,76	0,07	0,16
UK	Cambridge	158 434	42	3 763	0	0	0	0	1	0,36	0,15	0,49
UK	Cheltenham	118 866	47	2 550	0	0	0	0	1	0,75	0,06	0,20
UK	Corby	54 927	20	2 815	0	0	0	0	0	0,87	0,05	0,08
UK	Coventry	359 262	81	4 419	0	0	0	0	0	0,52	0,18	0,30
UK	Great Yarmouth	58 032	10	5 757	0	0	0	0	0	0,84	0,05	0,12
UK	High Wycombe	83 523	18	4 517	0	0	0	0	0	0,85	0,07	0,08
UK	Kettering	60 749	24	2 531	0	0	0	0	0	0,87	0,05	0,08
UK	Liverpool	910 000	199	4 573	0	0	0	0	1	0,60	0,17	0,23
UK	London	2 510 490	84	30 066	1	40	1	402	1	0,26	0,56	0,17
UK	Milton Keynes	256 385	89	2 881	0	0	0	0	1	0,84	0,08	0,08
UK	Newcastle upon Tyne	820 000	181	4 530	0	0	1	78	1	0,75	0,16	0,09
UK	Northampton	215 963	58	3 730	0	0	0	0	1	0,77	0,09	0,14
UK	Norwich	213 166	53	4 053	0	0	0	0	1	0,68	0,07	0,25
UK	Nottingham	768 638	75	10 302	1	32	0	0	1	0,71	0,16	0,13
UK	Oxford	171 380	37	4 582	0	0	0	0	1	0,40	0,24	0,36
UK	Peterborough	215 000	343	627	0	0	0	0	0	0,74	0,11	0,16
UK	Portsmouth	205 100	40	5 096	0	0	0	0	0	0,62	0,10	0,29
UK	Rushden	36 410	12	3 034	0	0	0	0	0	0,87	0,05	0,08
UK	Salford	103 886	21	4 954	1	6	0	0	0	0,78	0,11	0,11
UK	Slough	163 777	34	4 803	0	0	0	0	1	0,79	0,12	0,09
UK	Southampton	269 781	53	5 062	0	0	0	0	0	0,65	0,13	0,23
UK	Sunderland	335 415	84	4 017	0	0	1	78	0	0,72	0,15	0,13
UK	West Bromwich	344 210	86	4 002	1	20	0	0	0	0,70	0,19	0,11
UK	Whitehaven	22 942	19	1 201	0	0	0	0	0	0,82	0,08	0,10
UK	York	156 135	34	4 633	0	0	0	0	1	0,69	0,08	0,23
New Zealand	Auckland	1 413 000	523	2 702	0	0	0	0	0	0,86	0,09	0,05
New Zealand	Christchurch	380 600	295	1 290	0	0	0	0	0	0,87	0,04	0,09
New Zealand	Wellington	215 900	304	711	0	0	0	0	0	0,65	0,24	0,11
Australia	Hobart	252 000	1 726	146	0	0	0	0	0	0,74	0,07	0,19
Australia	Melbourne	5 078 000	9 992	508	1	250	1	965	0	0,75	0,19	0,06
Canada	Calgary	1 349 000	585	2 306	1	60	0	0	0	0,79	0,14	0,07
USA	Alexandria VA	159 467	40	4 012	0	0	0	0	0	0,92	0,05	0,03
USA	Arlington VA	238 640	70	1 340	0	0	1	15	1	0,58	0,32	0,11
USA	Atlanta GA	5 434 000	7 400	734	1	4	1	77	1	0,83	0,11	0,06
USA	Austin TX	1 922 000	1 368	1 405	0	0	0	0	1	0,92	0,04	0,03
USA	Brookline MA	63 191	18	3 590	1	3	0	0	1	0,43	0,33	0,23
USA	Denver CO	2 861 000	1 764	1 622	1	38	0	0	0	0,83	0,08	0,08
USA	Hoboken NJ	58 690	3	18 341	1	27	0	0	1	0,38	0,60	0,02

Country of study data	Location/city of study data	Population in (study data) built-up area	Built-up land area (sq.km)	Population density (pop./sq.km)	Tram / light rail in area	Km tram / light rail in area	Metro / subway in area	Km metro / subway in area	City bike scheme in area	Proportion commuting by private 2 or 4-wheeled motorised vehicle (PMV)	Proportion commuting by public transport (PT)	Proportion commuting by bicycle or on foot (AT)
USA	Oakland CA	440 646	145	3 042	0	0	1	187	1	0,81	0,13	0,06
USA	Portland OR	2 116 000	1 393	1 519	1	108	0	0	0	0,86	0,08	0,07
USA	Raleigh NC	467 665	380	1 232	0	0	0	0	0	0,95	0,02	0,02
USA	San Antonio TX	1 434 625	1 307	1 098	0	0	0	0	1	0,95	0,03	0,02
USA	San Francisco CA	6 481 000	2 872	2 257	1	77	1	187	1	0,70	0,22	0,08
USA	San Jose CA	1 797 166	740	2 430	1	68	0	0	1	0,90	0,05	0,04
USA	Seattle WA	4 084 000	3 263	1 252	1	46	0	0	1	0,84	0,11	0,05
USA	Tampa FL	2 819 000	2 600	1 084	0	0	0	0	0	0,97	0,02	0,01
USA	Washington DC	238 640	70	1 340	0	0	1	15	1	0,77	0,17	0,05

The (logit of the) proportions commuting by PMV (private motorised vehicles), or by PT (public transport) and by AT (active transport, by bicycle or on foot), the sum of these three normalised to 1, are the case area characteristics showing strongest association with induced travel due to e-scooter availability (see Section 2, below), as well as with e-scooter transport mode replacement (Fearnley & Veisten, 2025). The (LN of) the built-up land area size (Km^2) also show association with induced travel due to e-scooter availability.

Descriptive statistics of the outcomes from Europe, North America, Oceania

Table S1.3 lists the averages and distributions of the meta-data, split with respect to the continent of origin. There are 24 outcomes from North America (mostly USA), 8 studies from Oceania (the majority from New Zealand), and 160 from Europe (the majority from the UK, Scandinavia, and Germany).

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Table S1.3. Descriptive statistics of 192 outcomes (n) from 50 survey-based studies of e-scooter mode-replacement, in 95 case areas in North America, Oceania and Europe

Variable	North America, n=24 (20 studies)				Oceania, n=8 (5 studies)				Europe, n=160 (25 studies)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Proportion of e-scooter trips that are induced trips (outcome)	0.06	0.04	0.01	0.20	0.09	0.05	0.03	0.19	0.04	0.05	0.001	0.25
Proportion of e-scooter trips that replace PMV	0.39	0.11	0.20	0.78	0.23	0.12	0.07	0.44	0.19	0.10	0.03	0.50
Proportion of e-scooter trips that replace PT	0.08	0.06	0.01	0.24	0.09	0.06	0.04	0.22	0.23	0.11	0.02	0.54
Proportion of e-scooter trips that replace AT	0.47	0.11	0.15	0.66	0.57	0.10	0.44	0.72	0.51	0.09	0.26	0.73
Population of outcome site, in millions	2.3	2.1	0.06	6	1	1.7	0.22	5	0.8	0.8	0.02	4
Size of outcome site, in square km	1603	1697	3	7400	1718	3379	295	9992	219	232	10	1292
Population density, at outcome site	2493	3474	734	18,341	1008	782	146	2702	4439	5045	229	30,066
The outcome site has metro and/or tram - dummy=1	0.75	0.44	0	1	0.13	0.35	0	1	0.58	0.49	0	1
The length (km) of metro/tram lines, at outcome site	71	88	0	264	152	430	0	1215	86	115	0	442
Km of metro/tram lines relative to area size, at outcome site	0.48	1.74	0	8.56	0.02	0.04	0	0.12	0.47	0.94	0	5.29
The outcome site has municipality-supported bike rental system - dummy=1	0.63	0.49	0	1	0	0	0	0	0.74	0.44	0	1
The proportion, in the outcome site, commuting by PMV	0.76	0.18	0.28	0.97	0.7	0.14	0.5	0.87	0.49	0.17	0.2	0.87
The proportion, in the outcome site, commuting by PT	0.15	0.13	0.02	0.60	0.14	0.09	0.04	0.23	0.20	0.13	0.02	0.59
The proportion, in the outcome site, commuting by AT	0.06	0.04	0.01	0.23	0.1	0.04	0.05	0.17	0.28	0.12	0.06	0.50
Only rental e-scooter usage (not private or mixed) assessed for the outcome - dummy=1	0.83	0.38	0	1	0.63	0.52	0	1	0.88	0.32	0	1
Only private (not rental or mixed) e-scooter usage assessed for the outcome - dummy=1	0	0	0	0	0	0	0	0	0.01	0.08	0	1
Outcome sample consisting of e-scooter rental company-registered users - dummy=1	0.17	0.38	0	1	0.13	0.35	0	1	0.85	0.36	0	1
Outcome from e-scooter rental company - dummy=1	0	0	0	0	0	0	0	0	0.73	0.44	0	1
Outcome from confidential e-scooter rental company - dummy=1	0	0	0	0	0	0	0	0	0.68	0.47	0	1
Outcome from peer-review publication or PhD thesis - dummy=1	0.33	0.48	0	1	0	0	0	0	0.01	0.08	0	1
Female share in outcome sample	0.35	0.07	0	0	0.42	0.09	0	1	0.30	0.09	0	1
Age>30 share in outcome sample	0.67	0.13	0	1	0.64	0.10	1	1	0.45	0.10	0	1
Data collection year	2020		2018	2023	2020		2019	2022	2021		2019	2022
Outcome sample size	1561	1499	61	5312	1232	1571	97	3872	3251	11,473	31	80,147
No. of outcomes per study	1.2		1	4	1.6		1	3	6.4		1	42

Note: The number of outcomes, or outcomes per study (in the last row), can be considered an aggregate of four dependent proportions. In addition to the proportion responding: "would not have carried out the last trip if an e-scooter were not available" (induced travel), there are three proportions of transport mode (group) replacement due to e-scooter availability. That is, if non-availability of an e-scooter, the last trip would have been carried out by a private motorised vehicle (PMV, comprising private cars, shared cars, ridehailing/taxi, MC/moped/scooter), public transport (PT, comprising rail-based modes and bus/coach), or active transport (AT, comprising walking and cycling, both private and shared bicycles, including pedelec e-bikes). Many of the studies from Europe, as well as some North American, provide a set of outcomes from different areas (cities); thus, the descriptive statistics are more correctly presented for outcomes.

The average proportions of induced travel due to e-scooters (the simple average outcome value), in the upper row of Table S1.3, is highest in the meta-data from Oceania and lowest in the meta-data from Europe. There are also clear differences across the three continents in terms of case-area characteristics and outcome features.

Heterogeneity tests; and Egger's test

Table S1.4 shows estimated induced travel due to e-scooter accessibility, in a random effect (RE) model (without covariates).

Table S1.4. E-scooter induced travel based on random effects model of 192 outcomes, including heterogeneity measures and funnel plot bias test (Egger's test)

Induced travel due to e-scooter access (RE)	3.6%
τ^2 (between-outcome variance)	0.848
I^2 (residual heterogeneity)	99.6
H^2 (sampling variability)	231.7
No. of outcomes	192
Bias estimate	2.87
Standard error	0.90
p	0.002
Degrees of freedom	190

In Table S1.4, all tests reject homogeneity (thus, a random-effects model is clearly preferred to a fixed-effects model). For the I^2 test, the residual heterogeneity measure, sizes above 75% indicate strong heterogeneity (Higgins et al., 2003). The I^2 test is influenced by the precision level of the outcomes; it is the amount of variability beyond what is caused by sampling error (unaccounted variability). The tau-squared (τ^2) is significantly different from zero; τ^2 is neither influenced by the number of outcomes nor by their precision. In a RE model, the τ^2 is the between-outcome variance. (RE does not take into account that various outcomes originate from the same study; it does not differentiate within-study variance and between-study variance.) The H^2, the sampling variability, is far beyond the value of 1, which would be expected in the case of homogeneity; thus, the H^2 value also indicates strong heterogeneity (Harrer et al., 2021).

Table S1.4 also includes the result of an Egger's test, which is based on a plot of outcomes (induced travel proportions) against the inverse of the outcome standard error (the precision of the outcome), a so-called funnel plot. The null hypothesis of Egger's test implies a symmetric pattern of the plot, thus, broader at the bottom, with the less precise outcomes, and narrowing towards the top (Egger et al., 1997; Borenstein et al., 2009). The rejection of a symmetric funnel plot, a bias estimate significantly different from zero, might indicate, but does not have to implicate, publication bias.

S2 Meta-regression – comparing models

S2.1 Three types of meta-regression models

Table S2.1 shows parsimonious meta-regression models that resulted from testing larger sets of variables in Table S1.3. Three meta-regression models are compared: a random effects (RE) model, a multilevel model, and a robust variance estimation (RVE) model; the latter is another type of hierarchical model than the multilevel model (Hedges et al., 2010). These three types of meta-regression models are the same that were introduced and formally explained by Fearnley and Veisten (2025). The models are estimated in R, packages meta, metafor and robumeta (Schwarzer et al., 2015; Viechtbauer, 2010; Fisher et al., 2023).

Table S2.1. Meta-regression; explaining variation in logit-transformed proportions of the last e-scooter trips that would not have been carried out if e-scooters were not available, using the proportion of private motorised vehicles (PMV) in commuting

	Random effects (RE)	Multilevel	Robust variance estimation (RVE)
Intercept	-2.12*** (0.25)	-2.83*** (0.27)	-2.62*** (0.30)
Ln_area	-0.19*** (0.05)	-0.08☆ (0.05)	-0.13** (0.05)
Logit_pmv_commuting	0.39*** (0.06)	0.31*** (0.06)	0.43*** (0.09)
Three_conf_comp	-0.55*** (0.13)	-0.48☆ (0.25)	-0.44 (0.29)
R^2 (amount of heterogeneity accounted for)	38.6%		
F (test of moderators)	31.5 (p<0.0001)	12.8 (p<0.0001)	
AIC / BIC	550 / 566	505 / 524	
logLik	-269.9	-246.3	
QE (test for residual heterogeneity)	17,509 (p<0.0001)		
Sampling error (level 1)		0.7%	
Within-study variance share (level 2)		48.6%	
Between-study variance share (level 3)		50.7%	
Anova test of three levels vs. two levels	47.2 (p<0.0001)		
I^2 (residual heterogeneity)	99.1%	99.3%	96.7%
τ^2 (between-study variance)	0.50		0.57
H^2 (sampling variability)	106.2		
No. of studies / clusters		50	50
No. of outcomes (N)	192	192	192

Note: Standard errors in parentheses; significance levels: ***<0.001, **<0.01, *<0.05 ☆<0.1.

Table S2.1 shows that the logit-transformed proportion commuting by PMV (Logit_pmv_commuting) has a strong positive relationship with (the logit of) induced travel by e-scooter. The log of the outcome area (Ln_area) shows a negative association with induced travel by e-scooter; in the multilevel model the coefficient is only significant at the 10% level. The dummy variable of outcomes from three confidential e-scooter rental share companies (Three_conf_comp) also shows a negative association with (the logit of) induced travel by e-scooter; in the multilevel model the coefficient is only significant at the 10% level.

As already shown in the RE model of the outcomes, in Table S1.4, the indication of heterogeneity is very strong, based on the QE, the I^2, the τ^2, and the H^2. Moreover, tests based on the multilevel model, and an Anova test of the multilevel vs. the RE model, show that a hierarchical model, the multilevel model (and the RVE) is clearly preferable to the RE. The share of variance within-study almost reaches the size of the share of variance between-study (the sum of the two shares equals I^2). Both the multilevel model and the RVE will enable a type of correction of overfitting, that moderator coefficients that are significantly positive or negative in FE or RE models, will not necessarily retain statistically significant coefficient signs in the multilevel model and the RVE model. This is indicated for both Ln_area and Three_conf_comp, but somewhat differently between the two hierarchical models. We lack comparative goodness-of-fit measures to choose between the multilevel model and the RVE model. However, we have chosen the multilevel model as our default model, as it is more intuitive, a generalisation of the RE, including a large set of relevant goodness-of-fit and meta-analysis test measures.

Including the logit-transformed proportions of commuting by public transport and by active transport (cycling/walking), instead of the logit-transformed proportions of commuting by private motorized vehicles, those coefficients will have a significantly negative sign. That alternative specification has, however, slightly lower goodness-of-fit measures than the one shown in Table 2

Table S2.2 shows the same model comparison as in the table above but swapping the logit-transformed proportions commuting by PT and by AT (Logit_pt_commuting and Logit_at_commuting) for commuting by PMV (Logit_pmv_commuting).

Table S2.2. Meta-regression; explaining variation in logit-transformed proportions of the last e-scooter trips that would not have been carried out if e-scooters were not available, using the proportions of public transport (PT) and active transport (AT) in commuting

	Random effects (RE)	Multilevel	Robust variance estimation (RVE)
Intercept	-2.79*** (0.28)	-3.42*** (0.30)	-3.32*** (0.37)
Ln_area	-0.17*** (0.05)	-0.06 (0.05)	-0.11* (0.05)
Logit_pt_commuting	-0.31*** (0.07)	-0.20** (0.06)	-0.36*** (0.11)
Logit_at_commuting	-0.17* (0.08)	-0.20** (0.08)	-0.15 (0.09)
Three_conf_comp	-0.63*** (0.15)	-0.45 (0.27)	-0.52 (0.30)
R^2 (amount of heterogeneity accounted for)	36.2%		
F (test of moderators)	22.2 (p<0.0001)	9.1 (p<0.0001)	
AIC / BIC	553 / 573	506 / 529	
logLik	-269.9	-246.3	
QE (test for residual heterogeneity)	14,206 (p<0.0001)		
Sampling error (level 1)		0.7%	
Within-study variance share (level 2)		46.8%	
Between-study variance share (level 3)		52.5%	
Anova test of three levels vs. two levels	49.3 (p<0.0001)		
I^2 (residual heterogeneity)	99.0%	99.3%	96.4%
τ^2 (between-study variance)	0.52		0.57
H^2 (sampling variability)	98		
No. of studies / clusters		50	50
No. of outcomes (N)	192	192	192

Note: Standard errors in parentheses; significance levels: ***<0.001, **<0.01, *<0.05 ☆<0.1.

Table S2.2 shows that Logit_pt_commuting and Logit_at_commuting have a negative relationship with (the logit of) induced travel by e-scooter. The other moderators (Ln_area and Three_conf_comp) show somewhat weaker association when combined with the PT/AT commuting moderators. The goodness-of-fit measures are slightly lower for the models including commuting by PT and AT (Table S2.2), compared to those including commuting by PMV (Table S2.1). All test results regarding heterogeneity and hierarchical (three-level) structure of the outcome meta-data are the same for the models in Table S2.2 as for those in Table S2.1.

S2.2 Multilevel meta-regression based on only the mode distribution in commuting

Table 2.3 shows only multilevel meta-regression models, applying the package 'metafor' (Viechtbauer, 2010). In the multilevel model, only one of the case-area characteristics (and none of the outcome survey features) showed a significant association with the logit-transformed proportion of e-scooter-induced travel demand at the 5% significant level: the case-area (logit-transformed) proportions of commuting mode distribution (i.e., mode share). The table below compares models that include only one of the proportions, comparing the extent to which these three have similar explanatory strength. Further on, we can also compare whether the models predict similar point estimates for specific case-areas.

Table S2.3. Multilevel meta-regression; explaining variation in logit-transformed proportions of the last e-scooter trips that would not have been carried out if e-scooters were not available, using only the proportion of the three mode groups in commuting (192 outcomes from 50 studies)

	Model PMV	Model PT	Model AT
Intercept	-3.35 (0.11)	-3.59 (0.143)	-3.73 (0.17)
Logit_pmv_commuting	0.31 (0.06)		
Logit_pt_commuting		-0.26 (0.06)	
Logit_at_commuting			-0.30 (0.07)
F (test of moderators)	30.4	18.7	19.3
AIC / BIC	511 / 524	520 / 533	519 / 532
logLik	-251.3	-255.9	-255.5
QE (test for residual heterogeneity)	22,975	24,059	20,783
I^2 (residual heterogeneity / unaccounted variability)	99.4%	99.5%	99.4%
Anova test of three levels vs. two levels	73.1	83.3	78.8
Sampling error (level 1)	0.7%	0.6%	0.6%
Within-study variance share (level 2)	43.9%	41.5%	39.7%
Between-study variance share (level 3)	55.4%	57.9%	59.7%

Note: Standard errors in parentheses; significance levels: ***<0.001, **<0.01, *<0.05 ☆<0.1.

Table S2.3 shows that there is a positive association with the (logit of the) proportion of PMV in commuting; the association with PT and AT is negative.

The variation in the logit-transformed proportions of the 192 induced e-scooter travel outcomes are fairly well explained by the variation in commuting mode across outcomes and case-areas, for all three proportions of commuting mode. The values of F, AIC/BIC as well as the logLik indicate relative strength of the models, compared to similar models in Tables S2.1 and S2.2. "Model PMV" has slightly better goodness-of-fit measures (F, AIC/BIC, logLik) than the two others (Table S2.3). All models indicate very strong heterogeneity of the meta-data (QE, I^2), as well as a hierarchical structure appropriate for a multilevel model (three-level rather than two-level). The shares of variance within-study and between-study are similar and dominate completely the share from sampling error.

S2.3 Comparing (empirical) outcomes against estimates from the multilevel meta-regression based on only the mode distribution in commuting (Table S2.3)

Figure S2.1 shows a simple illustration of multilevel model-based point estimates of induced travel due to e-scooter availability, using the coefficients in Table S2.3. These are applied to a dozen case-areas (cities) across the three continents. The meta-regression model estimate is compared to the specific city outcome, from our meta-data. The 12 city outcomes of induced travel due to e-scooters, in Figure S2.1, represent a mix of single outcomes and multiple outcomes per city.

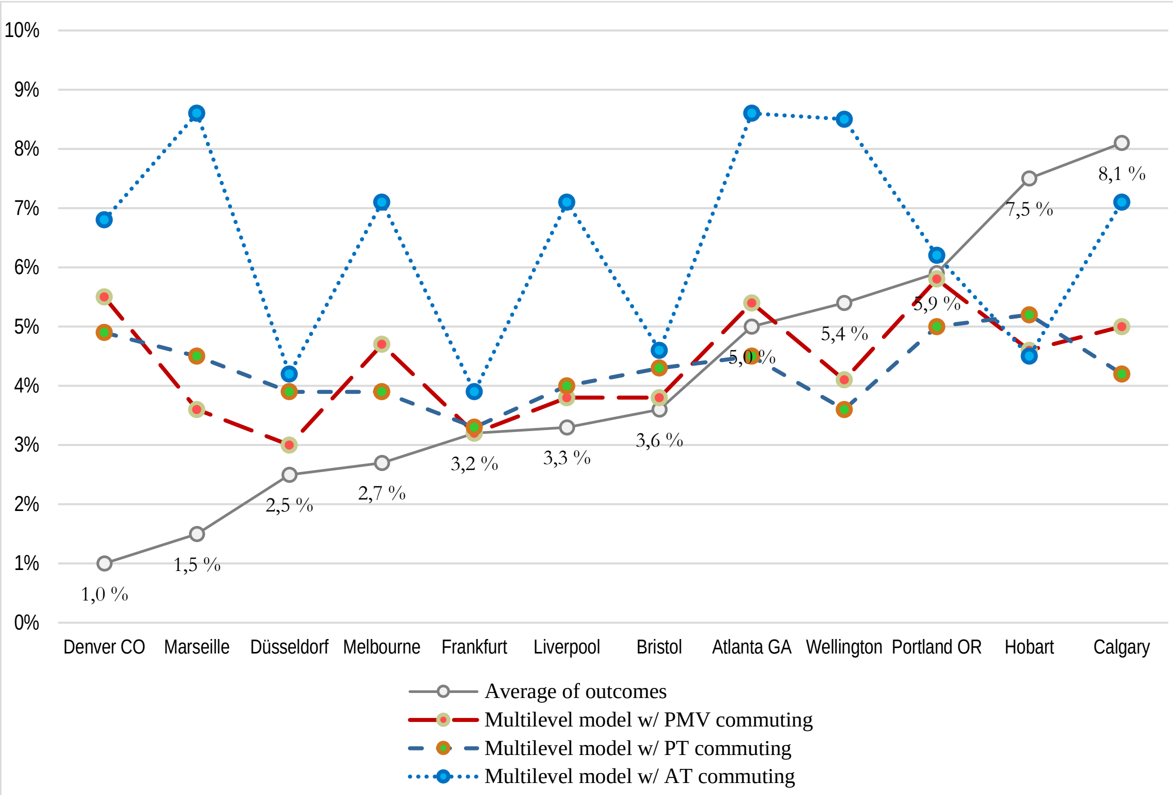

Figure S2.1. Predicted induced travel by e-scooter in cities with different levels of commuting by PMV, or by PT, or by AT (the models in Table S2.3), together with the averages of outcomes per city (the percentage of induced travel, in the reported last trips by e-scooter).

The “model PMV” and the “model PT” yield fairly similar point estimates of e-scooters’ induced travel, while the “model AT” yields more scattered point estimates. The “model PMV” and “model PT” estimates match the average of outcomes from the cities better when these are closer to the multilevel meta-analytical mean of about 4%. The lowest and highest city outcomes, in Figure S2.1, are predominantly based on only one outcome.

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