

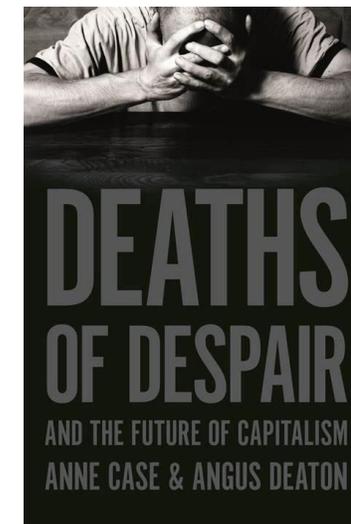
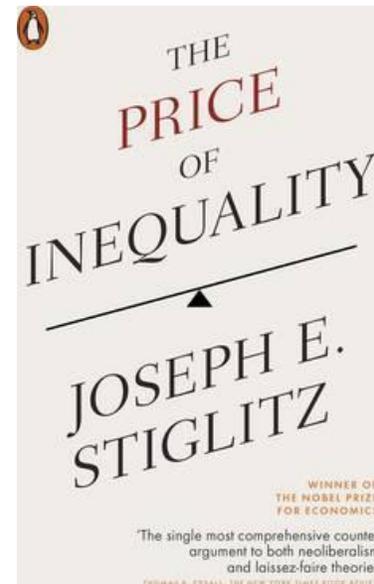
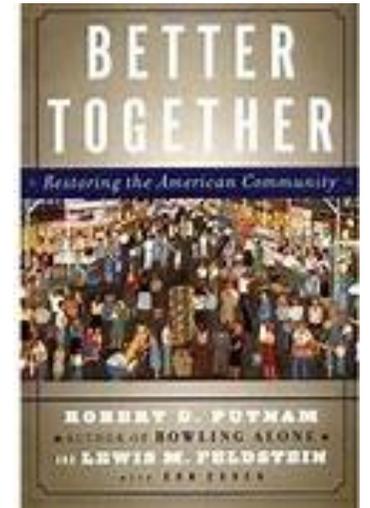
# The (In)Equalities of Human Mobility for Work and Play

Steve Bickley, Ho Fai Chan, Uwe Dulleck, Benno Torgler



# Introduction

- Arguably, lockdowns are effective measures to counter the spread of COVID-19. But are they efficient and/or equitable?
- **COVID-19 benefits** such as shorter travel time, adjusted work-leisure mix, less environment/accident risk?
- **COVID-19 costs** such as WFH vs non-WFH, fines for non-essential travel, loss of utility in fun from home?
- **Socio-economic status (SES)** differences in *work* vs *play* travel
- Also, SES differences in exposure to accidents, role of community/social infrastructure – **mobility and environment**
- Do the (less) advantaged have more (less) flexibility in handling the restrictions provided by COVID-19?



# Background

The challenges and opportunities that lockdowns and cities present for different socio-economic groups are not the same – *different work flexibilities, life circumstances, and social or environmental resources and affordances*

- “Different subpopulations have different risk profiles and attitudes about health-related choices” (Pentland et al., 2009, p. 9)  
i.e., different pandemic response for different SES (footnote 1)
- Evidence suggests lower SES find it more difficult to reduce work mobility during COVID-19 (Lou et al., 2020)
  - Essential workers (health, supermarket, transportation) or less connected
- Lower SES are also less able to switch to private transport (Brough et al., 2021; Pawar et al., 2020) and hence, at higher risk also *during* movements
- *We also know that...* there are positive relationships between design of “place” and social capital (Mazumdar et al., 2018)
  - i.e., mobility and environment (pro-social and pro-physical)

# Our Research Question(s)

In this study\*, we look at lockdown effect on travel time/distance/frequency for different SES:

1. How did *mobility change during and after* the COVID-19 lockdowns?
2. Is there *heterogeneity* of the “lockdown effect” along *socio-economic* and *geographic factors*?

*In other words, what is the “lockdown effect” of COVID-19 lockdown-style measures, and how does the “lockdown effect” vary for different SES groups?*

Further, how are our *preferences* for where we move affected by our *socio-economic situation*?

## Why does this matter?

- Costs and benefits of lockdowns are still very unclear...
- Teasing out the deep-rooted regularities (Song et al., 2010) in human mobility data provides empirical grounding, improves understanding, and informs response to future crises
- **Structural inequalities** and **infrastructure issues** can be addressed and targeted to different SES to “free up” time that people can dedicate to other pursuits, needs, and objectives
  - e.g., *identify groups that are worse off → quantify their losses → design and implement compensation policies*
- Further, to plan and design for more **resilient** urban (community) **hubs** within cities for future
  - Not just for efficiency but for **happiness**, **wellbeing**, and **human connection** also...

## Why is it innovative?

- Research question with high policy relevance
- Unique data – high temporal granularity over varied spatial scales (area-level only not *individual*)
- Few studies (first?) of its kind for Australia

# Data Overview

“...[I]t's the little data breadcrumbs that you leave behind you as you move around in the world. What those breadcrumbs tell is the story of your life. It tells what you've chosen to do.”

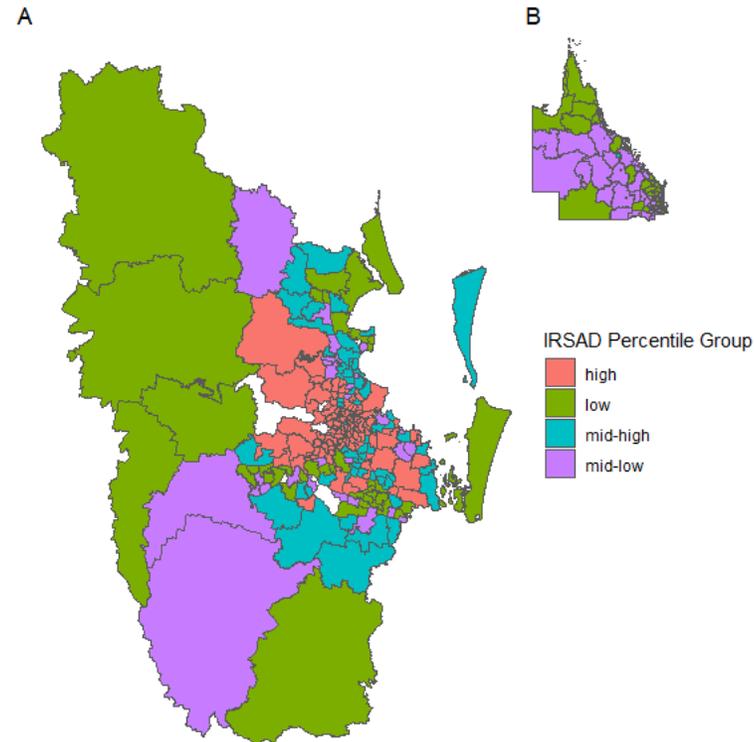
- Alex Pentland

1. ***DSpark Mobility Data*** – daily origin-destination pairs (SA2-SA3) of 3-10k and 30-130k population, respectively
2. ***SEIFA Indices*** – IRSAD index for relative advantage/disadvantage at SA2 statistical area
3. ***Meshblock Land Use Classifications*** – used in construction of all “higher level” statistical areas (SA1,2,3,4, GSSCA)
4. ***COVID-19 Lockdowns*** – manual coding of the five (5) Queensland lockdown events – 0 if no lockdown, 1 if during lockdown, 2 if 30-days post lockdown from *1 December 2018 to ongoing...*
5. ***COVID-19 Statistics*** – daily Queensland confirmed case numbers (cumulative), deaths (cumulative), vaccinations administered (cumulative), new cases (non-cumulative), new tests conducted (non-cumulative)
6. ***Supplementary Measures*** – monthly cumulative traffic incidents tied to SA2 and SA3 areas, and daily rainfall, maximum temperature, and minimum temperature tied to SA3 (destination) statistical areas
7. ***Others\**** – real-estate volume and pricing at area level, household income at area level

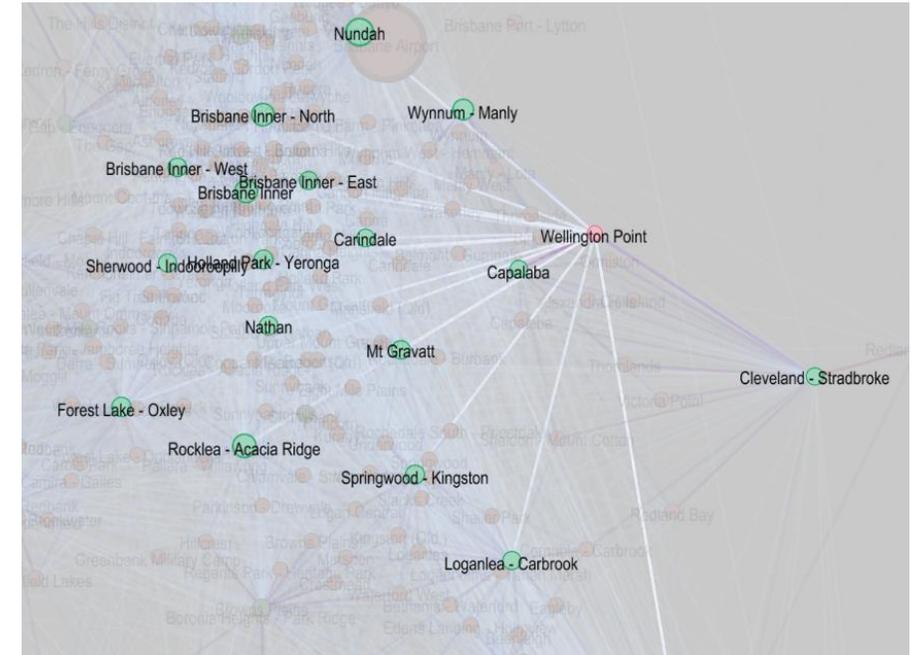
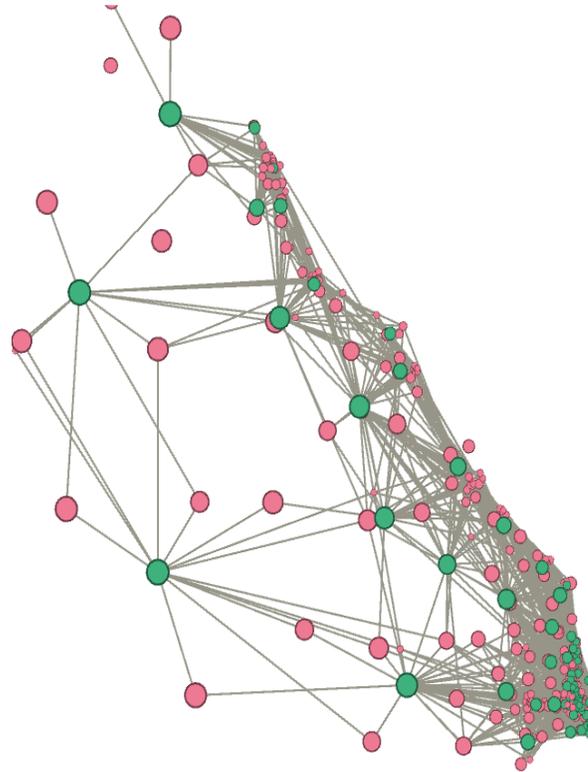
# The Socio-Economic Indexes for Areas (SEIFA)

Represent “collective socio-economic characteristics of people living in an area” (p. 5) (ABS, 2016)

*Relative advantage/disadvantage “in terms of people’s access to material and social resources, and their ability to participate in society” (p. 6) (ABS, 2016)*



# DSpark Origin-Destination



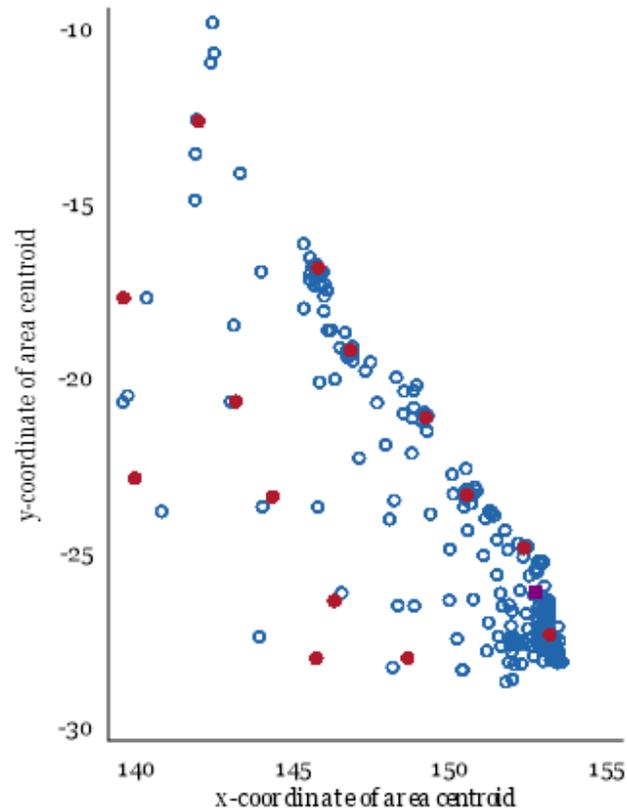
We look at daily travel between 513 SA2 (origin, red nodes) to 82 SA3 (destination, green nodes)

A network of origin-destination nodes of time-varying connectivity (no. edges and which ones)

Example (on right): 03 March 2020

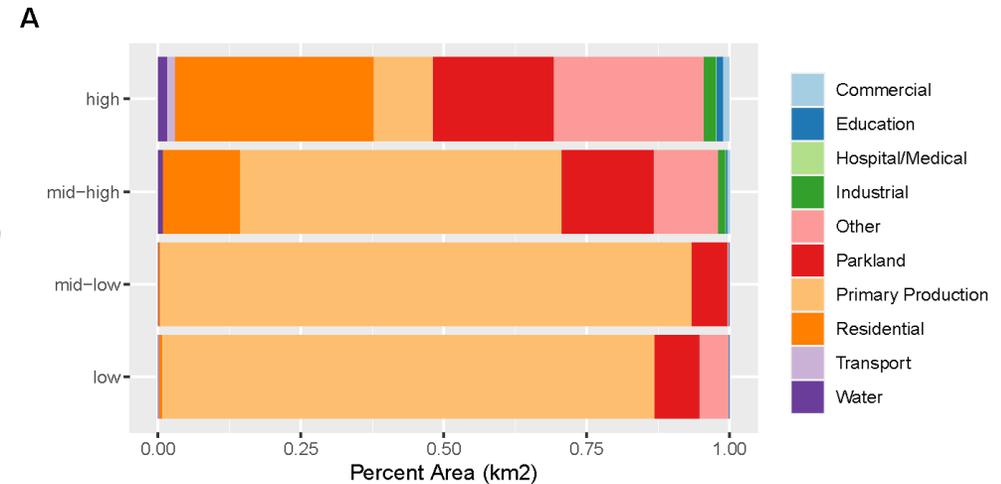
# Land Use / Weather

We take both **origin** (SA2) and **destination** (SA3) **land use / weather characteristics** into account in our final regression model as *fixed effects*

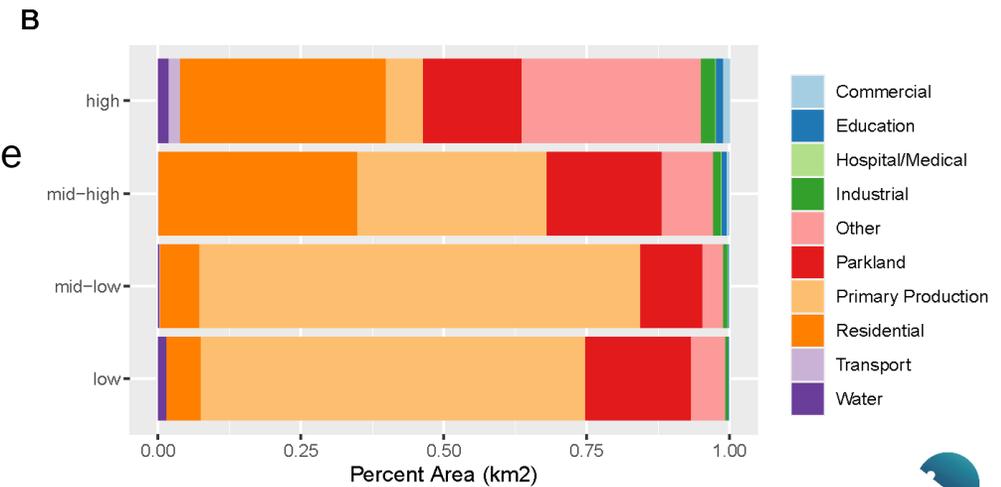


SA2 centroids (blue) and Weather Stations (red)

All of QLD



Greater Brisbane



# Estimating the Lockdown Effects

A diff-in-diff(-in-diff) framework:

$$Outcome_{ij} = \alpha_0 + \alpha_1 * lockdown + \alpha_2 * SES_i + \alpha_3 * lockdown * SES_i + \beta X + \epsilon_{ij} \quad (1)$$

$$Outcome_{ij} = (1) + \beta X_{ad.} + \epsilon_{ij} \quad (2)$$

- Outcomes are **travel patterns** (relative % SA2 population, trips/person, distance 50pc, duration 50pc) **between SA2i (residing/origin) to SA3j (destination)** statistical areas.
- **Lockdown** = categorical variable where 0 if there is no lockdown on this date (n=2,599,218), 1 if there is a lockdown (n=254,053), 2 if this date falls within the 30-day post-lockdown period (n=210,236)
- **SES** = Queensland relative IRSAD percentile rankings (1-100 percentile)
- **X (controls)**: *origin SA2 population, SA3 code of the origin (fixed geographical effects), monthly crashes in origin (SA2) and destination (SA3), binary variable for whether staying in same origin SA3 (od\_same), max. temp & rainfall in origin (SA2) and destination (SA3)*
- **X ad. (additional controls)**: origin SA2 land use characteristics (%km2), destination SA3 land use characteristics (%km2)

And... **Purpose** where 1 is work (n=596,749) and 2 is play (n=2,466,758) with **regressions run separately for each trip purpose**

# The effect of lockdown on the outcome, by SES (2)

unique\_normalise

Min. : 0.00128

1st Qu.: 0.00795

Median : 0.01757

Mean : 0.11165

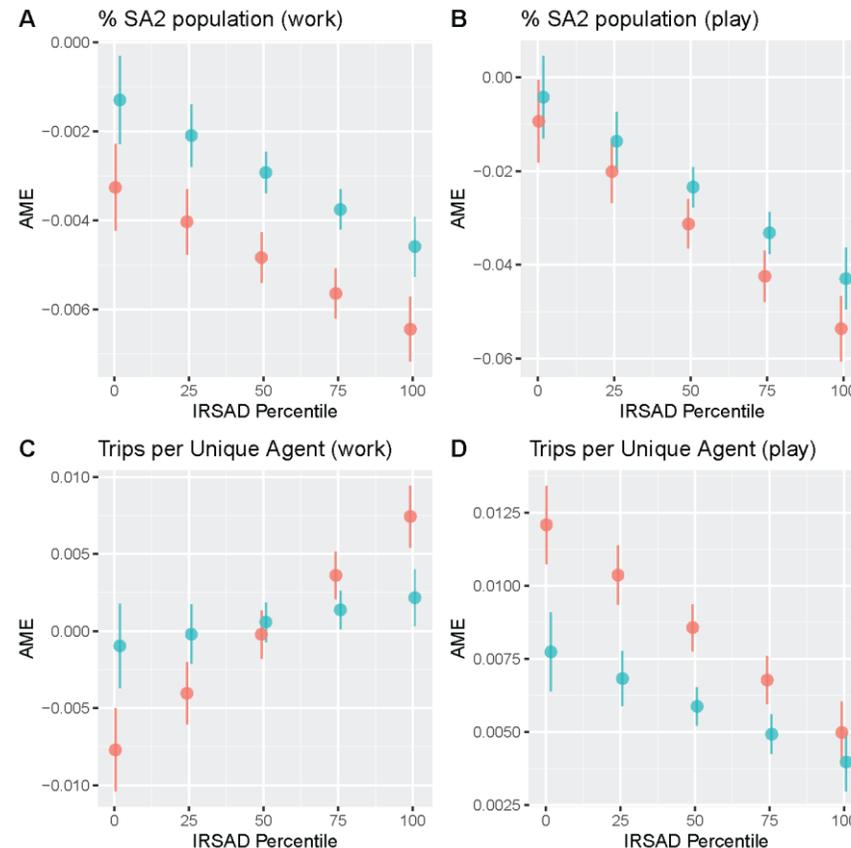
3rd Qu.: 0.05621

Max. :108.17347

SA2 population is 3,000 to 30,000, average 10,000

∴ a 0.02 unit-change equates to 200 people

**NOTE:** 0.02 unit-change is approx. 17.91% movement from mean



trip\_pp

Min. :1.000

1st Qu.:1.000

Median :1.000

Mean :1.068

3rd Qu.:1.043

Max. :5.798

Baseline is no lockdown (lockdown=0), during lockdown (=1), and post-lockdown (=2)

∴ a 0.01 unit-change equates to 100 trips

**NOTE:** 0.01 unit-change is approx. 0.94% movement from mean

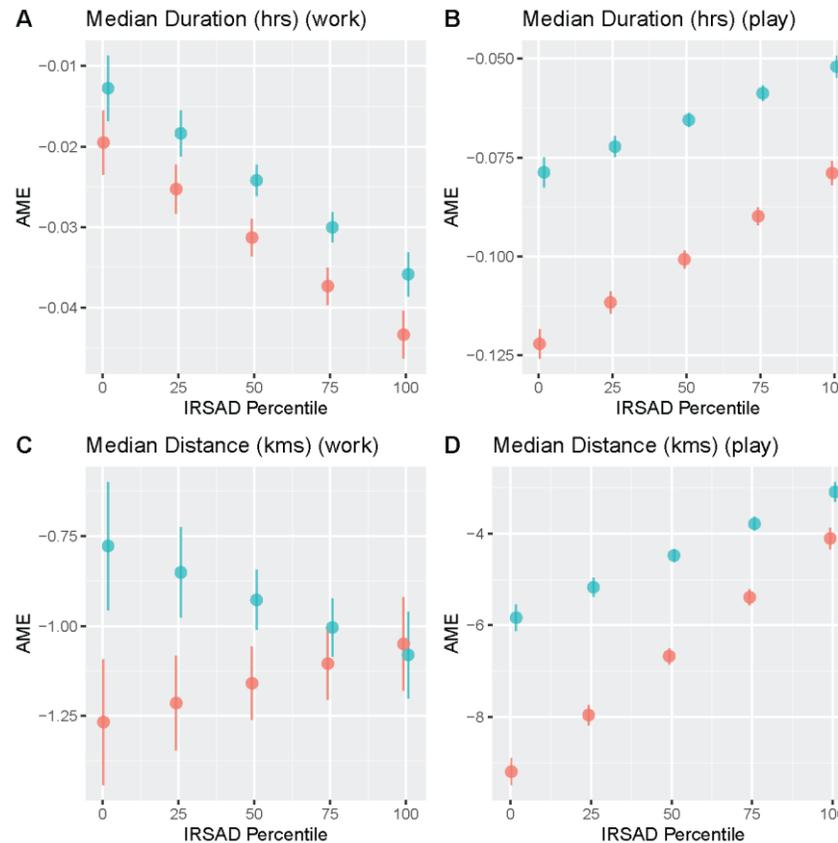
- Larger lockdown effect (%SA2) for higher SES on work trips and even larger effect for play trips
- Post-lockdown (blue) recovery from lockdowns (red) as % SA2 population - ~~pre-lockdown levels~~
- Lockdown effect increases work trips per person for higher SES during and after lockdown
- Lockdown effect increases play trips per person for Lower SES during and after lockdown

# How about travel time (to work or otherwise)? (2)

duration\_50pc\_dec  
 Min.: 0.003056  
 1st Qu.: 0.471111 (28m)  
 Median: 0.471111  
 Mean: 0.553065 (33m)  
 3rd Qu.: 0.694722 (41m)  
 Max.: 5.868333 (5h52m)

∴ a 0.1 unit-change  
 equates to 6 minutes / trip

**NOTE:** 0.1 unit-change is  
 approx. 18.08% movement  
 from mean



distance\_50pc\_dec  
 Min.: 0.1425  
 1st Qu.: 8.1033  
 Median: 17.1278  
 Mean: 25.0778  
 3rd Qu.: 30.5161  
 Max.: 1225.8431

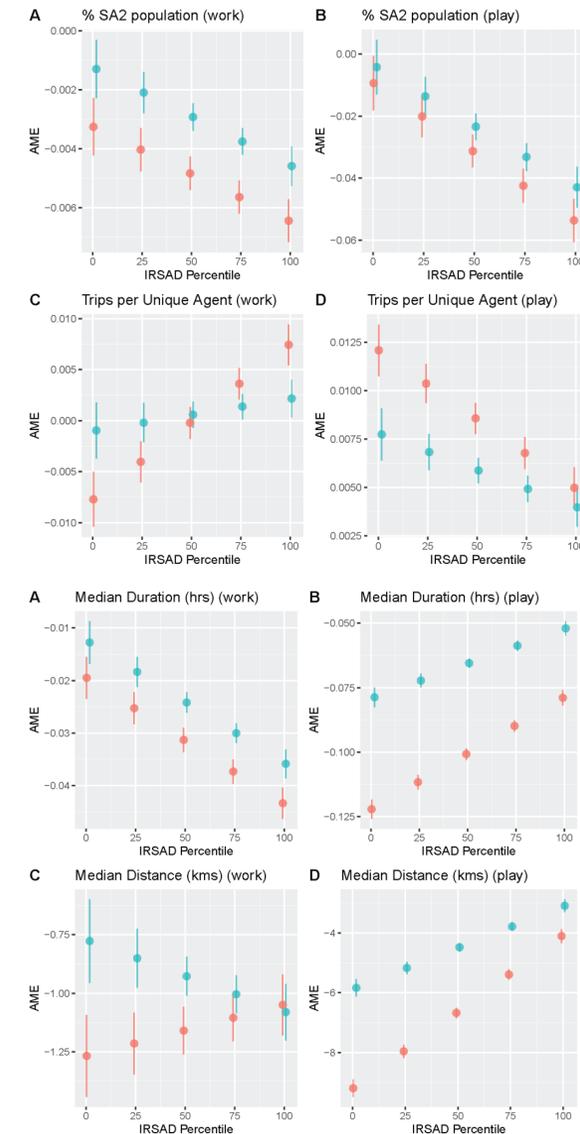
Baseline is no lockdown  
 (lockdown=0), **during lockdown**  
 (=1), and **post-lockdown** (=2)

**NOTE:** 1 unit-change is  
 approx. 3.99% movement  
 from mean

- Duration falls across the board (but again – only small reduction – a few minutes!)
- Larger lockdown effect for lower SES *play* duration– however, less distance also...
- Lockdown (*during*) favours higher SES for work purposes (same distance, less duration)
- **Polarity flip** in Panel C – lower SES coming back into the city post lockdown? Parking further?

# Summary

- We are seeing benefits flowing to all from less traffic on the road – *especially for higher SES during work* (same distance, less duration)
- In other words, we return discretionary time to all from reduced COVID traffic, but disproportionately so
- Median duration and distance falls for all – more for lower SES in play, more for higher SES in work
- Positive lockdown effects in trips per person for *play* (non-work) reasons – “short and sweet” (local) trips, travel, and mobility
- It seems it is harder for lower SES to WFH– *less change in work mobility* – but trips per person (activity), they are more compliant for *work* reasons (not play)
- Higher SES appears to take stay-at-home orders more seriously (or are more able to) (%SA2) – larger lockdown effects for both *work* and *play*
- Lockdown effects are rampant but there are lingering effects post-lockdown



# Future Directions

- Going beyond the Queensland and Brisbane areas (e.g., state-by-state comparisons)
- SES mixing and matching (**diversity**)?
- How do different ages / genders move?
- SES non-linearity and time-varying feedbacks?
- Natural disasters and severe weather?
- Social and physical infrastructures (**resilience**)?
- Do people travel to different SA3 to work / play?
- How about job and home location changes?
- Developed / less developed and emerging areas?
- Cultural and institutional values?



# Thank you!

We look forward to discussing and connecting with you over the coming days...

**Steve J. Bickley**

PhD Candidate

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Brough, R., Freedman, M., & Phillips, D. C. (2020). Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. *Journal of Regional Science*, 61, 753-774.

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Pawar, D. S., Yadav, A. K., Akolekar, N., & Velaga, N. R. (2020). Impact of physical distancing due to novel coronavirus (SARS-CoV-2) on daily travel for work during transition to lockdown. *Transportation Research Interdisciplinary Perspectives*, 7, 100203.

Pentland, A., Lazer, D., Brewer, D., & Heibeck, T. (2009). Improving public health and medicine by use of reality mining. *Studies in Health Technology Informatics*, 149, 93-102.

Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. *Science*, 327(5968), 1018-1021.

# Appendices

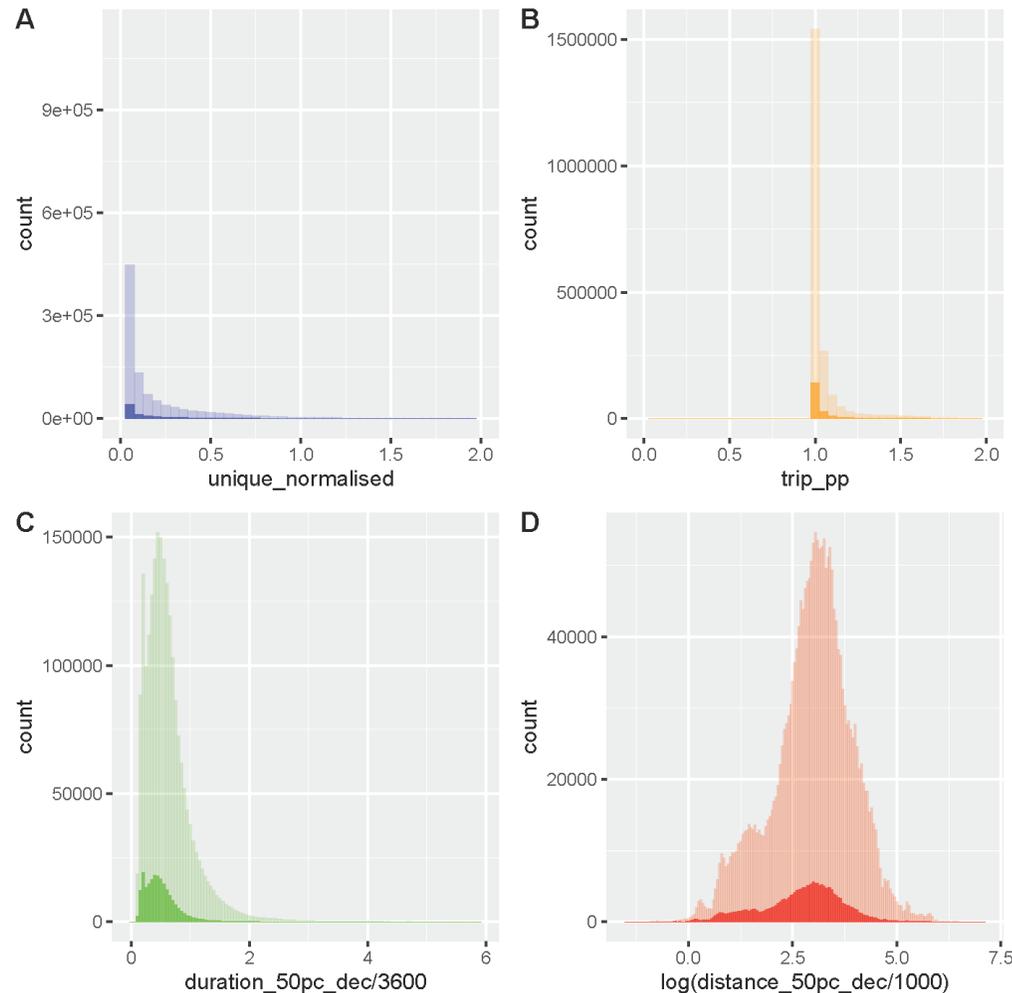
1. Empirical Strategy
2. Results – pre/post lockdown distributions, correlations
3. Comparing Models' Fit (adj R2, F-stat, p-val of F-stat)
4. Model 1 – Effect of Lockdowns, by SES – %SA2 and Trips/Person
5. Model 1 – Effect of Lockdowns, by SES – Median Duration, Median Distance
6. Locations of Weather Stations
7. DSpark Data Features
8. DSpark Data Collection/Cleaning Process\*
9. OD Matrix Data Variables
10. Land Use Classifications defined by ABS in ASGS
11. SEIFA 2016 IRSAD Variable List
12. SES Land Use by Count

\* Slide by DSpark Pty Ltd

# Empirical Strategy

1. We begin with descriptive analyses (diff-in-diff) exploring the role of lockdowns (during) on travel patterns including:
  - proportion of agents travelled (no. unique agents / origin SA2 population),
  - trips per agent (total trips divided by no. unique agents),
  - median distance travelled, and
  - median duration travelled
  - proportion of locals/nonlocals\*
  - median duration stayed\*
2. Also, focusing on how **SES** lockdown effects differ for *work* and *play* mobility (diff-in-diff-in-diff)
3. Correlations between each of the four mobility measures and IRSAD relative percentile ranking (1-100 percentile relative to other SA2s in QLD only)
4. Finally, we apply ordinary least squares (OLS) regression to estimate the two models described later – **lockdown\*SES interactions** for *work* and *play*  
i.e., estimate the effect of (post) lockdown, and interaction terms with SES and ENV variables on travel patterns

# Pre-During Lockdown Distributions – Overview



How have travel behaviours changed during and in response to COVID-19 lockdowns?

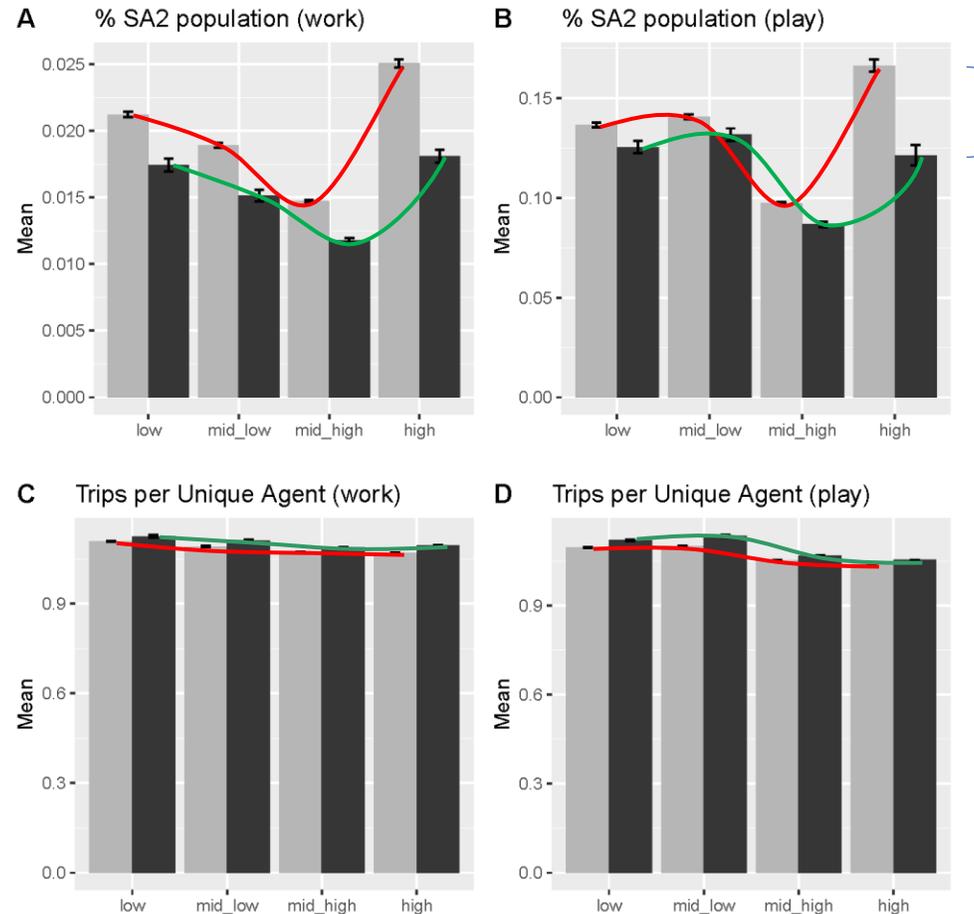
## DSpark – ODMatrix

1. Number of people making a trip (unique agents) normalized (unique agents / SA2 population)
2. Number of trips per person (unique agents / total records)
3. Median duration of the trip (hr)
4. Median distance of the trip (km)

The shapes of distribution remain fairly consistent for *pre-* (lighter) and *during* (darker) lockdown periods

# Pre-During Lockdown Distributions (%SA2, trip/pp)

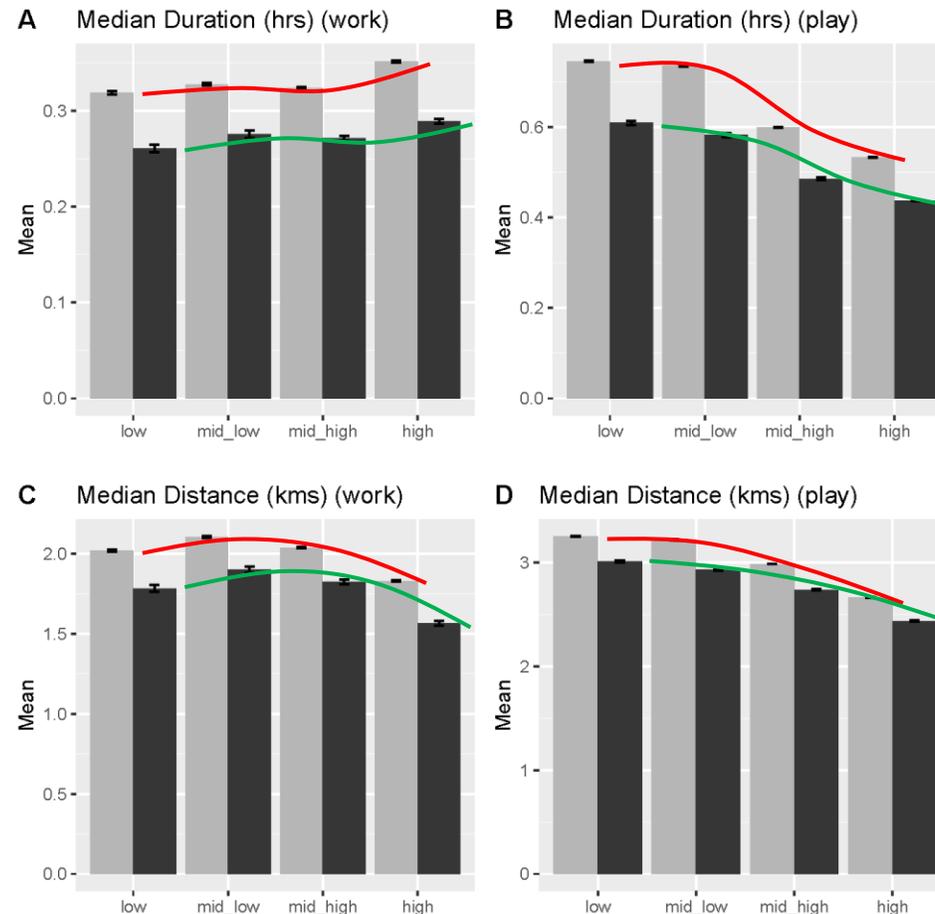
How much of this is explained by socioeconomic advantage and disadvantage (for work and for play reasons)?



Pre- (lighter / red) and during lockdown (darker / green) number of people / trips, by work and play (non-work) trips

# Pre-During Lockdown Distributions (*dur.*, *dist.*)

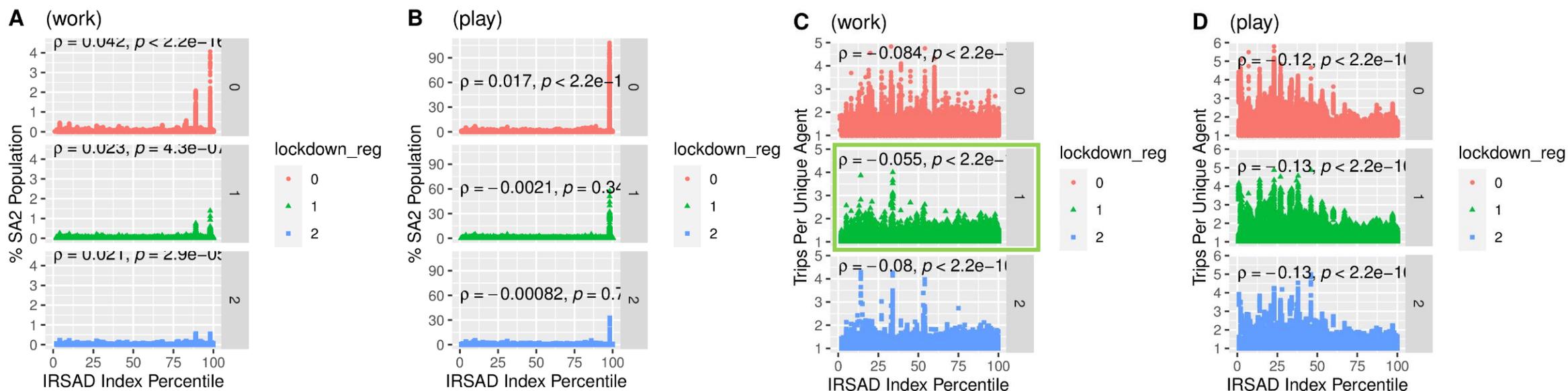
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Pre- (lighter / red) and during lockdown (darker / green) median trips duration and distance, by work and play (non-work) trips

# Correlations (%SA2, trip/pp)

How much of this is explained by socioeconomic advantage and disadvantage (for work and for play reasons)?

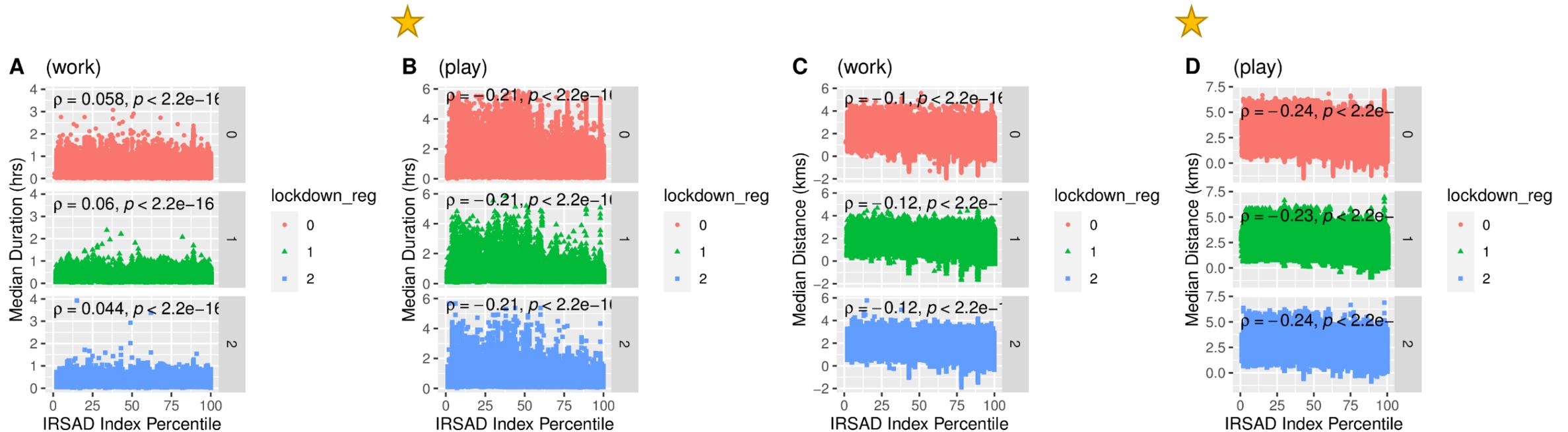


Comparing the *no* lockdown, *during* lockdown, and *after* lockdown periods

\*\* (spearman) correlations for every SA2-SA3 OD pair over entire sample

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Comparing the *no* lockdown, *during* lockdown, and *after* lockdown periods.

\*\* (spearman) correlations for every SA2-SA3 OD pair over entire sample

# Comparing Models' Fit

Model fit in *adjusted R2* with (*F-stat*, and *P-val of F-stat*) for Models 1 and 2

Model	% SA2 population		Trips per person		Duration 50pc		Distance 50pc		
Model 1	0.1444 (1040, <2.2e-16)	0.1039 (2949, <2.2e-16)	0.4968 (6076, <2.2e-16)	0.6469 (4.659e+04, <2.2e-16)	0.3108 (2775, <2.2e-16)	0.355 (1.4e+04, <2.2e-16)	0.3234 (2941, <2.2e-16)	0.3743 (1.522e+04, <2.2e-16)	(1)
Model 2 ★	0.2825 (2009, <2.2e-16)	0.1663 (4205, <2.2e-16)	0.5036 (5176, <2.2e-16)	0.655 (4.004e+04, <2.2e-16)	0.4313 (3870, <2.2e-16)	0.3943 (1.373e+04, <2.2e-16)	0.399 (3387, <2.2e-16)	0.4069 (1.446e+04, <2.2e-16)	(2)

# The effect of lockdown on the outcome, by SES (1)

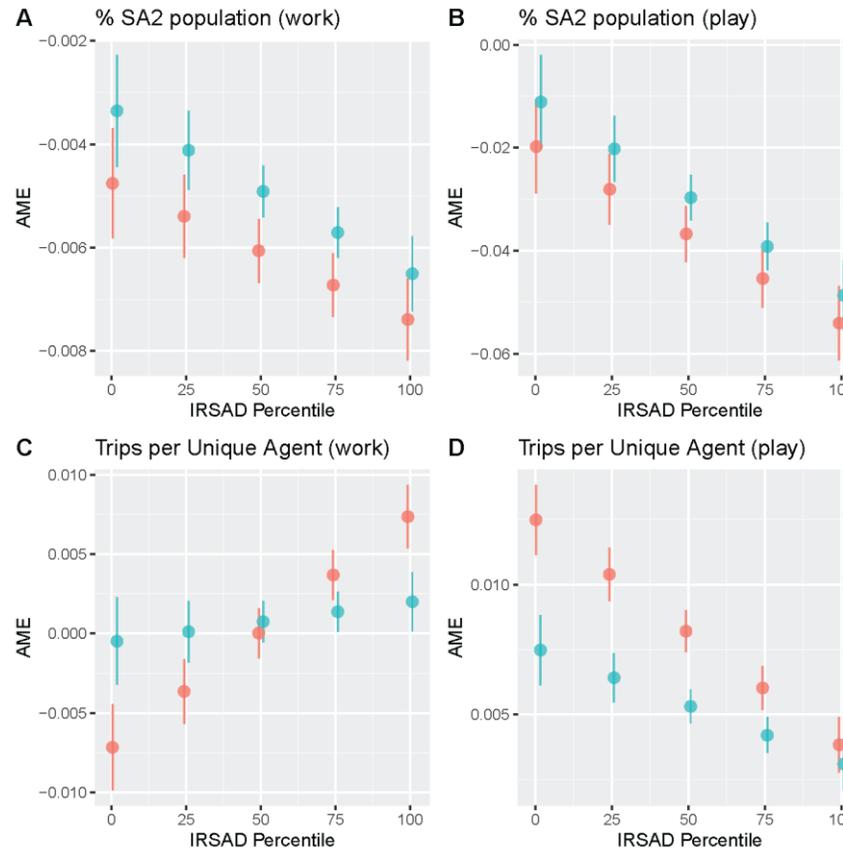
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NOTE: 0.02 unit-change is approx. 17.91% movement from mean



Baseline is no lockdown (lockdown=0), during lockdown (=1), and post-lockdown (=2)

NOTE: 0.01 unit-change is approx. 0.94% movement from mean

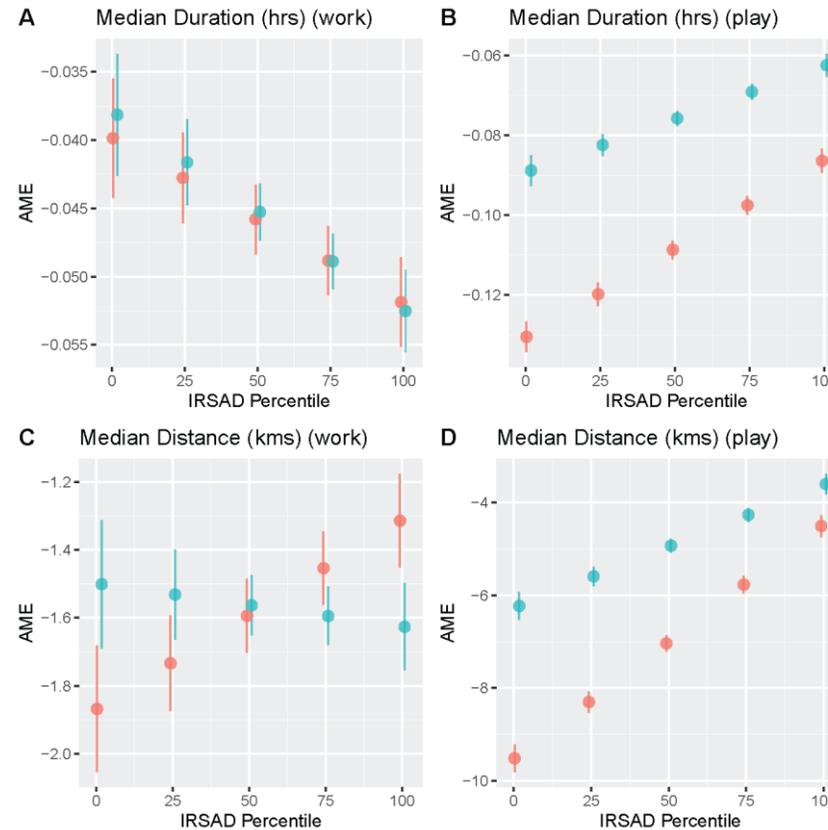
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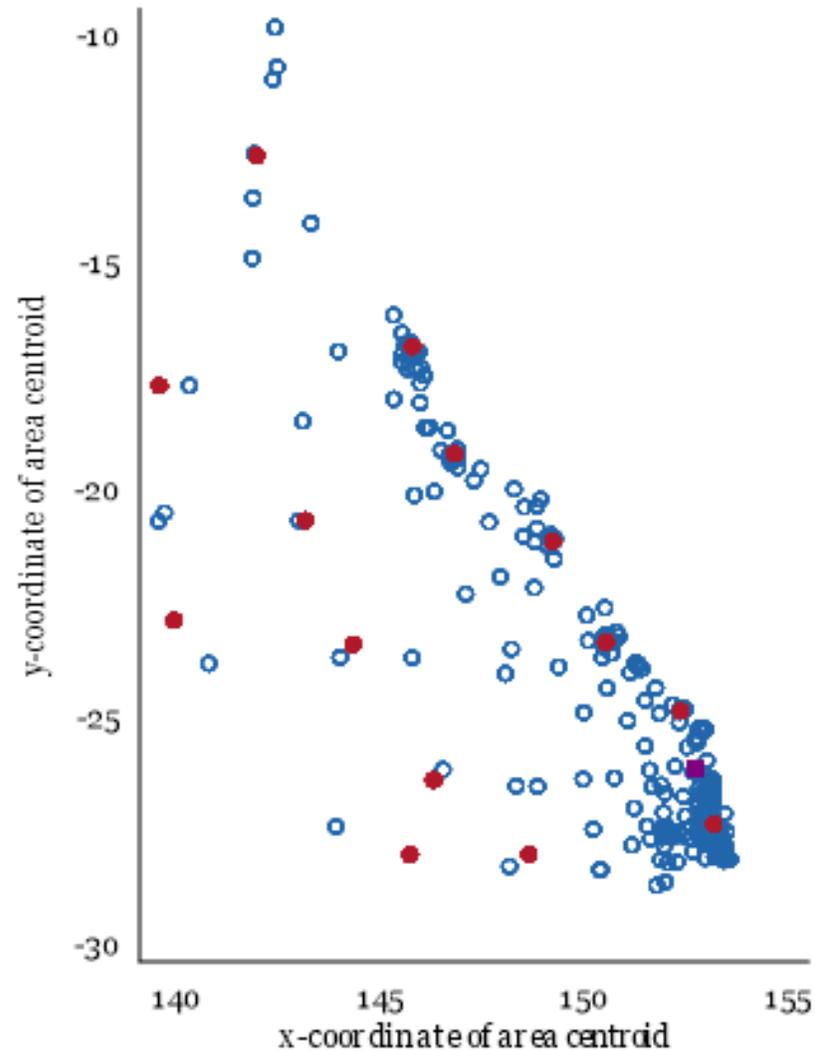
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- Lockdown (*during*) favours higher SES for work purposes (same distance, less duration)
- **Polarity flip** in Panel C – lower SES coming back into the city post lockdown? Parking further?

# Locations of Weather Stations

SA2 centroids (blue) and  
Weather Stations (red)

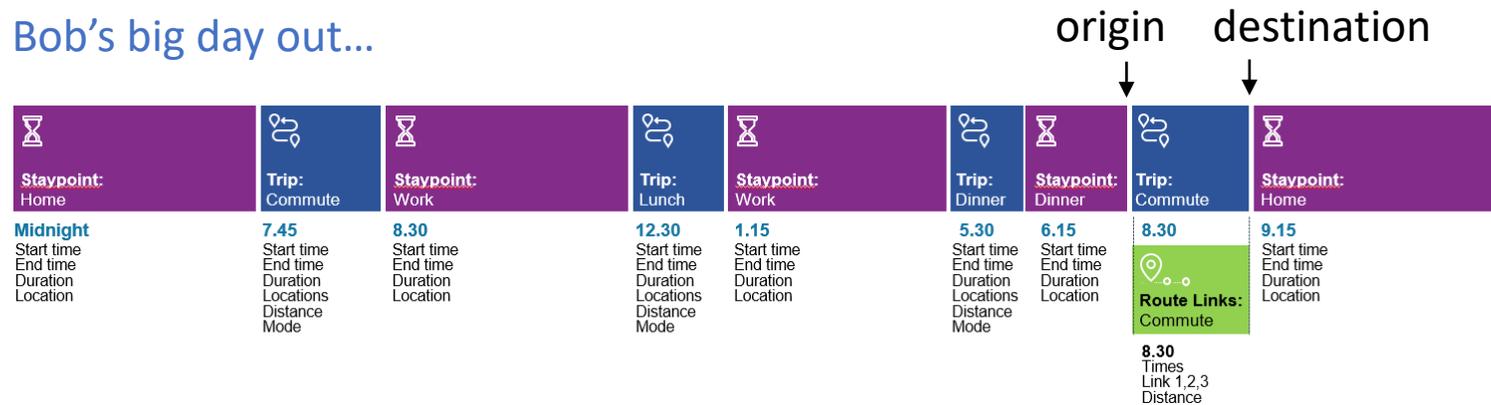


# DSpark Data Features\*

*Daily* geo-locations of mobiles collected and then cleaned, incl. de-identification and collecting de-identified attributes like [age](#), [gender](#), [country of origin](#)

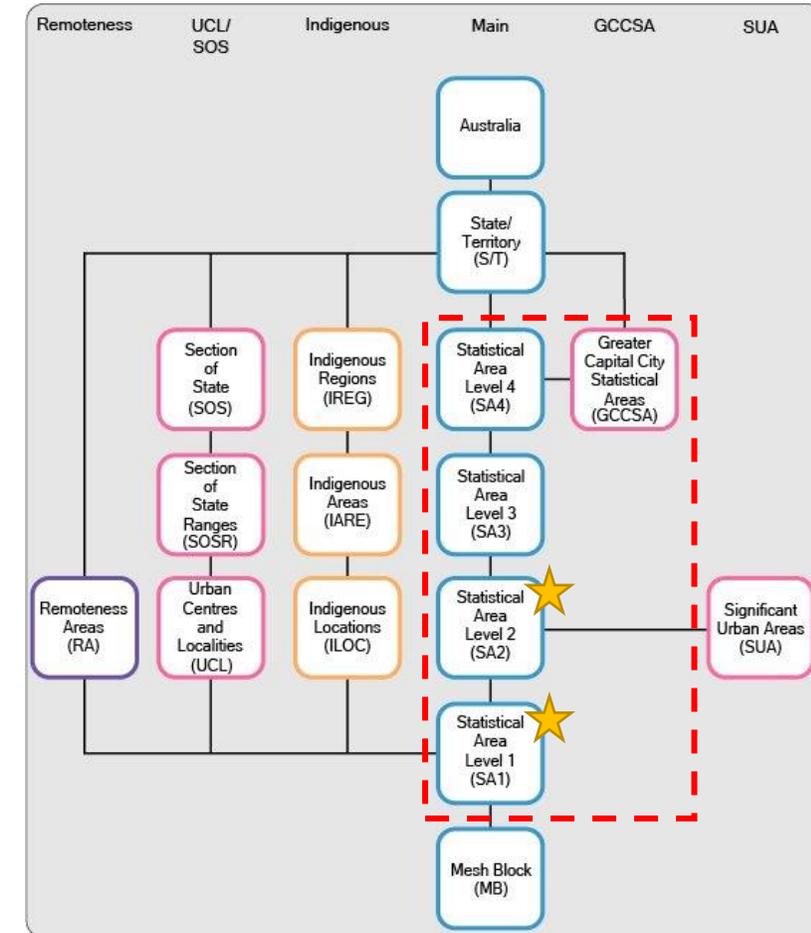
[Home and work locations](#) are derived *from behaviours* also [travel mode](#), [route](#), etc.

## Bob's big day out...



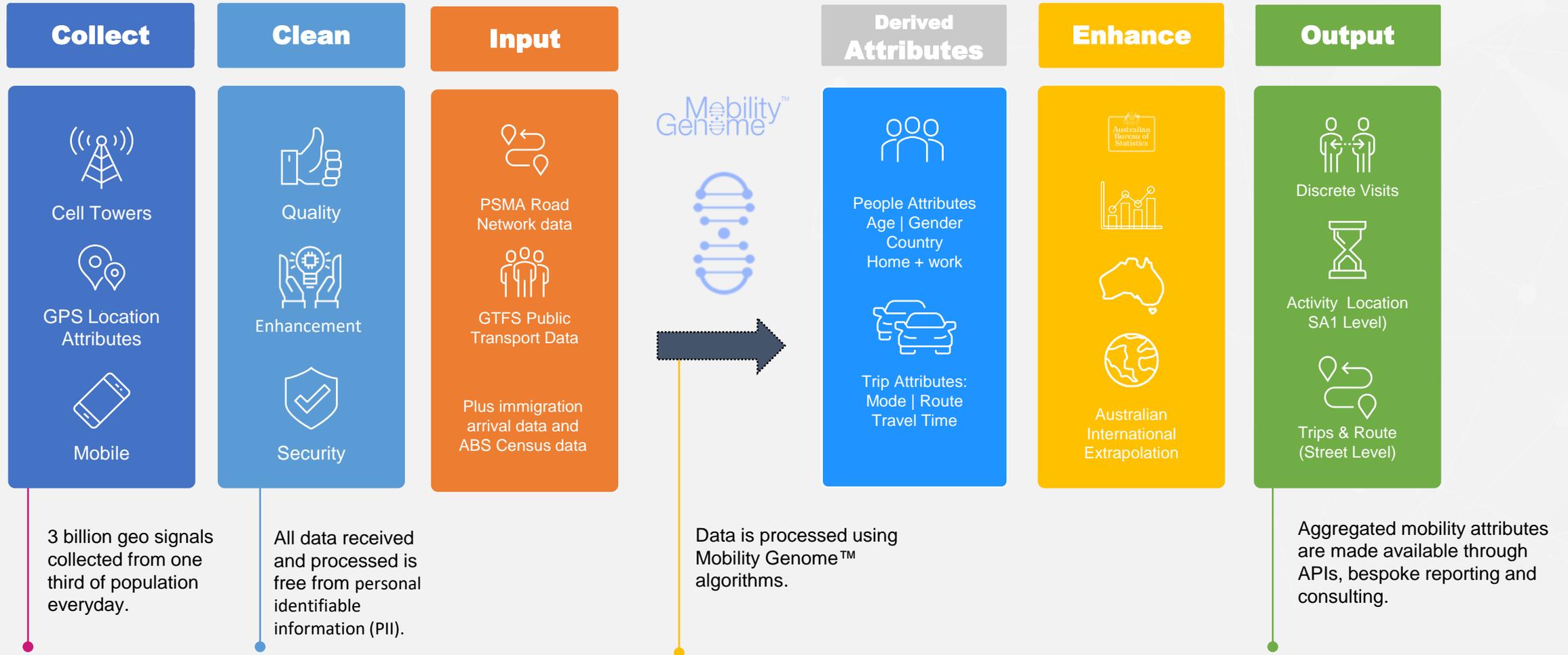
## DSpark – ODMatrix

1. Proportion of *unique* number of people making a trip (unique agents / SA2 population) in [SA2-SA3 OD pair](#)
2. Number of trips per person (unique agents / total records) in [SA2-SA3 OD pair](#)
3. Median duration of the trip (hr) of [SA2-SA3 OD pair](#)
4. Median distance of the trip (km) of [SA2-SA3 OD pair](#)



# Data is collected, cleaned, aligned and enhanced\*

HOW DSPARK WORKS.



# OD Matrix

Field	Data Type	Units	Description
Date	Timestamp	DD-MM-YYYY	The indexed time of the trip end-time at the daily level, i.e., registered when the trip ends.
Time of Day	String	{AM Peak, Lunch, School Run, PM Peak, Overall}	The indexed time of the trip end-time at the time of day level as “AM Peak” (7-10am), “Lunch” (11-2pm), “School Run” (3-4pm), “PM Peak” (5-7pm), and “Overall”.
Origin SA2 SES	String	1DECILE – 10DECILE	Relative socio-economic standing of SA2 statistical areas as provided by SEIFA data product (see section 2.1.2).
Trip Purpose	String	{Work, Play, NAN}	Inferred purpose of trip as “work” (home-work, work-home, other-work, work-other), “play” (home-other, other-home, other-other), or NAN (i.e., unable to infer purpose).
Transport Mode	String	{Car, Public Transport, Walk, Overall}	Inferred dominant mode of travel for the entire trip as “car”, “walk”, and “public transport” (bus, rail, subway, tram, ferry).
Unique Agents	Metric	People	Unique count of agents taking trips in certain area/time.
Total Records	Metric	Trips	Total number of trips in certain area/time.
Sum Duration	Metric	Hours	Total duration of all trips between origin and destination.
Sum Distance	Metric	Kilometres	Total distance of all trips between origin and destination.
Trips Per Person	Metric	Trips Per Person	Trips per person = total records / unique agents
Average Duration	Metric	Hours	Average duration = Sum duration / total records
Average Distance	Metric	Kilometres	Average distance = Sum distance / total records

# Land Use Classifications by ABS in ASGS

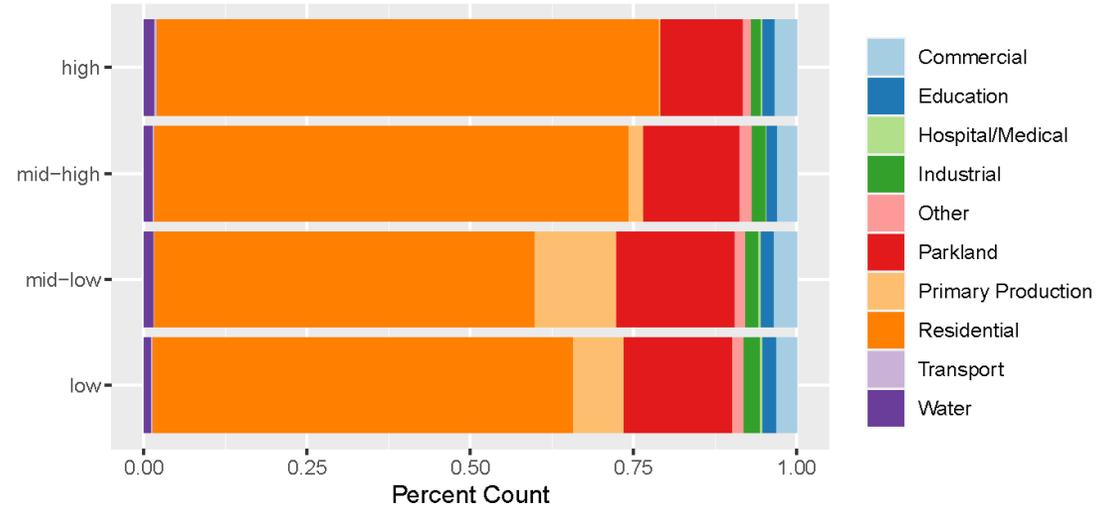
Land Use	Description
Residential	Land mostly dedicated as a place for people to live (high relative population count), e.g., houses, apartments, gated communities.
Commercial	Contain a number of businesses, used for retail, wholesale trade, or office-based work, and where possible should have zero population count but in some cases may, e.g., apartment flats above retail or wholesale trades, mixed apartment-office buildings.
Industrial	Contain a number of businesses, used for production and assembly activities of industrial or manufacturing process, and where possible have zero population count e.g., warehouses, factories.
Parkland	Parklands, nature reserves, and other protected or conserved areas and may also include any public (green) space, golf course, or sport field whether open to the public or not.
Education	Education facilities such as schools, universities, and may contain population.
Hospital/Medical	Hospital or medical facilities including aged care facilities.
Transport	Road or rail features.
Primary Production	Land used mainly (>50% in km <sup>2</sup> ) for cultivation or maintenance of livestock, where done in pursuit of monetary gains.
Water	Identify water bodies where possible, e.g., rivers, lakes.
Other	Mesh blocks that are less easily categorised due to nature of land use or evidence of high mixed use.

# SEIFA 2016 IRSAD Variable List

Variable	Adv / Disadv	Description
INC_HIGH	Advantage	% People with stated annual household equivalised income between \$1 and \$25,999 (approx. 1st and 2nd deciles)
INC_LOW	Disadvantage	% People with stated annual household equivalised income greater than or equal to \$78,000 (approx. 9th and 10th deciles)
NOYR12ORHIGHER	Disadvantage	% People aged 15 years and over whose highest level of educational attainment is Year 11 or lower (includes Certificate Levels I and II; excludes those still at secondary school)
NOEDU	Disadvantage	% People aged 15 years and over who have no educational attainment
CERTIFICATE	Disadvantage	% People aged 15 years and over whose highest level of educational attainment is a Certificate Level III or IV qualification
ATUNI	Advantage	% People aged 15 years and over attending university or other tertiary institution
DIPLOMA	Advantage	% People aged 15 years and over whose highest level of educational attainment is an advanced diploma or diploma qualification
UNEMPLOYED	Disadvantage	% People in the labour force who are unemployed
OCC_LABOUR	Disadvantage	% Employed people classified as Labourers
OCC_DRIVERS	Disadvantage	% Employed people classified as Machinery Operators and Drivers
OCC_SERVICE_L	Disadvantage	% Employed people classified as Low-Skill Community and Personal Service Workers
OCC_SALES_L	Disadvantage	% Employed people classified as Low-Skill Sales Workers
OCC_PROF	Advantage	% Employed people classified as Professionals
OCC_MANAGER	Advantage	% Employed people classified as Managers
LOWRENT	Disadvantage	% Occupied private dwellings paying less than \$215 per week in rent (excluding \$0 per week)
OVERCROWD	Disadvantage	% Occupied private dwellings requiring one or more extra bedrooms (based on Canadian National Occupancy Standard)
HIGHBED	Advantage	% Occupied private dwellings with four or more bedrooms
HIGHRENT	Advantage	% Occupied private dwellings paying more than \$470 per week in rent
HIGHMORTGAGE	Advantage	% Occupied private dwellings paying more than \$2,800 per month in mortgage repayments
CHILDJOBLESS	Disadvantage	% Families with children under 15 years of age and jobless parents
ONEPARENT	Disadvantage	% Families that are one parent families with dependent offspring only
NOCAR	Disadvantage	% Occupied private dwellings with no cars
DISABILITYU70	Disadvantage	% People aged under 70 who need assistance with core activities due to a long-term health condition, disability or old age
SEPDIVORSED	Disadvantage	% People aged 15 and over who are separated or divorced
NONET	Disadvantage	% Occupied private dwellings with no Internet connection

# SES Land Use by Count

A



B

