AN INEXACT SCIENCE:

MEASUREMENT ERROR IN MODE AND LOCATION CHOICE MODELS

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Outline

1. Main findings
2. Motivation & zeitgeist
3. Data & results
4. Summary

"Although this may seem a paradox, all exact science is dominated by the idea of approximation. When a man tells you that he knows the exact truth about anything, you are safe in inferring that he is an inexact man ..." – Bertrand Russell

“Aggregate statistics can sometimes mask important information …” – Ben Bernanke

Motivation #1: Is statistical uncertainty a first-order problem?

Like transport models, macroeconomic models are **calibrated by adjusting parameters** in the underlying behavioural models to replicate observed data.

Calibration is an **ad-hoc process of matching "moments"**, where moments means a characteristic, or property, of a statistical distribution, e.g. the mean ("annual average daily traffic").

Usually, **calibration does not (formally) consider uncertainty** in model parameters. Recent research, however, subjects macroeconomic ("DSGE") models to formal statistical tests (link) and finds:

> "Taken together, these findings cast serious doubt on the meaningfulness of parameter estimates for this DSGE, and on whether this specification represents anything structural about the economy.

Takeaway: In many models, statistical uncertainty may be a first-order problem.

Motivation #2: Are macroscopic transport models “insensitive”?

- **Common refrain:** Macroscopic transport models are too insensitive.
- **If this is true, then why?** Implies that people’s behaviour is more sensitive to changes in transport outcomes than the models assume.
- **Where might such biases arise?** Possible sources include but are not limited to:
  - *Model structure*, e.g. generation / distribution / mode choice / assignment steps are not “separable”; and/or
  - *Omitted variables*, e.g. factors that influence people’s choices (like departure time) are not included; and/or
  - ***Biased parameters*, e.g. inaccurately estimated due to endogeneity or measurement error …**

Question: Doesn’t measurement error simply introduce random noise? Let’s see!

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Zeitgeist: Of “iron laws”, measurement error, and attenuation

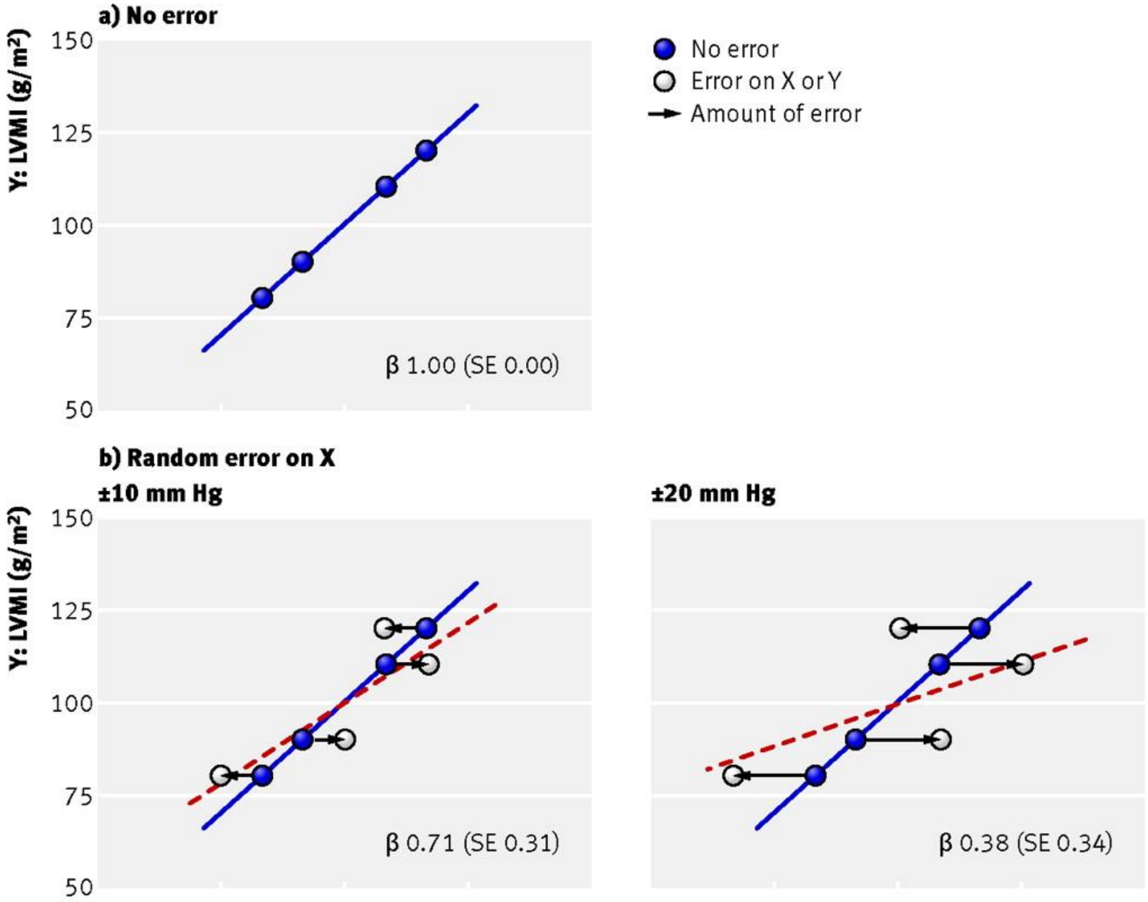
- **Hausman’s “Iron law” (2001):** In the presence of random ME "*… the magnitude of the estimate is usually smaller than expected. It is also called `attenuation’ in the statistics literature.*"

- **Hutcheon et al. (2010) discuss ME in a medical context:** "*Regression dilution bias” is where “… random measurement error in the values of an exposure variable (X) causes an attenuation or “flattening” of the slope of the line … between the X and an outcome (Y) of interest.*"

- In the last decade, some transportation studies allow for ME in travel-times. **Walker et al. (2010)**, for example, considers differences between *self-reported* vis-à-vis *estimated* travel-times and concludes that not allowing for ME tends to underestimate people’s value of time.

Takeaway: Random ME is *not* a neutral statistical process. Rather, it biases parameters towards zero.

Zeitgeist: Visualising measurement error



Source: Hutcheon, J. A., Chiolero, A., & Hanley, J. A. (2010). Random measurement error and regression dilution bias. *BMJ*, *340*.

- **Top-left panel:** X is deterministic; ie zero measurement error ($\beta = 1.00$, s.e. 0.00)
- **Bottom-left panel:** X measured with small random error ($\beta = 0.71$, s.e. 0.31)
- **Bottom-left panel:** X measured will large random error ($\beta = 0.38$, s.e. 0.34)

Takeaway: Random ME “flattens” the slope.

Footnote: “Random” = no selection effects, e.g. publication bias or strategic misrepresentation.

Potential sources of measurement error in commuting data

Consider the following (typical) situation:

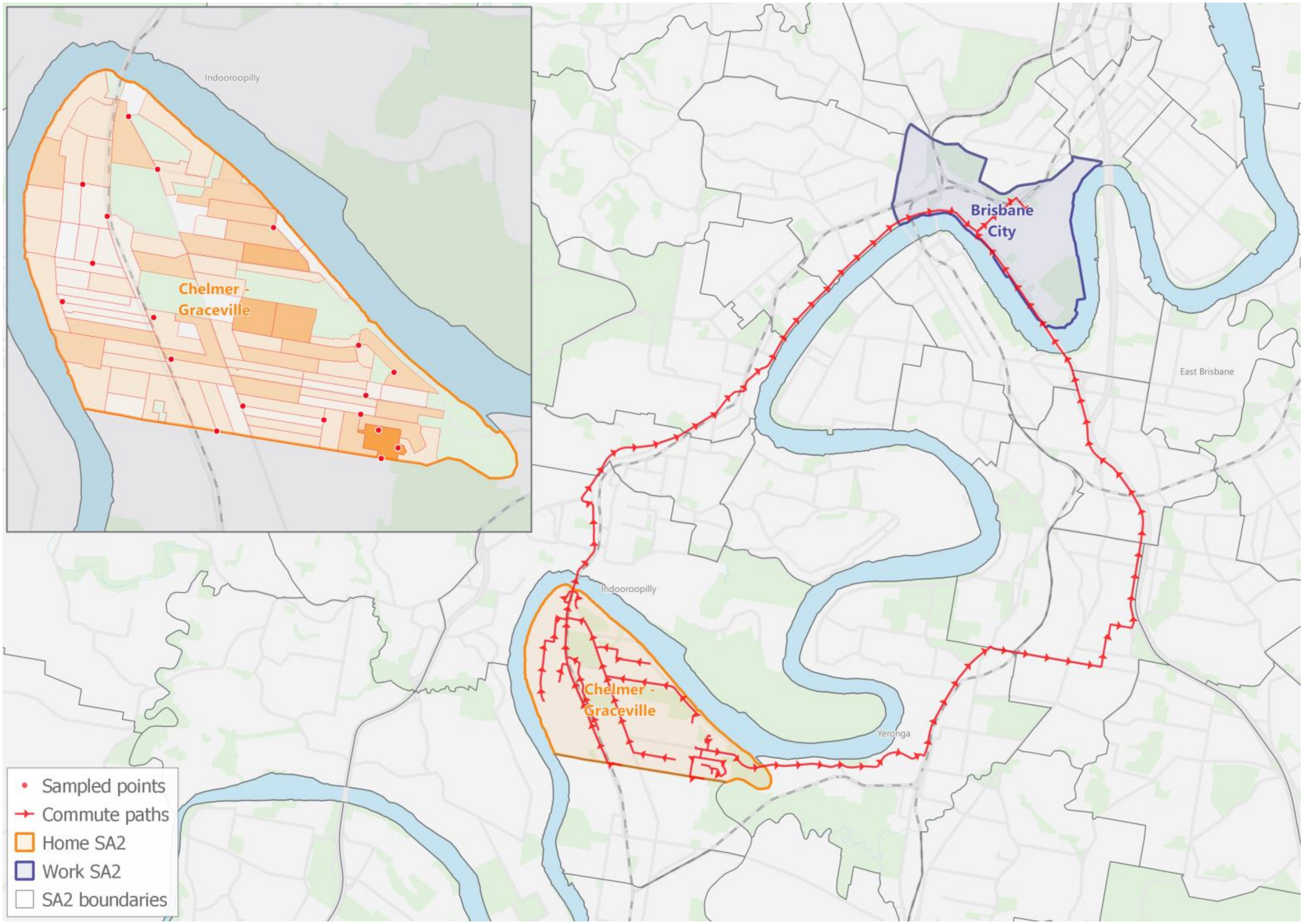
- **We know** (1) the zones where people live / work and (2) the main mode of transport that they use to commute (e.g. from census data)

- **We want to measure** the travel-time and -distance involved in commuting between home and work zones (e.g. to use in the estimation of destination and mode choice models).

- **BUT we don't know:**
  - **Precise home locations (within the origin zone)**
  - Precise work locations (within the destination zone)
  - Route, including intermediate destinations, e.g. schools
  - Exactly where drivers park their car (both at home and at work)
  - Frequency of commute across the week
  - Time-of-departure

These "unknowns" (and others) introduce ME into estimates of travel-times and –distances.

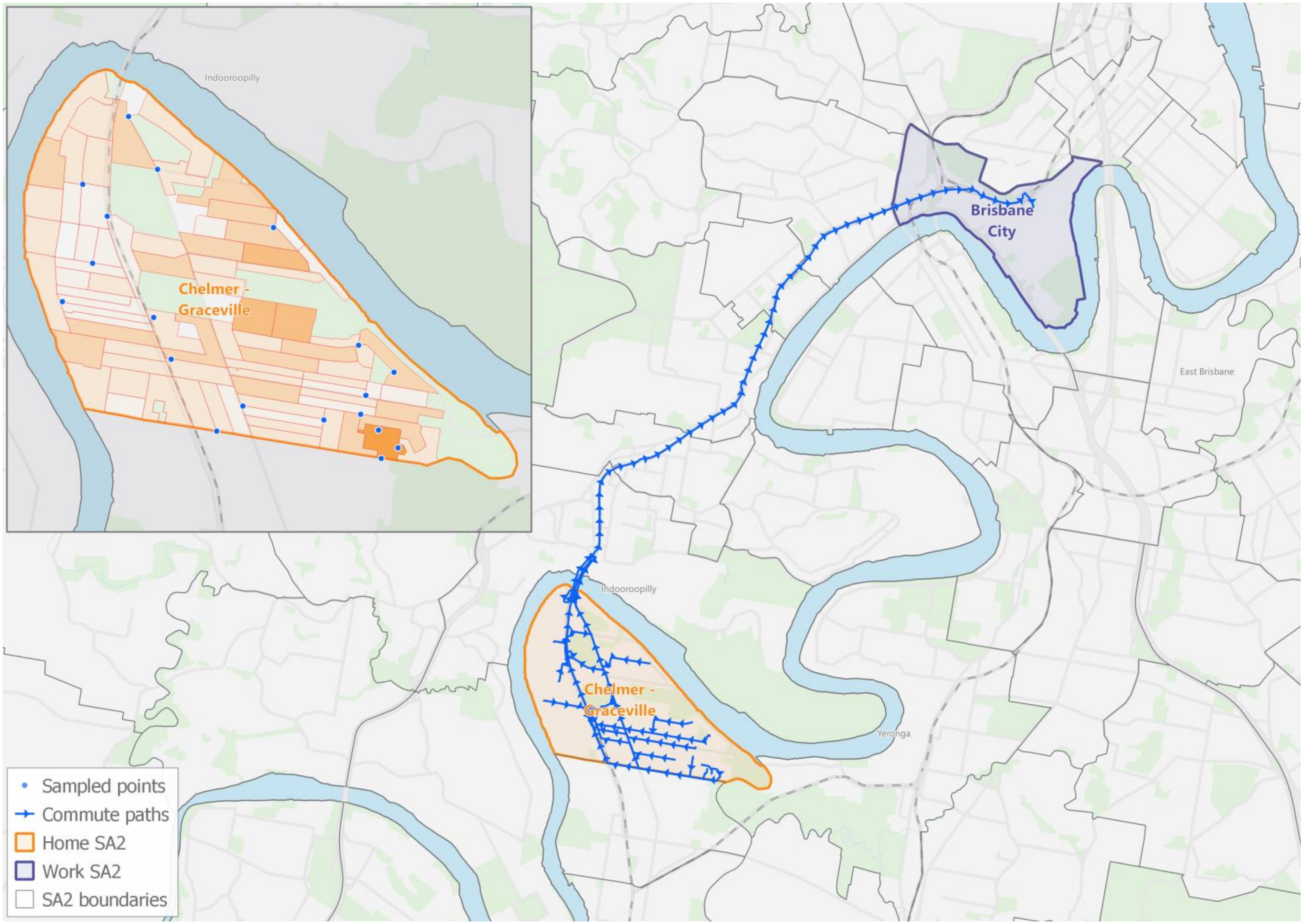
Data: Model zones → Measurement error (Car)



Focus on measurement error induced by uncertainty in workers' home location.

- Use Open Street Maps to sample 20 home locations within each zone (SA2) weighted by the population of meshblocks within individual SA2s.
- We then calculate car and PT travel-times from these 20 "home" locations to all other SA2s (centroids) → distribution of travel-times for each OD pair in our data.
- **The figure to the left shows the paths taken for 20 car journeys from Chelmer – Graceville to Brisbane City.**

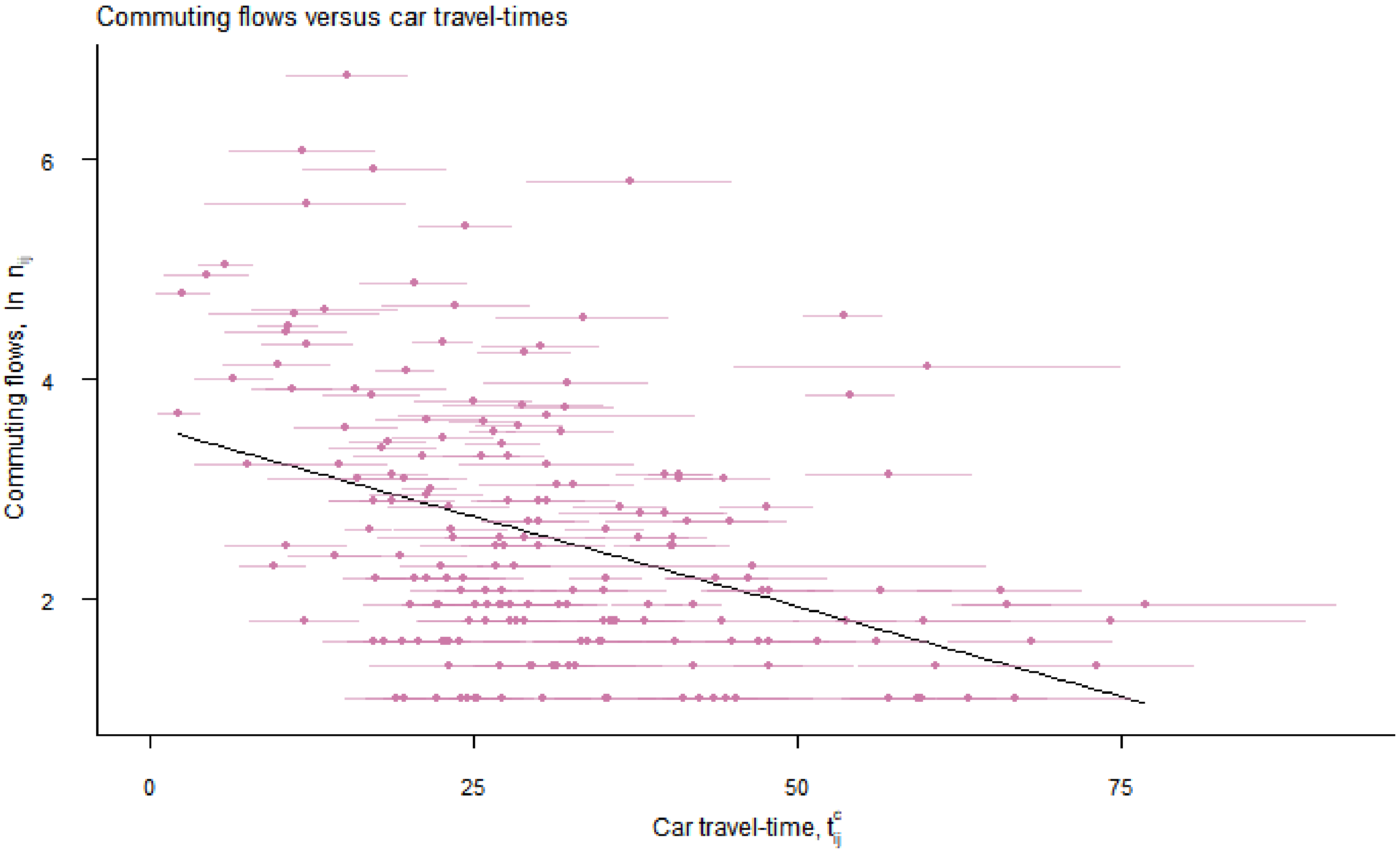
Data: Model zones → Measurement error (PT)



Focus on measurement error induced by uncertainty in workers' home location.

- **The figure to the left shows the paths taken for 20 PT journeys from Chelmer – Graceville to Brisbane City.**

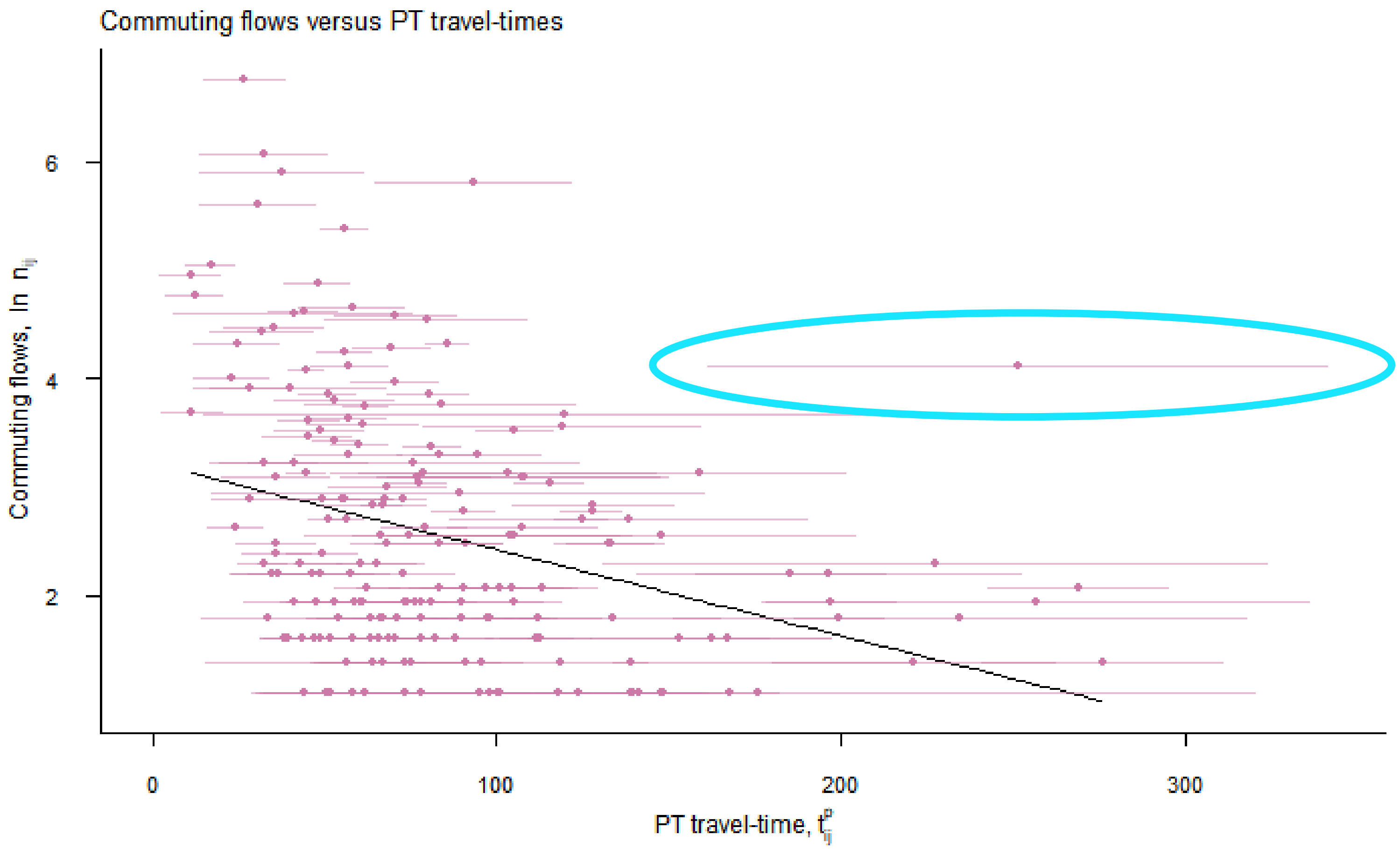
Data: Measurement error in car travel-times



Note: Random sample of 200 observations (from a total of 49,793).

- Vertical axis measures the log of total commuting flows whereas horizontal axis measures car travel-times.
- For car travel-times, the pink market denotes the mean whereas the bars denote the (approximate) 95% confidence intervals (that is, plus and minus two standard deviations). This interval is defined by the sampled data.
- We observe a clear downwards association (black trend line) as well as considerable heterogeneity in measurement error, especially towards the lower right-hand corner.

Data: Measurement error in PT travel-times



Note: Random sample of 200 observations (from a total of 49,793).

- Similar story for PT.
- Blue oval highlights an observation with an unusually high mean travel-time that is also measured imprecisely (error bars).
- When treated deterministically (i.e. no ME), such **observations are likely to exert considerable influence over the estimated coefficients.**
- If we allow for ME, however, then the model can "shrink" the travel-time to accord better with other information (e.g. model and other data).

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Results: Estimated parameters increase in magnitude

	Model	Without measurement error				With measurement error			
		A	B	C	D	A	B	C	D
Car	μ_c	−1.925	0.009	−0.103	−0.820	−5.881	−2.574	−2.003	−4.116
		(0.011)	(0.025)	(0.031)	(0.102)	(0.073)	(0.063)	(0.065)	(0.106)
PT	μ_p	4.267	1.931	3.876	4.215	14.581	7.764	9.370	11.591
		(0.021)	(0.044)	(0.178)	(0.227)	(0.164)	(0.135)	(0.318)	(0.305)
	ζ_i, ζ_j	No	Yes	Yes	Yes	No	Yes	Yes	Yes
	$t^p_{ij} \times \zeta$	No	No	Yes	Yes	No	No	Yes	Yes
	C.F.	No	No	No	Yes	No	No	No	Yes
	loo-ic	182,439	50,858	43,534	42,152	40,710	37,044	35,203	31,244
	R^2	0.869	0.992	0.996	0.997	0.999	0.999	0.999	0.999

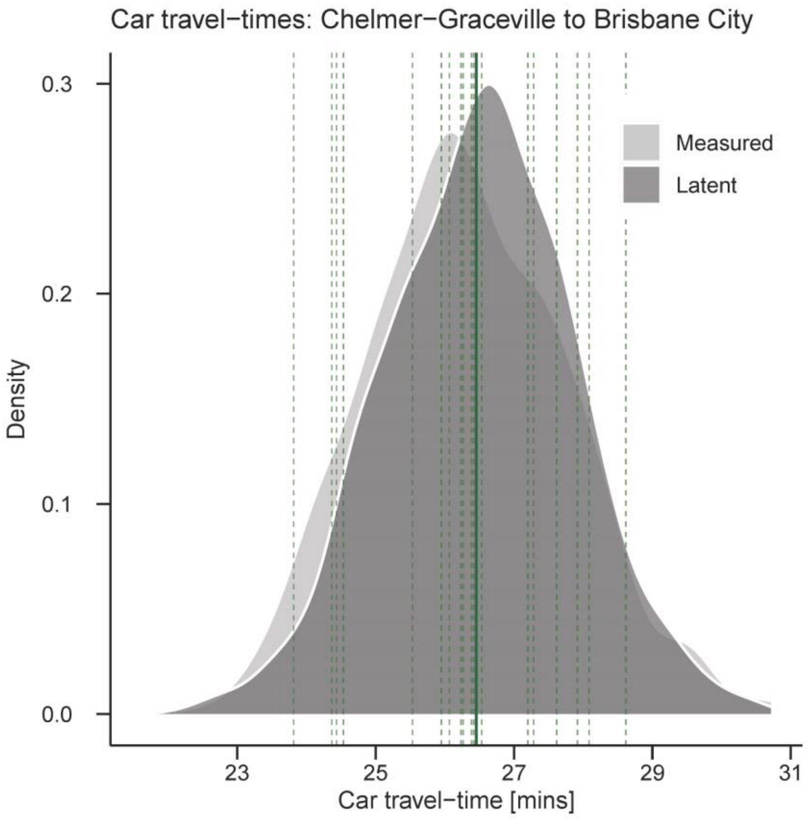
We present standardized coefficients, which denote the effect of a one s.d. increase in travel-times.

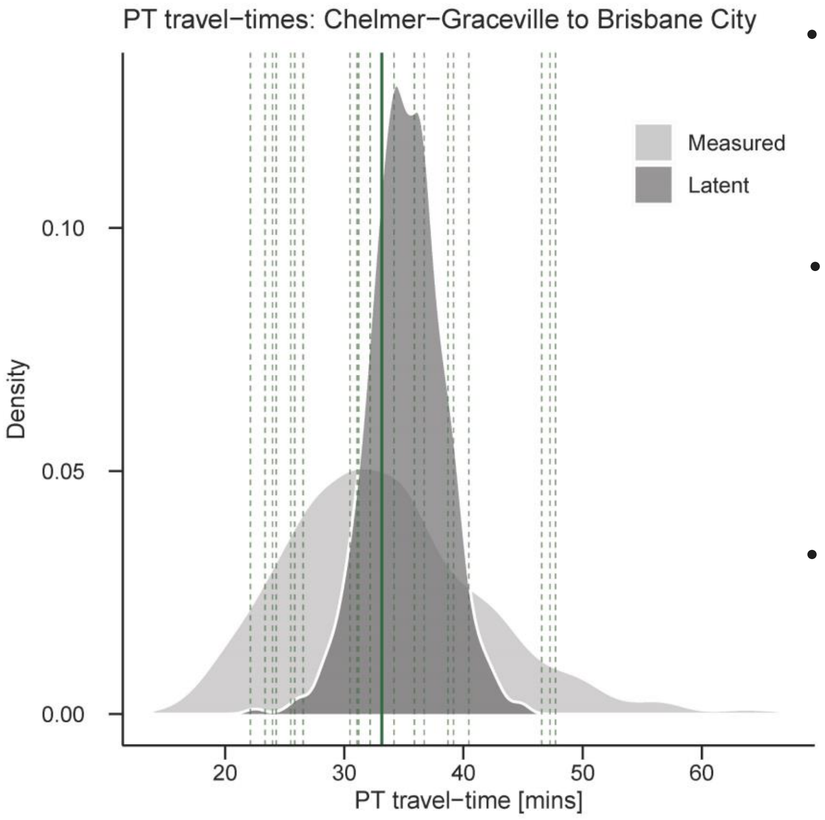
The loo-ic measures external model performance

Table 1: Regression results for mode share models as per Section 4.1. Columns 1–4 and 5–8 report results without and with measurement error, respectively. Model A includes only car and PT travel-times, t^c_{ij} and t^p_{ij}, respectively. Model B includes group-level effects for individual origins and destinations, ζ_i and ζ_j, respectively. Model C includes group-level interaction effects between t^p_{ij} and both ζ_i and ζ_j. Finally, Model D uses a control function ("C.F.") to address endogeneity in travel-times, including the residuals from a first stage in which t^c_{ij} and t^p_{ij} are regressed against the crow-flies distance between the centroids of i and j, Z_{ij}. All models use 49,793 observations; s.e. in parentheses.

Takeaway: The effect of car and PT travel-times on mode choice is much larger when we allow for ME

Results: Latent (“true”) travel-times “emerge from the ether”





- Dashed green vertical lines denote the 20 sampled travel-times; the solid green vertical lines denotes the mean.
- The light-grey denotes the “log-normal” distribution of mean travel-times implied by the sampled data (mean and variance).
- The dark-grey denote the estimated distribution of latent (“true”) mean travel-times estimated by the model.

$$n_{ij}^c \sim \mathcal{B}(n_{ij}, \mu^c t_{ij}^{c*} + \mu^p t_{ij}^{p*} + \zeta)$$
$$t_{ij}^{c*} \sim \mathrm{Logn}(t_{ij}^c, (s_{ij}^c)^2) \; t_{ij}^{p*} \sim \mathrm{Logn}(t_{ij}^p, (s_{ij}^p)^2)$$

Latent travel-times (t_{ij}^{c*} and t_{ij}^{p*}) are estimated as part of the Bayesian “multi-level” model.

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Summary

- Measurement error (ME) is a potentially important source of bias in the estimation of mode and location choice models. **We should definitely take ME more seriously!**

- Correcting for ME tends to increase the magnitude of parameters (possibly by a lot). **Implies people respond even more strongly to transport outcomes!**

- Even when ME is unknown, estimating models that allow for ME can significantly improve model performance and yield less biased parameters. **Why wouldn’t you allow for ME!?!**

Suggestion: Re-estimate the destination and mode choice models that are currently used in macroscopic transport models to allow for measurement error.

THANK YOU AND QUESTIONS

References

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