

## **On the central role of Somers' $D$**

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The Avon Longitudinal Study of Parents and Children (ALSPAC)

<http://www.alspac.bris.ac.uk/>

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<http://ideas.repec.org/s/boc/usug06.html>

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- These definitions can be extended to cases where the  $X$ -values and/or the  $Y$ -values may be weighted and/or left-censored and/or right-censored.

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- *However*,  $D_{YX}$  exists whether or not  $X$  is binary, and is used to define...

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- The **Theil-Sen median slope** of  $Y$  with respect to  $X$  is defined as a solution in  $\beta$  to the equation

$$D_{Y-\beta X, X} = 0$$

or (in words) as a linear effect of  $X$  on  $Y$  sufficient to explain the observed Somers'  $D$ .



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- If  $X$  is binary, then the Theil-Sen median slope is known as the **Hodges-Lehmann median difference** between groups  $X = 1$  and  $X = 0$ .

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- The module `somersd` estimates Somers'  $D$ , Harrell's  $c$  or Kendall's  $\tau_a$ , saving the results as estimation results.
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All of these rank parameters have multiple versions for multiple sampling designs, with data weighted and/or censored and/or clustered and/or stratified.

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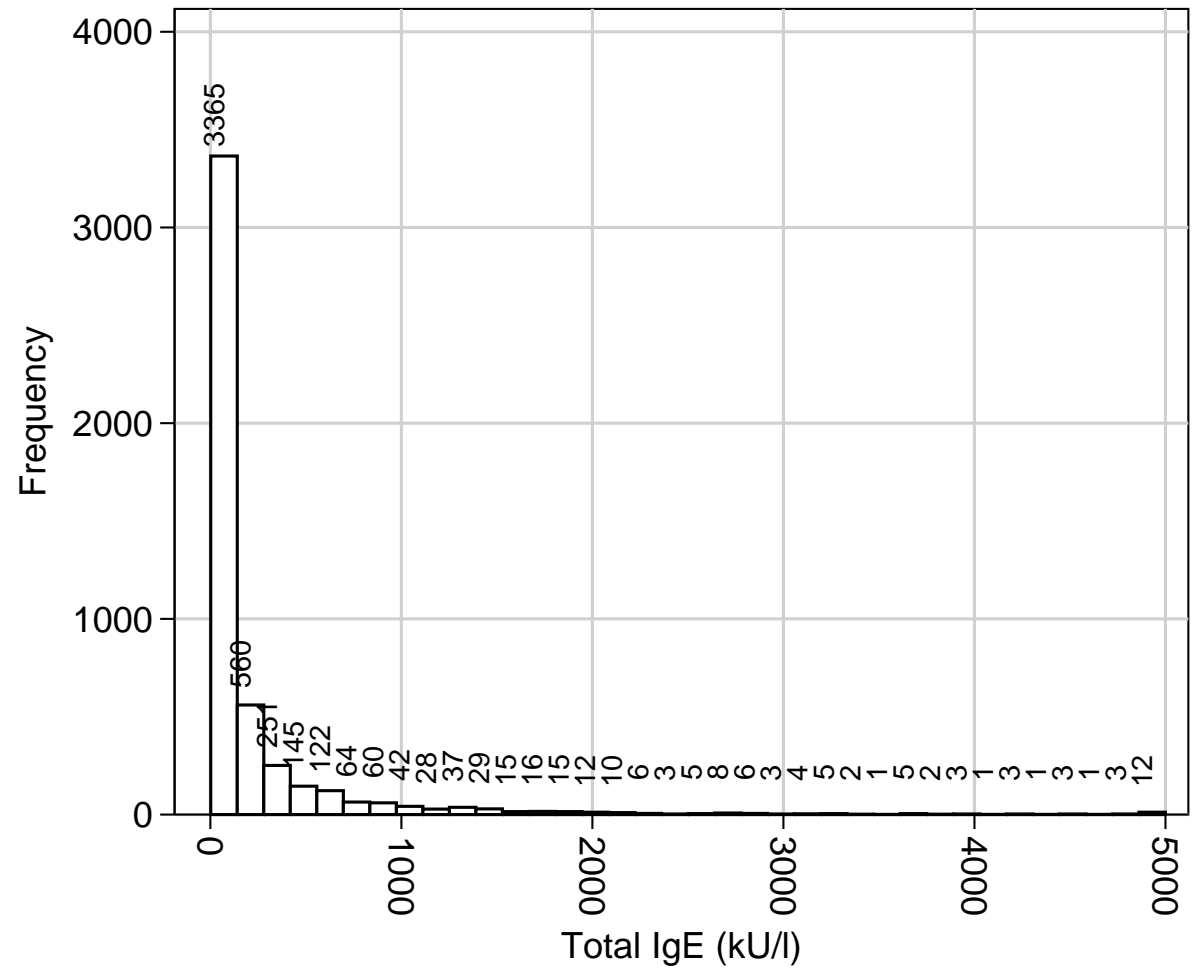
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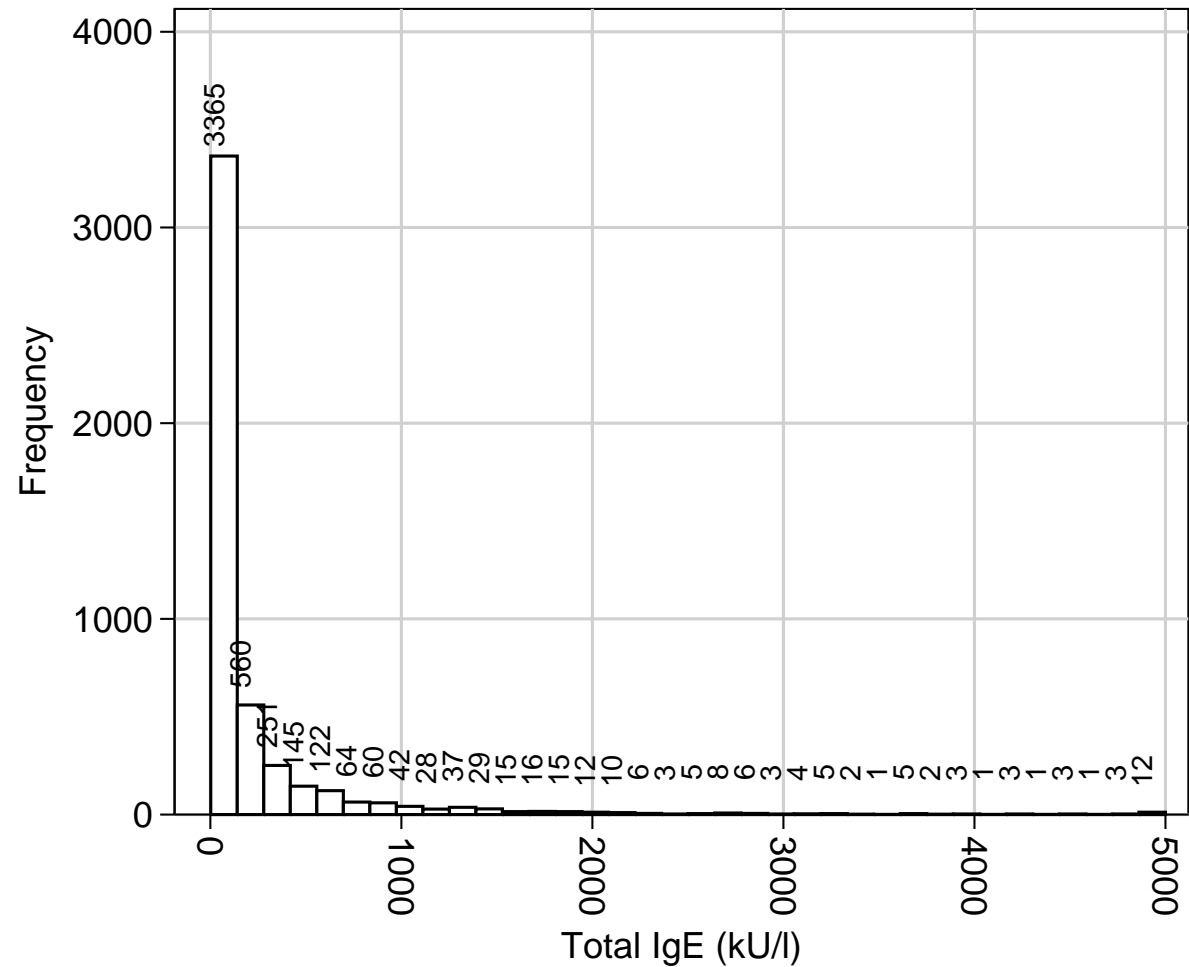
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- We will re-measure this association, using `censlope` to estimate Somers'  $D$  and Hodges–Lehmann median ratios.

# Distribution of IgE in the 4848 children with IgE and paracetamol data



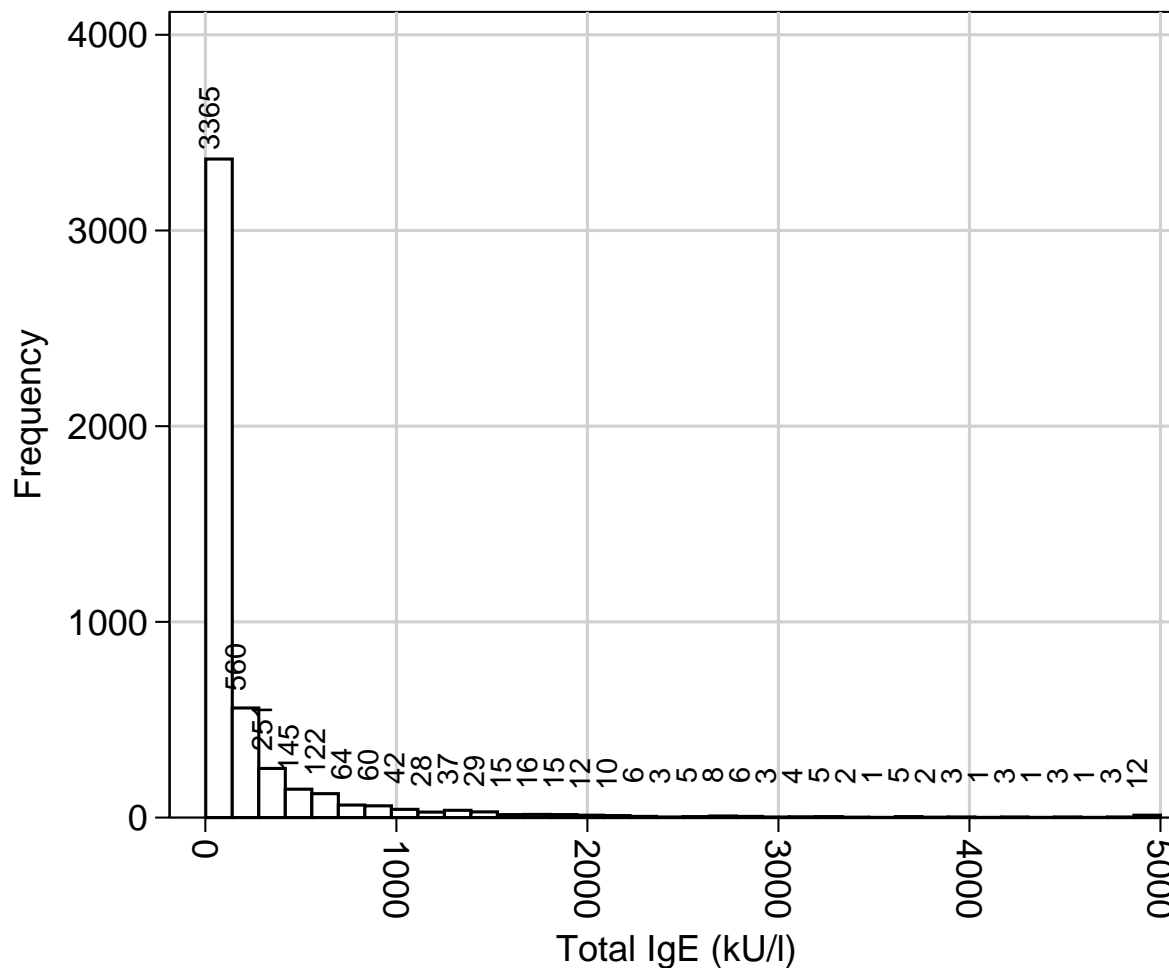
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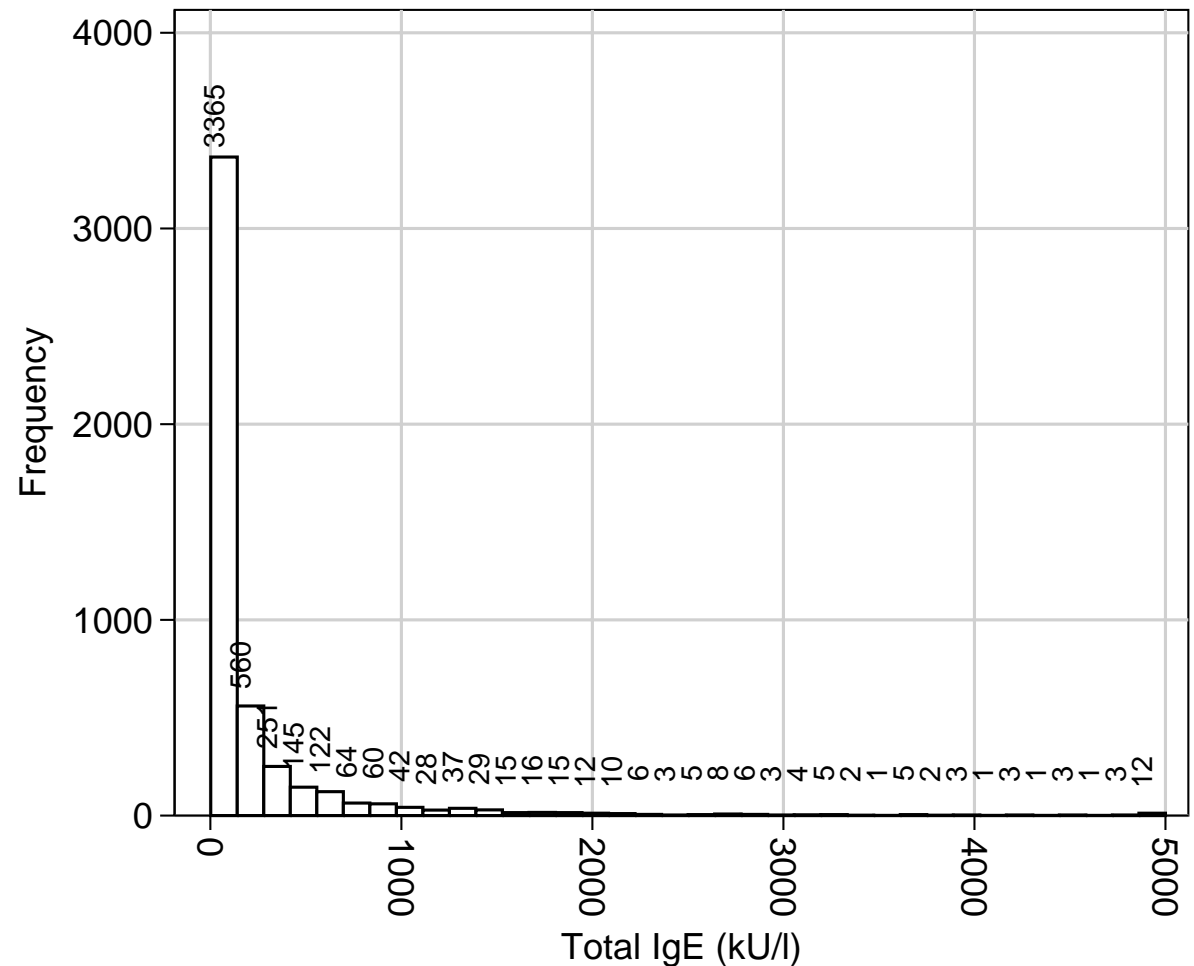
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- Total IgE, measured in kilounits/litre (kU/l), is raised in individuals with allergic diseases such as asthma.
- In the 4848 children with IgE and paracetamol data, its overall distribution is non-Normal.
- We wish to compare typical levels in the children of paracetamol users and non-users.



**Comparing IgE levels using censlope**

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- The Hodges–Lehmann median ratio is the median ratio of IgE levels between two such randomly–chosen children.
- (It is defined as the exponential of the Hodges–Lehmann median difference between the logged IgE values.)
- We will calculate confidence intervals for these two parameters, using `censlope` with Fisher's  $z$  transform.

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Outcome variable: lnigetot

Somers' D with variable: para32g

Transformation: Fisher's z

Valid observations: 4848

Symmetric 95% CI for transformed Somers' D

	para32g	Coef.	Jackknife Std. Err.	z	P> z	[95% Conf. Interval]	
lnigetot	.0533954	.0168421	3.17	0.002	.0203856	.0864053	

Asymmetric 95% CI for untransformed Somers' D

	Somers_D	Minimum	Maximum
lnigetot	.05334475	.02038276	.0861909

95% CI(s) for percentile ratio(s)

Percent	Pctl_Ratio	Minimum	Maximum
50	1.172549	1.0616111	1.2944986



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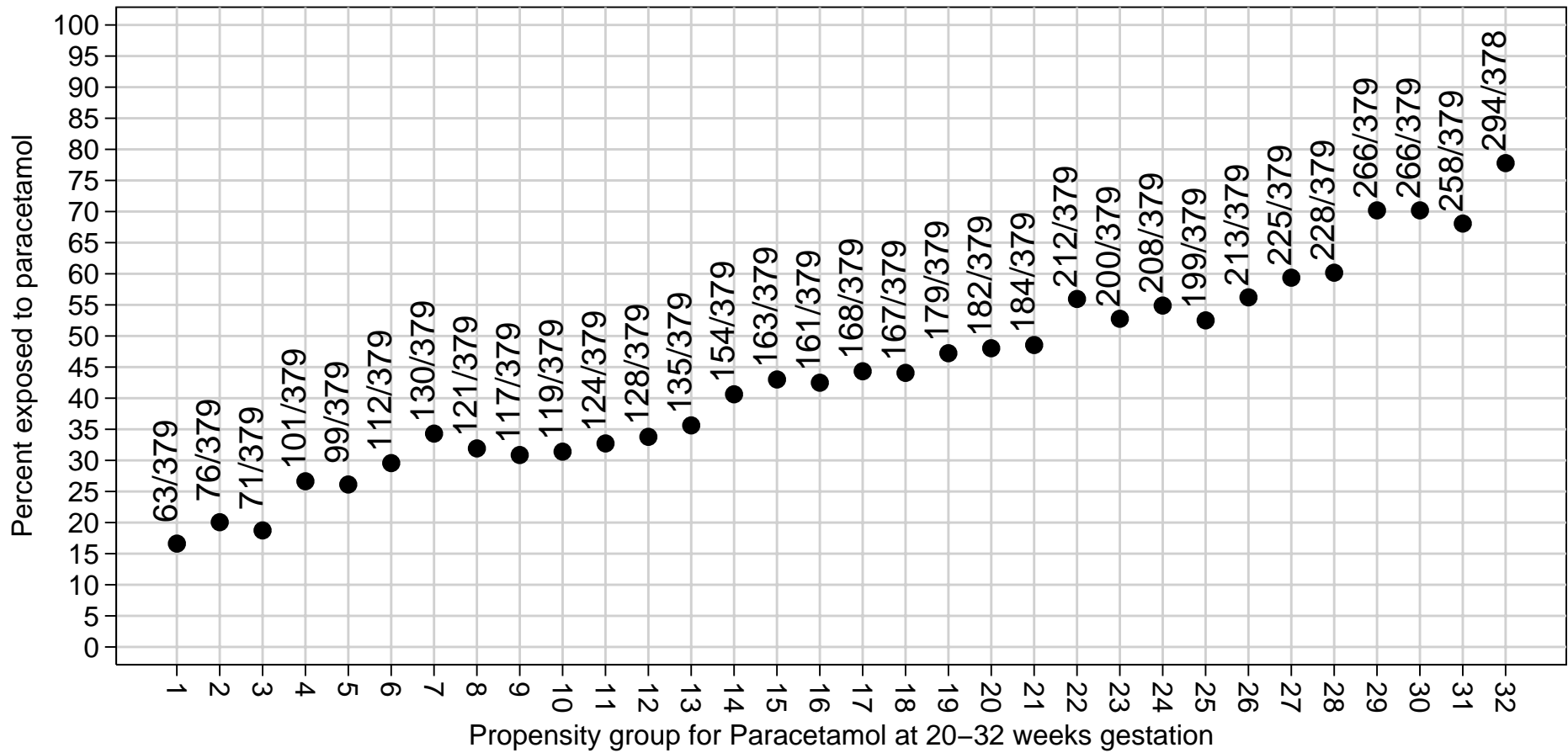
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- We fitted a logistic regression model to data from the 12127 children with data on maternal paracetamol use in late pregnancy.
- Paracetamol exposure was regressed with respect to the following confounders: gender, maternal age, prenatal tobacco exposure, mother's education, housing tenure, parity, maternal anxiety, maternal ethnic origin, multiple pregnancy, birth weight, gestational age at birth, head circumference, antibiotics in pregnancy, alcohol intake in pregnancy, maternal disease and infection history, younger siblings, presence of pets, breast feeding, day care, dampness problems, passive smoking exposure after birth, obesity index at 7 years.

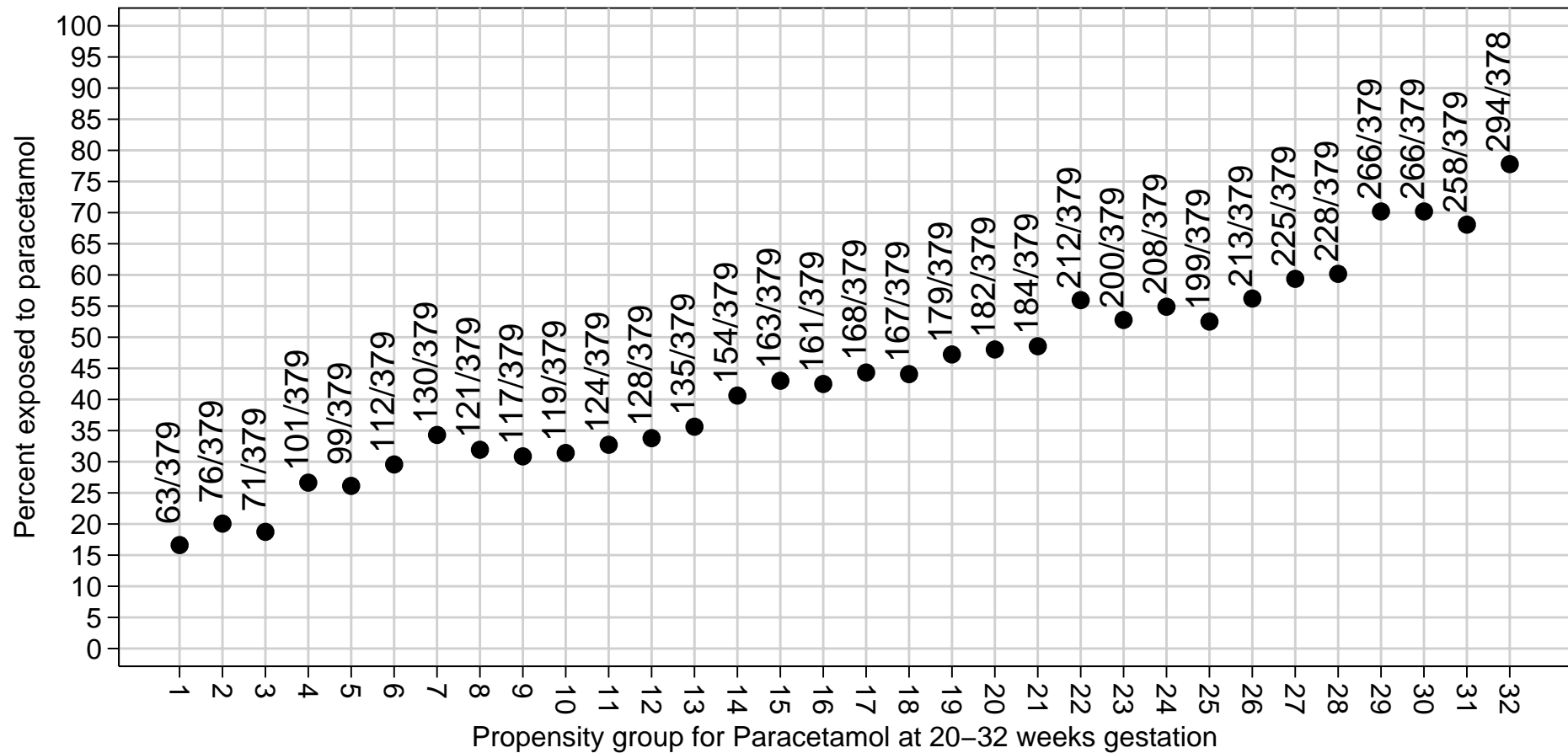
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- The predicted log paracetamol odds, or propensity score, was grouped into 32 propensity strata, using `xtile`.

# Paracetamol exposure prevalence in the 32 propensity groups



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Paracetamol propensity predicts paracetamol exposure, but not *too* well!

**Within-strata rank statistics using somersd**



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- *Therefore*, so can median slopes, differences and ratios.
- We can therefore adjust our rank statistics for confounders by restricting to comparisons within the 32 propensity groups.
- We will now estimate a propensity-adjusted Somers'  $D$  and median ratio, using `censlope`.

```
. censlope lnigetot para32g, transf(z) eform wstrata(pg_para32g);
```

Outcome variable: lnigetot

Somers' D with variable: para32g

Transformation: Fisher's z

Within strata defined by: pg\_para32g

Valid observations: 4848

Symmetric 95% CI for transformed Somers' D

	Coef.	Jackknife Std. Err.	z	P> z	[95% Conf. Interval]	
para32g						
lnigetot	.0416191	.018089	2.30	0.021	.0061653	.0770729

Asymmetric 95% CI for untransformed Somers' D

	Somers_D	Minimum	Maximum
lnigetot	.04159508	.00616518	.07692067

95% CI(s) for percentile ratio(s)

Percent	Pctl_Ratio	Minimum	Maximum
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- *Therefore*, the association between paracetamol exposure and IgE within paracetamol propensity groups *might possibly* be due to a residual association of both variables with the paracetamol propensity score.
- Fortunately, `somersd` can help us to check this possibility.

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- Alternatively, we may interpret  $D_{XY}$  as a **performance indicator** for  $X$  as a predictor of  $Y$ , for comparison with another predictor  $W$ .

The second interpretation is possible because, *if* a positive association of  $Y$  with  $X$  is caused entirely by a positive association of both variables with a third variable  $W$ , *then* we must have the inequality

$$D_{XY} \leq D_{WY}$$

(see Newson (2002) and Newson (2006)), and we can test this inequality using `somersd` and `lincom`.

**Comparing Somers'  $D$  parameters for paracetamol and paracetamol propensity**



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- We then compare the  $z$ -transformed  $D_{XY}$  and  $D_{WY}$ , using `lincom`.

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Somers' D with variable: lnigetot

Transformation: Fisher's z

Within strata defined by: pg\_para32g

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Symmetric 95% CI for transformed Somers' D

lnigetot	Coef.	Jackknife Std. Err.	z	P> z	[95% Conf. Interval]	
para32g	.0181683	.0078918	2.30	0.021	.0027006	.033636
ps_para32g	-.0082111	.0099832	-0.82	0.411	-.0277777	.0113556

Asymmetric 95% CI for untransformed Somers' D

	Somers_D	Minimum	Maximum
para32g	.0181663	.00270058	.03362334
ps_para32g	-.00821087	-.0277706	.01135515

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ps_para32g	-.0082111	.0099832	-0.82	0.411	-.0277777	.0113556

Asymmetric 95% CI for untransformed Somers' D

	Somers_D	Minimum	Maximum
para32g	.0181663	.00270058	.03362334
ps_para32g	-.00821087	-.0277706	.01135515

Paracetamol exposure (para32g) is a significant positive predictor, and paracetamol propensity (ps\_para32g) is a non-significant negative predictor.

*However*, to test the inequality, we use `lincom` to define a confidence interval and a  $P$ -value for half the difference between the two  $z$ -transformed Somers'  $D$  parameters, as follows:

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```
. lincom (para32g-ps_para32g)/2;
```

```
( 1)  .5 para32g - .5 ps_para32g = 0
```

```
-----
      lnigetot |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
           (1) |   .0131897   .0063639    2.07   0.038   .0007167   .0256626
-----
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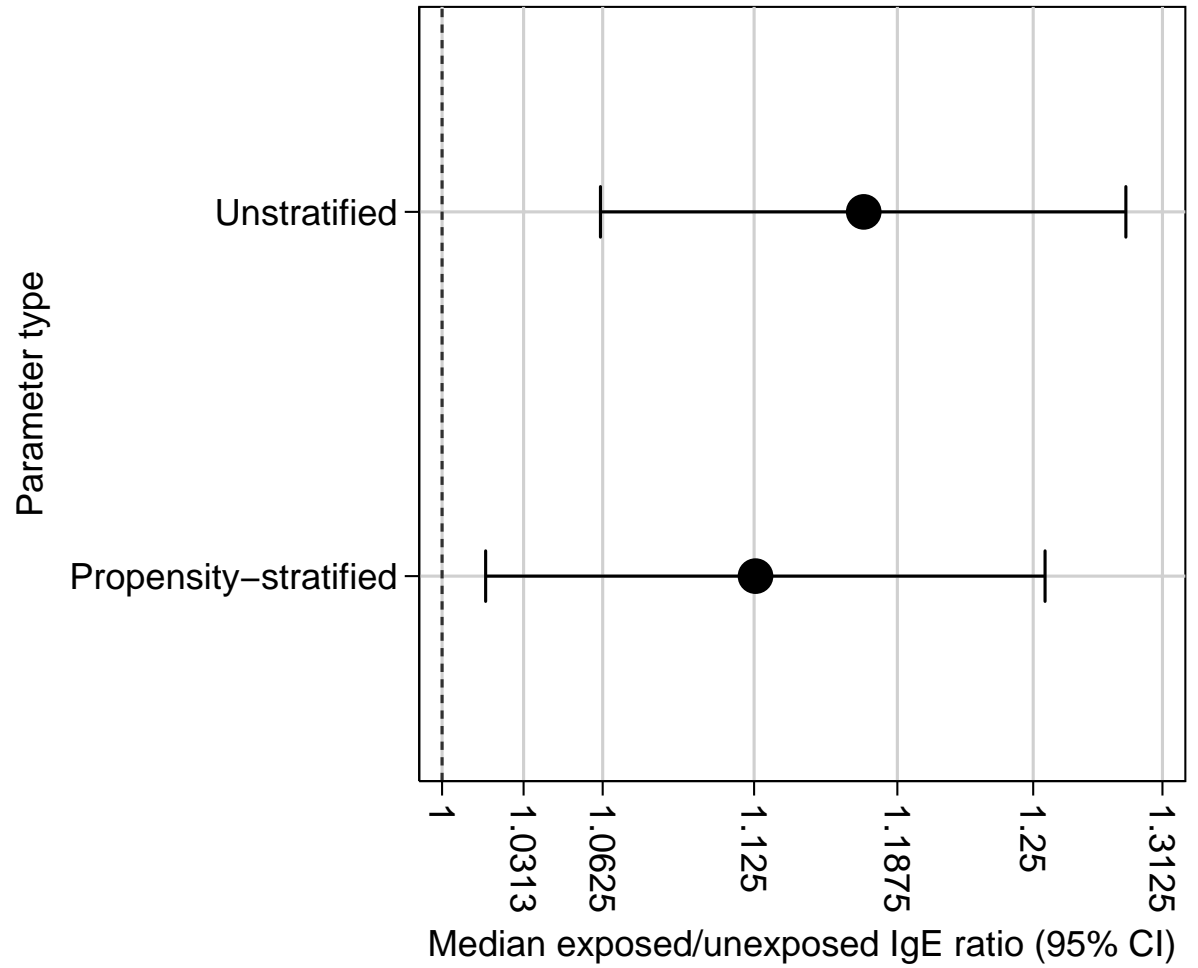
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lnigetot	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
(1)	.0131897	.0063639	2.07	0.038	.0007167 .0256626

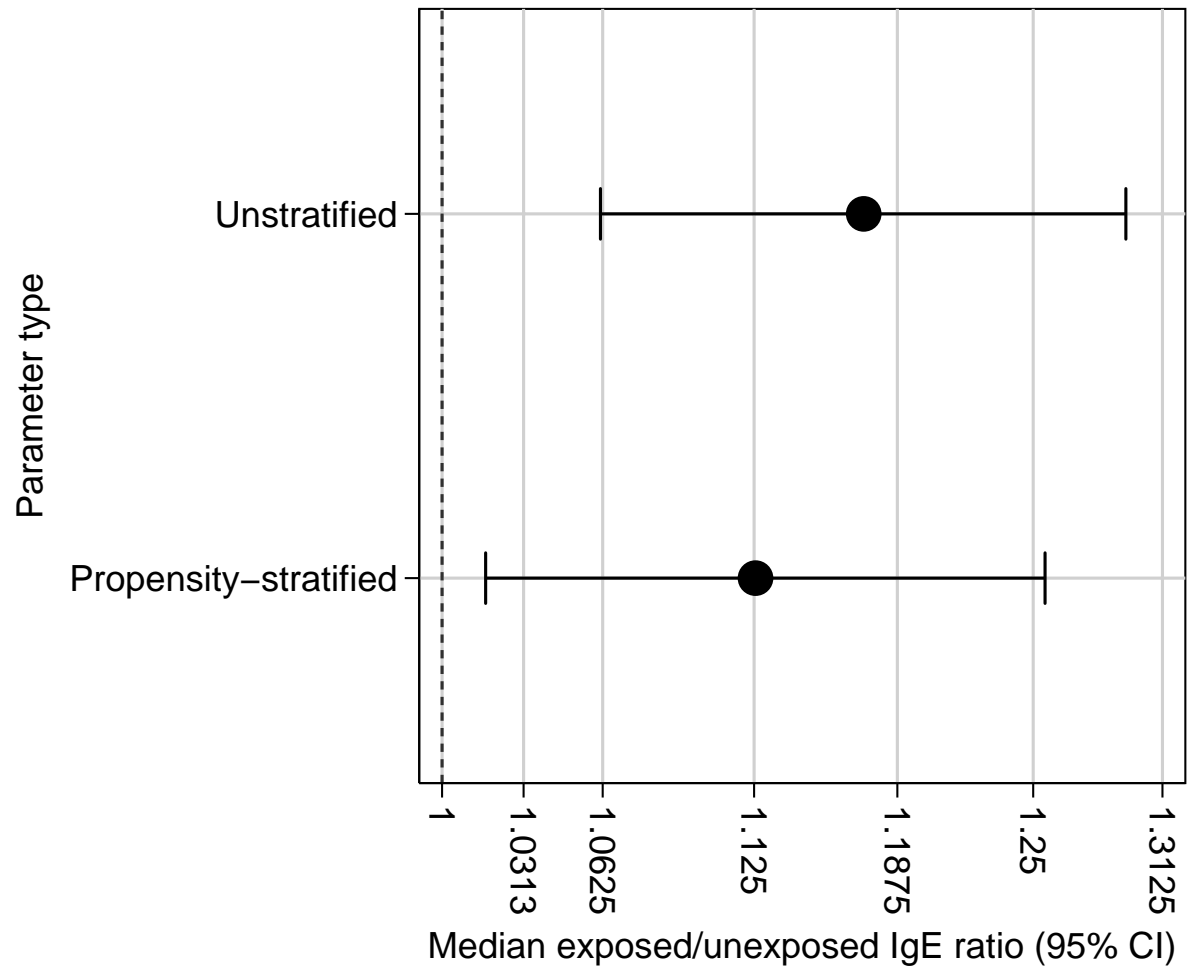
We see that the difference is (just) significantly positive. So the positive association between IgE and paracetamol exposure within paracetamol propensity *groups* is probably *not* due to a residual positive association of both variables with paracetamol propensity *score*.

# IgE and prenatal paracetamol exposure: summary



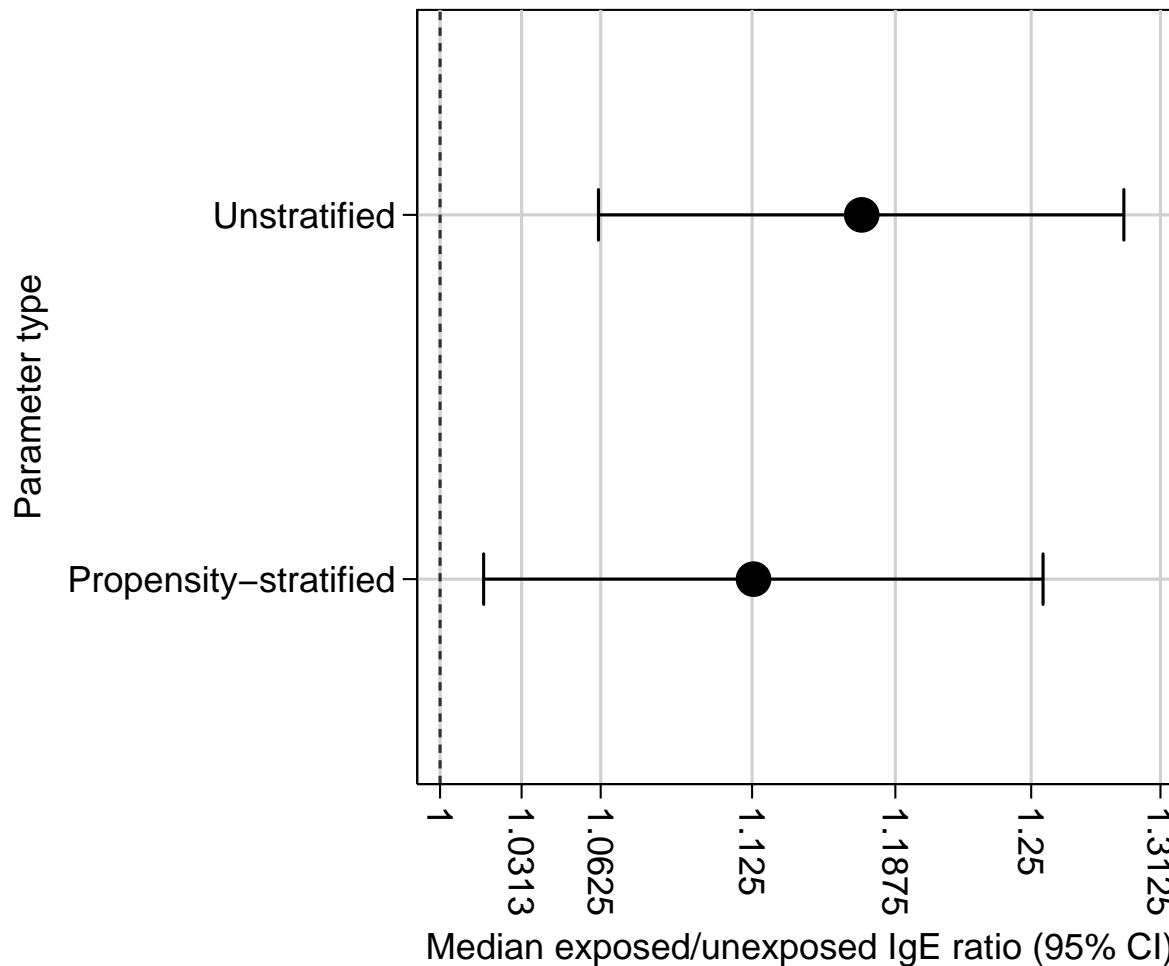
## IgE and prenatal paracetamol exposure: summary

- A random exposed child typically has 6% to 29% more IgE than a random unexposed child.



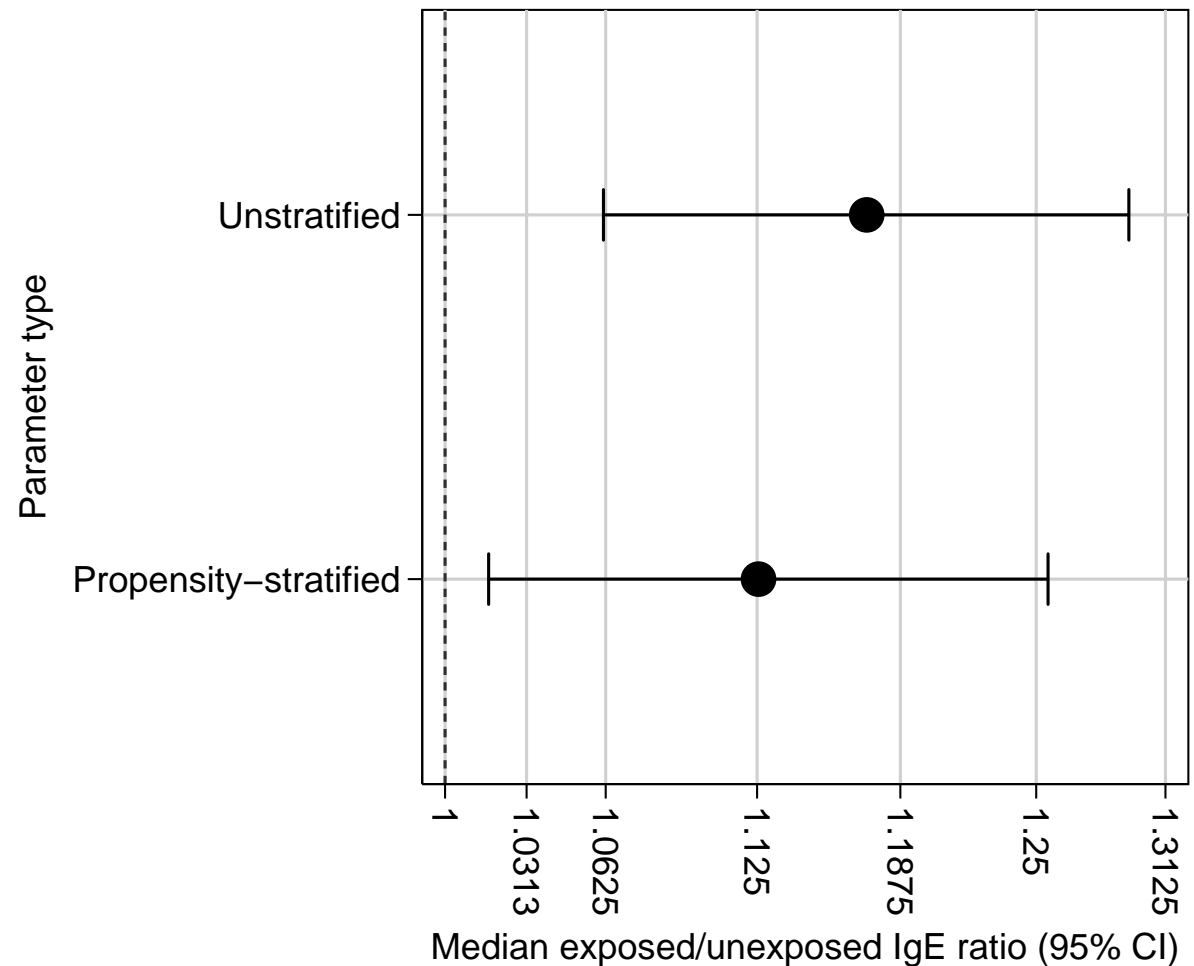
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## IgE and prenatal paracetamol exposure: summary

- A random exposed child typically has 6% to 29% more IgE than a random unexposed child.
- If they are in the same paracetamol propensity group, then the exposed child typically has 2% to 26% more IgE.
- This relative difference is probably *not* caused by paracetamol propensity (as defined here).



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- This in turn implies that the Central Limit Theorem *typically* works faster for rank parameters than for regression parameters.
- *Also*, rank parameters are often easier to interpret (as differences between proportions, or as median differences or ratios).
- By contrast, an arithmetic mean difference is *usually* a proxy for a median difference, and *may* be expressed in incomprehensible units, such as a symptom score after a Normalizing transformation.

**The case *against* rank methods**

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- A more valid argument is that of Fisher (1935), which implies that, if we know the distributional family *a priori*, then we can define narrower confidence intervals using maximum-likelihood methods than using rank methods.
- *For instance*, using a  $t$ -test instead of `censlope` may reduce the minimum detectable difference by a modest 5%, when comparing 2 samples of 40. Or from infinity to a finite difference, when comparing 2 samples of 3.

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- *However*, they are less robust to small sample numbers.
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- *Meanwhile*, I would like to thank StataCorp for the Mata programming language, which made `somersd` possible in its present form.

## References

Fisher, R. A. 1935. The logic of inductive inference. *Journal of the Royal Statistical Society* **98(1)**: 39–82.

Newson, R. 2002. Parameters behind “nonparametric” statistics: Kendall’s tau, Somers’  $D$  and median differences. *The Stata Journal* **2(1)**: 45–64.

Newson, R. 2006. Confidence intervals for rank statistics: Somers’  $D$  and extensions. *The Stata Journal* **6(2)**: 309–334.

Rosenbaum, P. R. and D. B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* **70(1)**: 41–55.

Shaheen, S. O., R. B. Newson, A. J. Henderson, J. E. Headley, F. D. Stratton, R. W. Jones, D. P. Strachan and the ALSPAC Study Team. 2005. Prenatal paracetamol exposure and risk of asthma and elevated immunoglobulin E in childhood. *Clinical and Experimental Allergy* **35**: 18–25.