

**School closure and child hunger during COVID-19 pandemic:  
A gendered analysis**

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# Introduction & Motivation

- There is a gendered pattern in living arrangement in South Africa (Posel et al, 2016; Hatch & Posel, 2018; Posel, 2021)
  - There is a decline in rate of union formation
  - Children are more likely to household with women than men
- This paper examine the implication of the gendered pattern in living arrangement on wellbeing during the COVID-19 pandemic
- The hypothesis is that the gendered pattern of household structures may interact with the economic shock to produce gendered wellbeing effects
- Specifically, in the context of COVID
  - We explore the robustness of the relationship between school closure and child hunger in South Africa
  - We examine plausible gendered effects in this relationship

# Summary of results

- We find that household size (mostly driven by children) is correlated with report of child hunger.
- Evidence suggests that the relationship between school closure and child hunger is causal in South Africa (both in-sample and survey weighted results)
- Even though the data suggests that women are no more likely to report child hunger, we find weak evidence for the gendered effect of school closure and child hunger
- Specifically, while in disaggregated analysis supports a gendered effect, the model that use interaction to test gendered effects is only significant in the unweighted analysis and only when the sample includes the first 3 waves of data.
- Gender differences in living arrangement may have negative impact on the wellbeing of women.

# Review

- In 2020 an estimated 388 million schoolchildren across 161 countries benefit from school meals every day (World Food Programme, 2020)
- This programme has been found to be successful in improving various outcomes including school attendance (Afridi, 2011), educational attainment (Hinrichs, 2010), enrollment (He, 2009), cognition (Afridi et al., 2019) and nutritional outcomes of benefiting children (Hochfeld et al., 2016)
- However, COVID-19 cut-off access to School Feeding programmes through the closure of schools which serve as the primary delivery channel
- By April 2020, 199 countries have adopted the school closure policy to curb the spread of the virus, cutting off access for an approximated 370 million children (World Food Programme, 2020).
- This has implication for a higher level of food insecurity in children and their households during the pandemic

## Review (contd)

- There is evidence that COVID-19 lockdown in general increase the report of hunger (Ahmed et al., 2021; Gelo and Dikgang, 2022; Rudin-Rush et al., 2022; Tabe-Ojong Jr et al., 2022; Tefera et al., 2022)
- Unlike the literature on the pandemic and hunger the literature on the role of school closure is thinner and relies mostly on correlation between the two variables e.g. Delbiso et al, (2021) use qualitative analysis , Amolegbe (2020) and Owusu & Frimpong-Manso (2020) relied on expert opinion, while others present bivariate analysis (Alvi and Gupta, 2020; Jamieson and Van Blerk, 2022; Obiakor and Adeniran, 2020)
- A notable exception is that paper by Abay et al, (2020) that uses a two-period difference-in-difference (DiD)
- There is therefore need for more empirical (and perhaps causal) evidence on this, particularly in the South African case

# SFP in South Africa

- Perhaps school closure does not impact child hunger in SA because of alternative programmes put in place by the government (and NGOs) to mitigate the effect of school closure on child hunger (van der Berg et al., 2022).
- These includes
  - top-up of the Child Support Grant (CSG)
  - Introduction of Temporary Employee/Employer Relief Scheme (TERS)
  - Social Relief of Distress (SRD) are targeted at unemployed adults
- This contingency plans implicitly assumes that this interventions will cover the population of children benefiting from the SFP, Did this work?
- National School Nutrition Programme (NSNP) was introduced in 1994 and targets the poorest 60% of the schools in South Africa with an estimated 9 million children benefiting.

# Data

- Data is sourced from the 5 waves of the National Income Dynamic Study – Coronavirus Rapid Mobile (NIDS-CRAM) Survey
- The outcome of interest is a dummy variable that captures reports of child hunger (“In the last 7 days, has a child gone hungry because of lack of food”)
- Data on school closures are sourced from the Our World in Data database (note this is a daily national level data merged to NIDS-CRAM by date to exploit intertemporal variation induced by the date of interview).
- The school closure index has 4 categories represented by numbers 0 to 3 (Ritchie et al., 2020)
  - “0” if there is no measure;
  - “1” all schools open with alterations resulting in significant differences compared to non-Covid-19 operations
  - “2” closing required for some levels
  - “3” closing required at all levels
- The variable is modelled as a dummy variable that is equal to 1 if the index is equal to 3 within the last 7 days before the date of the interview
- The analysis included control for a number of covariates including loss of hh income, negative employment transition, grant receipt, geolocation, type of hh, hh size, age, gender, education, number of hh members below 18 yrs old and covid risk perception

# Methodology

- Weighted and unweighted analysis were performed to see if the proposition holds in-sample and in the population
- For the unweighted analysis we consider fixed effects (including TWFE) estimator.
- $\beta^{TWFE}$  is often interpreted as a causal parameter similar to  $\beta^{DiD}$ . However, this is only the case in a two-group and two-period design where ATE is homogeneous (Borusyak and Jaravel, 2017; de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021).
- Once the design is a multiperiod set-up, as would be the case during COVID, ATE computed by  $\beta^{TWFE}$  aggregates different  $\beta^{DiD}$  estimators
- $\beta^{TWFE}$  identify a weighted average of several  $\beta^{DiD}$  which compares evolution of outcome between *consecutive time periods* across pairs of groups
- However, because regression is variation hungry the control groups in some of the  $\beta^{DiD}$  are treated in both periods i.e. the so-called forbidden control groups



# Methodology

- The problem is illustrated in diagrams 1 and 2 (3), where 1 is exploiting good variation and 2 is exploiting bad or “forbidden” variation (bcs the associated estimate will have negative weight in the weighted sum)
- Under the plausible assumption that treatment effect is heterogeneous, the estimate will not satisfy the no-sign reversal property i.e.  $\beta^{TWFE}$  can be negative even when the constituent estimates (for every group and time period) are all positive (De Chaisemartin and d’Haultfoeuille, 2023). We check how much of a problem this is for the sample (bacon decomposition).
- Further De Chaisemartin and d’Haultfoeuille (2020) consider estimators that rule out dynamic effects (an assumption that is plausible in this application)
- They propose the  $DiD_M$  which is a weighted average of  $DiD_+ + DiD_-$ , where  $DiD_+$  is the same as diagram 1 and is consistent under the // assumption on untreated outcomes and  $DiD_-$  is illustrated in diagram 3 and is consistent under the // assumption on treated outcomes
- Note that diagram 3 implies non-staggered design (the estimator aggregate the DiDs into relative time).

[Diagram 1](#)

Time 1	Time 2
C	T
C	C

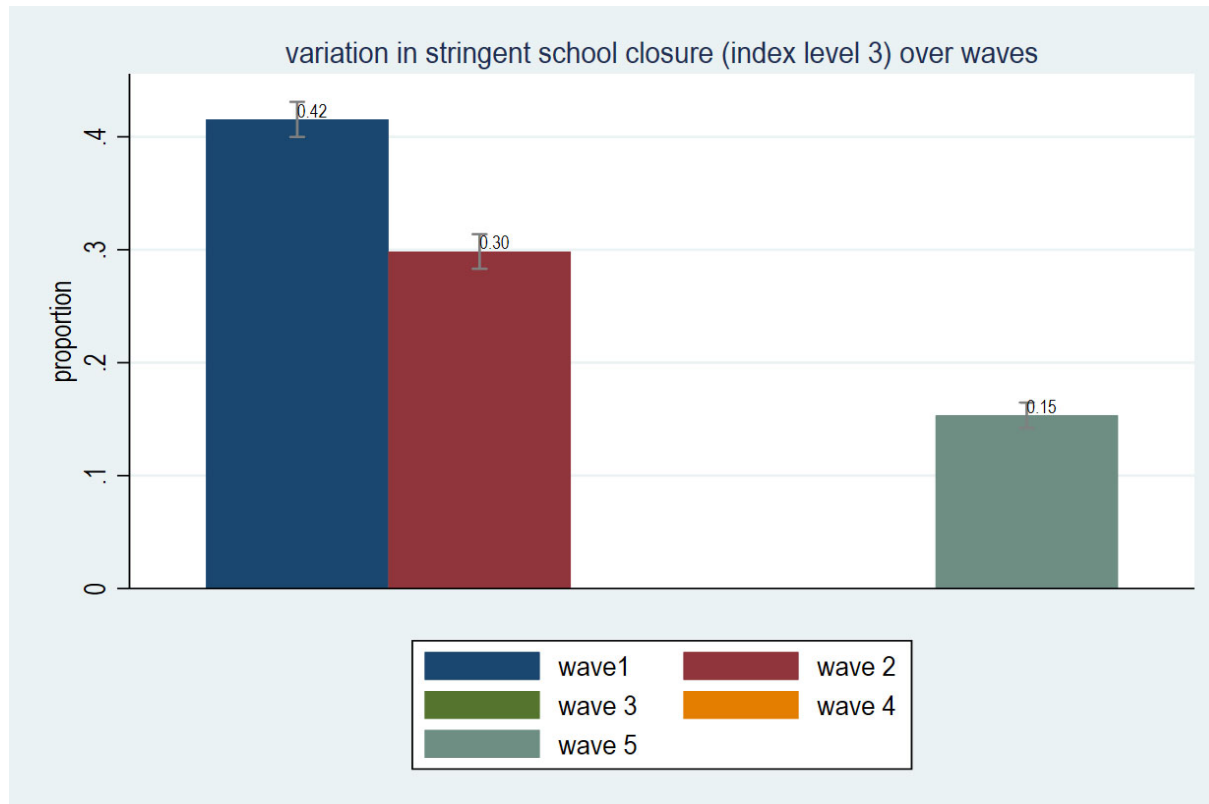
Diagram 2

C	T
T	T

[Diagram 3](#)

T	C
T	T

# Variation in School closures over waves



Variation is off in waves 3 and 4

# Methodology

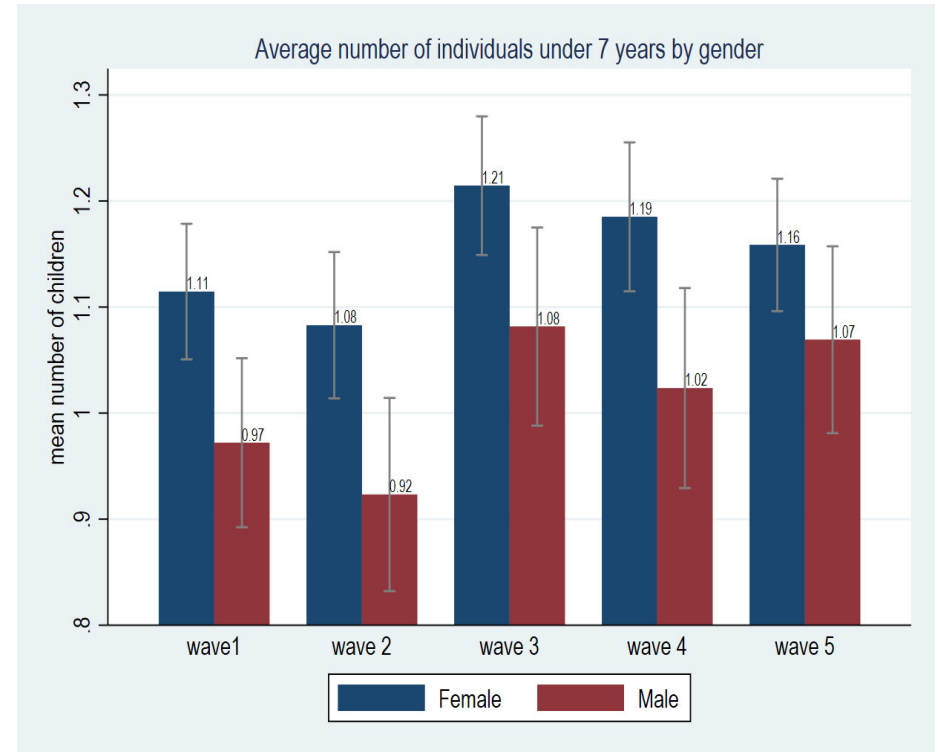
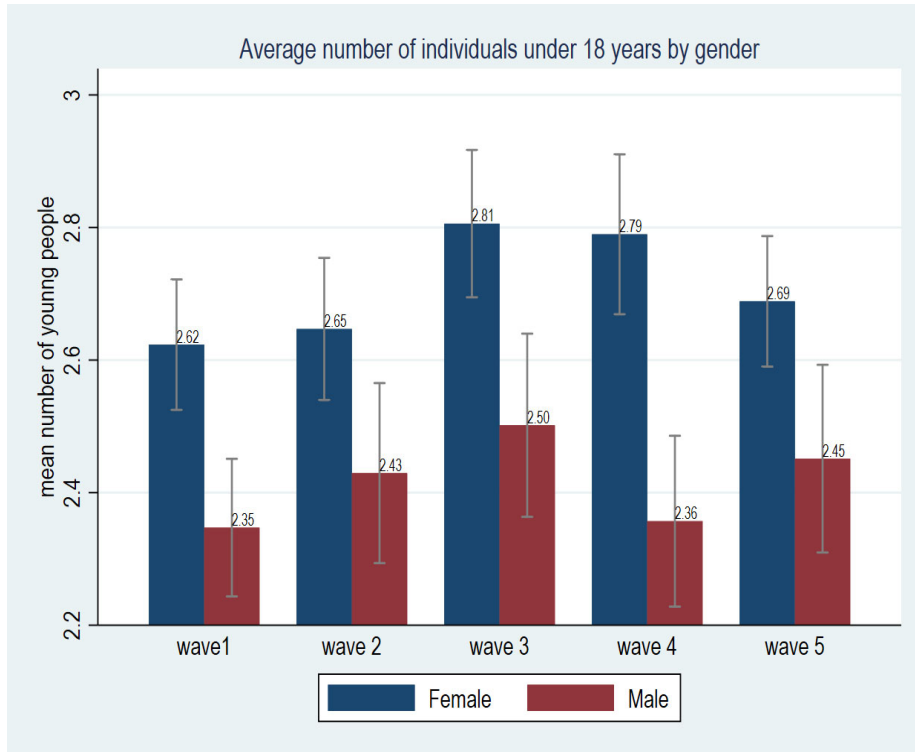
- The unsatisfactory part of the De Chaisemartin and d'Haultfoeuille (2020) estimator is that
  - It does not allow for survey weights
  - The only way to check gendered effect is disaggregated analysis
- To deal with this I use the recent development in the Mundlak (1978) CRE estimator (Wooldridge, 2019).
- CRE is computed as a pooled OLS

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \gamma + \bar{\mathbf{x}}_i\boldsymbol{\delta} + \varepsilon_{it}$$

- Specifically, Wooldridge (2019) show that  $\beta^{FE}$  is equivalent to  $\beta^{CRE}$  for unbalanced panel data, provided only complete cases is used to compute the average of covariates  $\bar{\mathbf{x}}_i$  over time
- While this is weaker in terms of causal inference than the DiD approach, it allows for survey weights and one can test gendered effects using interaction between gender and school closure.

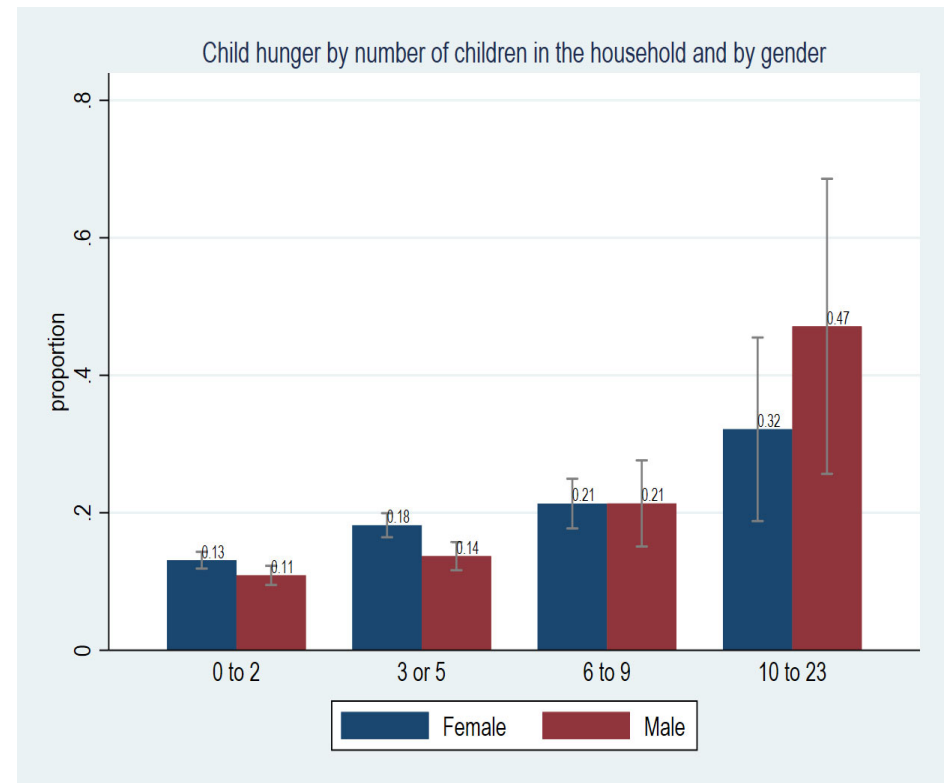
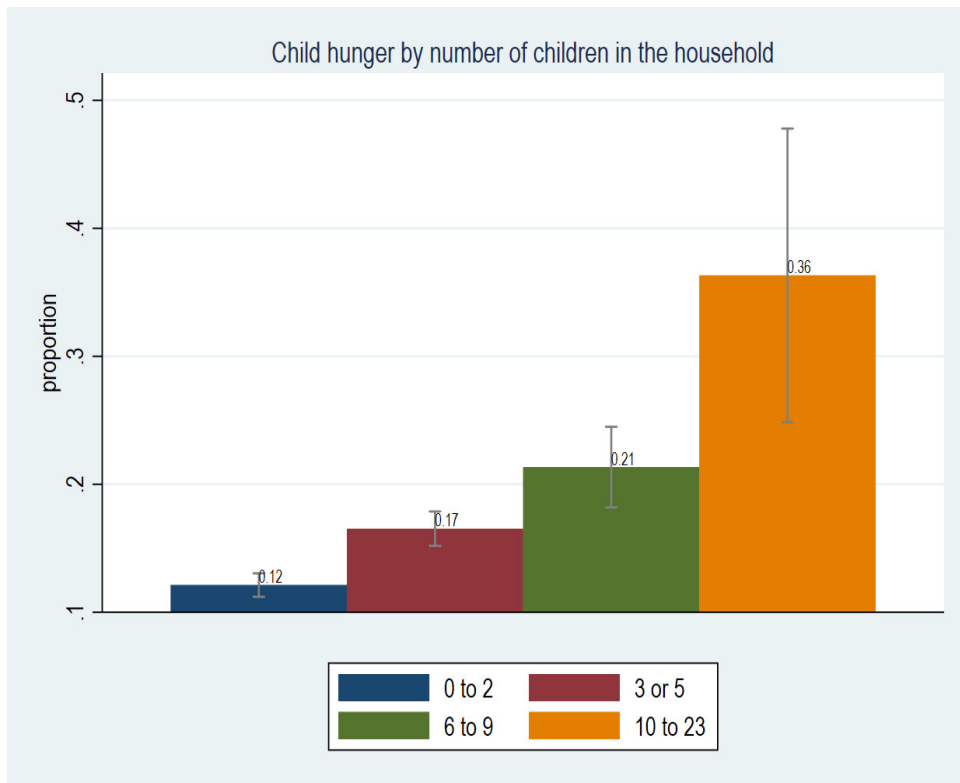
# Results (Descriptives)

- Posel & Casale (2020) co-residence of men with children changed (compared to 2017) at the start of the pandemic. Did this change alter the pre-pandemic finding of children being more likely to live with women?



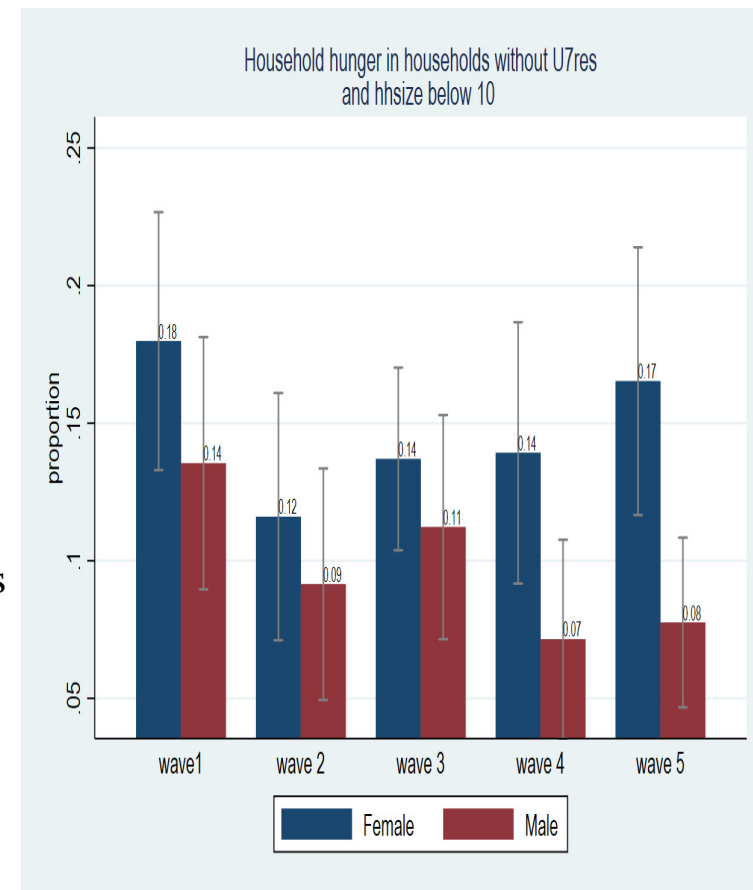
# Results (Descriptives)

- Does presence of children increase the probability of reporting hunger? And does this differ by gender?



# Results (Descriptives)

- Are women more likely to report child hunger?
- So..
- Children (under 18) are more likely to live with women
- The higher the population of children the more likely it is for the adult to report child hunger
- Women are no more likely to report hunger (even in households with relatively smaller sizes and no children (under 7 residents) or at most a weak evidence (the only meaningful difference is in wave 5)



# Results (TWFE only significant estimates presented)

VARIABLES	(1) all	(2) female	(3) male
Outcome: Child hunger ( <b>unweighted</b> )			
max_sc4	<b>0.020***</b> (0.007)	<b>0.027***</b> (0.009)	0.004 (0.013)
lost_inc	0.033*** (0.006)	0.028*** (0.008)	0.045*** (0.011)
no_csg	<b>-0.009***</b> (0.003)	-0.010** (0.004)	<b>-0.008</b> (0.005)
no_oap	-0.018** (0.008)	-0.014 (0.010)	-0.026** (0.013)
govt_grant	<b>-0.011*</b> (0.006)	-0.005 (0.008)	<b>-0.029**</b> (0.013)
2.wave	-0.033*** (0.008)	-0.040*** (0.010)	-0.018 (0.013)
3.wave	-0.011 (0.008)	-0.012 (0.010)	-0.005 (0.014)
4.wave	-0.029*** (0.009)	-0.028** (0.011)	-0.029* (0.015)
5.wave	-0.030*** (0.009)	-0.026** (0.011)	-0.040*** (0.015)
Constant	-0.240 (0.322)	-0.384 (0.394)	-0.072 (0.566)
Observations	20,500	13,805	6,695
R-squared	0.010	0.010	0.015

VARIABLES	(1) all	(2) female	(3) male
Outcome: Child hunger ( <b>weighted</b> )			
max_sc4	<b>0.022*</b> (0.012)	<b>0.028*</b> (0.015)	0.013 (0.019)
lost_inc	0.030*** (0.010)	0.025** (0.012)	0.038** (0.017)
no_csg	0.004 (0.007)	-0.002 (0.008)	0.009 (0.012)
no_oap	-0.019** (0.009)	-0.012 (0.011)	-0.026* (0.015)
govt_grant	0.003 (0.009)	0.010 (0.011)	-0.016 (0.016)
2.wave	-0.033*** (0.011)	-0.040*** (0.013)	-0.024 (0.019)
3.wave	-0.018 (0.012)	-0.023 (0.015)	-0.006 (0.018)
4.wave	-0.023** (0.012)	-0.032** (0.014)	-0.009 (0.019)
5.wave	-0.021* (0.011)	-0.021 (0.014)	-0.020 (0.019)
Constant	-0.472 (0.446)	-0.392 (0.556)	-0.856 (0.761)
Observations	20,500	13,805	6,695
R-squared	0.009	0.012	0.013

# Results (FE)

- Could wave fixed effects be correlated with variation in School closure?
- In both cases weights does not change the substantive result although it is much weaker with weights

VARIABLES	(1) all	(2) Female	(3) male
Outcome: Child hunger ( <b>unweighted</b> )			
max_sc4	<b>0.023***</b> (0.007)	<b>0.029***</b> (0.008)	0.006 (0.011)
lost_inc	0.043*** (0.006)	0.039*** (0.007)	0.053*** (0.011)
no_csg	-0.009*** (0.003)	-0.010** (0.004)	-0.008 (0.005)
no_oap	-0.017** (0.008)	-0.013 (0.010)	-0.024* (0.013)
govt_grant	-0.015** (0.006)	-0.010 (0.007)	-0.031** (0.012)
Constant	0.018 (0.298)	-0.259 (0.370)	0.565 (0.508)
Observations	20,500	13,805	6,695
R-squared	0.008	0.008	0.012
Number of pid	6,540	4,206	2,334

VARIABLES	(1) all	(2) female	(3) male
Outcome: Child hunger ( <b>weighted</b> )			
max_sc4	<b>0.026**</b> (0.011)	<b>0.033**</b> (0.014)	0.013 (0.017)
lost_inc	0.036*** (0.010)	0.032*** (0.012)	0.044** (0.017)
no_csg	0.003 (0.007)	-0.002 (0.008)	0.009 (0.012)
no_oap	-0.018** (0.009)	-0.011 (0.011)	-0.025* (0.015)
govt_grant	-0.001 (0.009)	0.004 (0.011)	-0.017 (0.015)
Constant	-0.345 (0.420)	-0.258 (0.523)	-0.709 (0.723)
Observations	20,500	13,805	6,695
R-squared	0.008	0.010	0.012
Number of pid	6,540	4,206	2,334



# Results (Is TWFE robust? Bacon Decomposition)

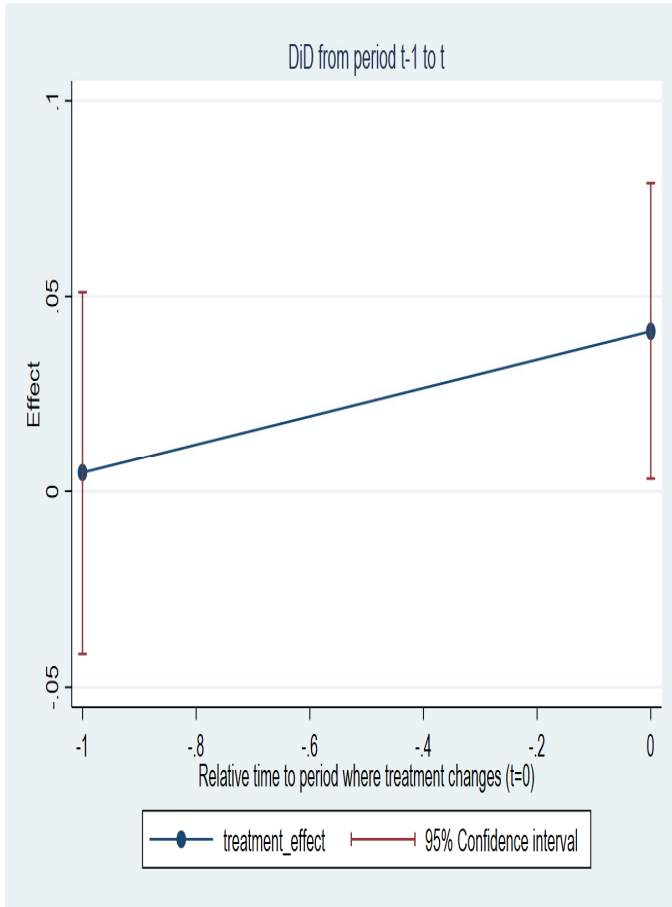
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	ALL	FEMALE	MALE
beta estimates a weighted sum of # LATES	2860	2008	852
# LATEs receive a positive weight	2805	1963	842
# LATEs receive a negative weight	55	45	10
The sum of the positive weights is equal	1.004646	1.00524	1.003269
The sum of the negative weights is equal	-0.00465	-0.00524	-0.00327

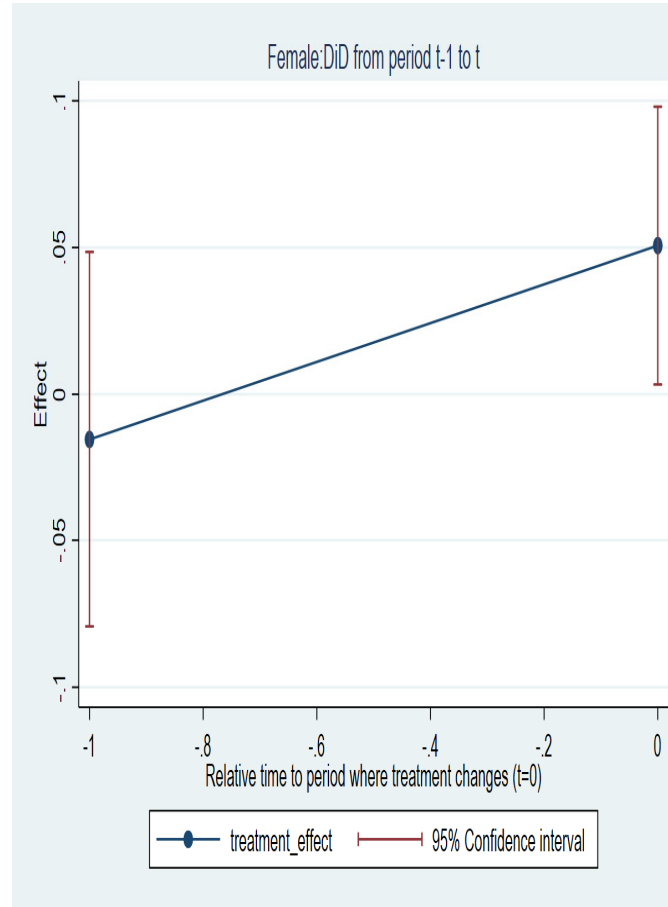
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- Even though the number of observation receiving negative weights is small, the inference is still that the result might be biased i.e.
  - beta is compatible with a DGP where the average of those LATEs is equal to 0
  - beta is compatible with a DGP where those LATEs all are of a different sign than beta
- It is important to note that most of the variation is for female respondents (only 29% of the variation is attributable to males)

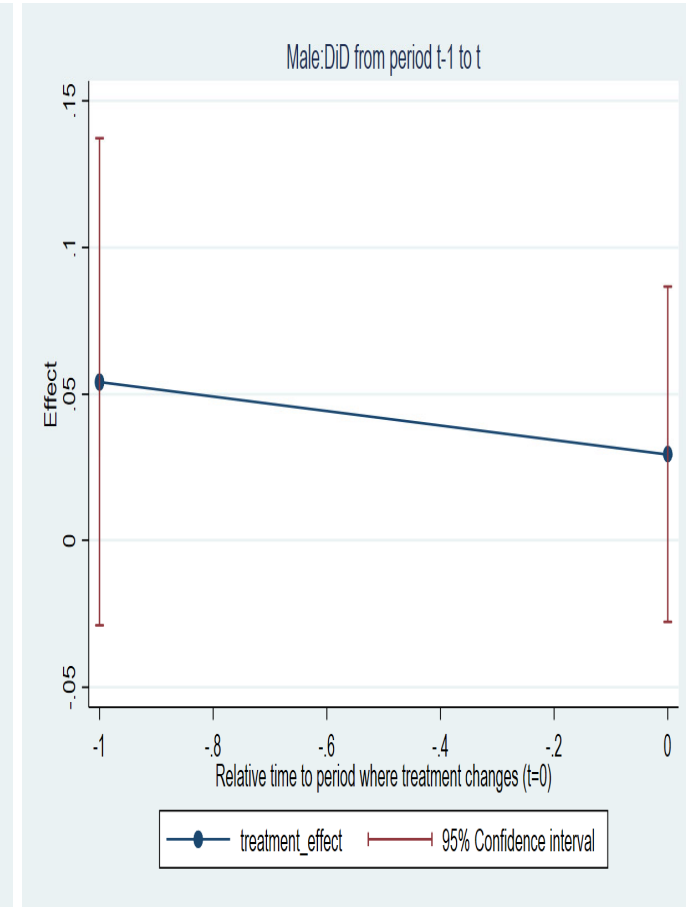
# Results (DiD from relative period t-1 to t)



Full sample



Female sample



Male sample

# Results (DiD from relative period t-1 to t)

DID estimators of the instantaneous treatment effect						
Full sample						
	Estimate	SE	LB CI	UB CI	N	Switchers
Effect	0.04**	0.02	0.00	0.08	6208	2102
Placebo_1	0.00	0.02	-0.04	0.05	2717	430
Female						
	Estimate	SE	LB CI	UB CI	N	Switchers
Effect	0.05**	0.02	0.00	0.10	4329	1480
Placebo_1	-0.02	0.03	-0.08	0.05	1938	306
Male						
	Estimate	SE	LB CI	UB CI	N	Switchers
Effect	0.03	0.03	-0.03	0.09	1879	622
Placebo_1	0.05	0.04	-0.03	0.14	779	124

- The result is consistent with TWFE and FE results, the effect is significant particularly in the female sample
- in addition, Placebo effect is not statistically significant
- Consistent with Bacon-decomposition most of the variation is attributable to females in the sample
- Lack of formal test is still a problem

# Results (CRE allows for weighting and formal test of interaction term)

VARIABLES	(1) all	(2) female	(3) male
	Outcome: Child hunger ( <b>weighted</b> )		
max_sc4	<b>0.022*</b> (0.012)	<b>0.028*</b> (0.015)	0.013 (0.019)
male	-0.026** (0.012)		
lost_inc	0.030*** (0.010)	0.025** (0.012)	0.038** (0.017)
no_csg	0.004 (0.007)	-0.002 (0.008)	0.009 (0.012)
no_oap	-0.019** (0.009)	-0.012 (0.011)	-0.026* (0.015)
govt_grant	0.003 (0.009)	0.010 (0.011)	-0.016 (0.016)
w1	0.021* (0.011)	0.021 (0.014)	0.020 (0.019)
w2	-0.012 (0.011)	-0.019 (0.014)	-0.004 (0.017)
w3	0.003 (0.010)	-0.002 (0.013)	0.014 (0.013)
w4	-0.002 (0.009)	-0.010 (0.011)	0.011 (0.015)
Constant	-0.481 (0.450)	-0.410 (0.559)	-0.872 (0.770)
Observations	19,183	13,066	6,117

VARIABLES	(1) all	(2) female	(3) male
	Outcome: Child hunger ( <b>weighted</b> )		
max_sc4	<b>0.026**</b> (0.011)	<b>0.033**</b> (0.014)	0.013 (0.017)
male	-0.026** (0.012)		
lost_inc	0.036*** (0.010)	0.032*** (0.012)	0.044** (0.017)
no_csg	0.003 (0.007)	-0.002 (0.008)	0.009 (0.012)
no_oap	-0.018** (0.009)	-0.011 (0.011)	-0.025* (0.015)
govt_grant	-0.001 (0.009)	0.004 (0.011)	-0.017 (0.015)
Constant	-0.333 (0.420)	-0.255 (0.523)	-0.705 (0.724)
Observations	19,183	13,066	6,117
R-squared	0.055	0.052	0.068

- CRE with and without wave dummies
- Under the assumption that wave dummies are correlated with SC the effect is stronger (larger estimates)

# Results (CRE allows for weighting and formal test of interaction term)

- Result of interaction term (male\*sc) not significant in analysis
  - That is weighted
  - that include the 5 waves
- Only significant for unweighted analysis for the first 3 waves of data
- This may have to do with the variation in school closure and its correlation with waves of data.
- It suggests weak evidence for gendered effect of school closure on child hunger since result is sensitive to data and method

VARIABLES	(1) full sample
1.max_sc4	0.037*** (0.011)
1.male	-0.001 (0.010)
1.max_sc4#1.male	<b>-0.029*</b> (0.017)
lost_inc	0.045*** (0.009)
no_csg	-0.016*** (0.005)
no_oap	-0.024** (0.011)
govt_grant	-0.008 (0.010)
Constant	0.017 (0.528)
Observations	11,333
R-squared	0.046

# References

- Posel, D., Casale, D. and Grapsa, E., 2016. Re-estimating gender differences in income in South Africa: The implications of equivalence scales. *Development Southern Africa*, 33(4), pp.425-441.
- Hatch, M., Posel, D., 2018. Who cares for children? A quantitative study of childcare in South Africa. *Development Southern Africa* 35, 267–282.
- Posel, D. and Casale, D., 2020. Who moves during times of crisis? Mobility, living arrangements and COVID-19 in South Africa. *NIDS-CRAM Wave*, 1.

# DiD proof for $DiD_+$

The two-period, two group DiD estimator for groups n and s is given by (we assume group “s” is moving from untreated to treated while group “n” is untreated at both times)

$$DiD = Y_{s,t_2} - Y_{s,t_1} - (Y_{n,t_2} - Y_{n,t_1})$$

The parallel trend assumption is given by

$$E[Y_{s,t_2}(0) - Y_{s,t_1}(0)] = E[Y_{n,t_2}(0) - Y_{n,t_1}(0)]$$

Under the parallel trend assumption

$$E[DiD] = E[Y_{s,t_2}(1) - Y_{s,t_1}(0)] - E[Y_{n,t_2}(0) - Y_{n,t_1}(0)]$$

<u>Time 1</u>	Time 2
C	T
C	C

Note that only the potential outcome in group “s” at  $t_2$  is the only treated potential outcome, the rest are untreated. Now add and subtract the untreated outcome in group “s”

$$\begin{aligned}
 &= E[Y_{s,t_2}(1) - Y_{s,t_1}(0)] - E[Y_{n,t_2}(0) - Y_{n,t_1}(0)] - E[Y_{s,t_2}(0) + Y_{s,t_2}(0)] \\
 &= E[Y_{s,t_2}(1) - Y_{s,t_2}(0)] + E[Y_{s,t_2}(0) - Y_{s,t_1}(0)] - E[Y_{n,t_2}(0) - Y_{n,t_1}(0)]
 \end{aligned}$$

The last two terms cancel out because of the parallel trend assumption

# DiD proof for $DiD_{-}$

The two-period, two group DiD estimator for groups n and s is given by (we assume group “s” is moving from untreated to treated while group “n” is untreated at both times)

$$DiD = Y_{s,t_2} - Y_{s,t_1} - (Y_{n,t_2} - Y_{n,t_1})$$

The parallel trend assumption is given by

$$E[Y_{s,t_2}(1) - Y_{s,t_1}(1)] = E[Y_{n,t_2}(1) - Y_{n,t_1}(1)]$$

Under the parallel trend assumption

$$E[DiD] = E[Y_{s,t_2}(0) - Y_{s,t_1}(1)] - E[Y_{n,t_2}(1) - Y_{n,t_1}(1)]$$

Time 1	Time 2
T	C
T	T

Note that only the potential outcome in group “s” at  $t_2$  is the only **untreated** potential outcome, the rest are treated. Now add and subtract the treated outcome in group “s”

$$\begin{aligned}
 &= E[Y_{s,t_2}(0) - Y_{s,t_1}(1)] - E[Y_{n,t_2}(1) - Y_{n,t_1}(1)] - E[Y_{s,t_2}(1) + Y_{s,t_2}(1)] \\
 &= E[Y_{s,t_2}(0) - Y_{s,t_2}(1)] + E[Y_{s,t_2}(1) - Y_{s,t_1}(1)] - E[Y_{n,t_2}(1) - Y_{n,t_1}(1)]
 \end{aligned}$$

The last two terms cancel out because of the parallel trend assumption (on treated outcomes)