Evaluating "Uneven impacts of COVID-19 on the attendance rates of secondary school students from different socioeconomic backgrounds in Australia" by Tomaszewski et al. (2022)

Introduction: The Policy Context

In efforts to safeguard public health and prevent the spread of Covid-19, policymakers worldwide implemented school closures – impacting nearly 1.6 billion students across 196 countries and causing substantial disruption to the global education system (UNESCO, 2020; as cited in Donohue & Miller, 2020; Donnelly & Patrinos, 2022). For many, educational continuity was maintained through online learning; however, early evidence made clear that socioeconomically disadvantaged students faced compounding challenges, including limited access to digital learning resources, reduced parental support, and poorer health and wellbeing (Cullinane & Montacute, 2020; Bansak & Starr, 2021; Dietrich, Patzina & Lerche, 2021). In Australia, educational inequality was already a longstanding policy issue, underscored by a persistent attainment gap equivalent to three years between students from low and high socioeconomic status (SES) backgrounds (Goss & Sonnemann, 2020; Productivity Commission, 2022; Morris, 2024). Therefore, school closures raised plausible policy concerns regarding the exacerbation of these pre-existing educational disparities between socioeconomic groups (Andrew et al., 2020).

Much of the early empirical focus on COVID-19's educational impact centralised on 'learning loss' – a decline in educational progress in comparison to previous years (Pier et al., 2021; as cited in Donnelly & Patrinos, 2021), predominantly using academic achievement scores as a proxy and yielding inconsistent results. However, Australian policy emphasises that school attendance constitutes a critical precondition for social development, educational attainment and long-term achievement, especially for disadvantaged students (Hancock et al., 2013; Burnie Works, n.d.) – positioning attendance as a policy-relevant, though underexplored, outcome indicator.

Australian states implemented different school closure policies during Covid-19 based on local health advice, and Tasmania's relatively brief school closures (30-40 days of home learning) and profound SES disparities (Productivity Commission, 2021; as cited in Tomaszewski et al., 2022) provides an opportunity to estimate the minimum, lower-bound educational impact of

school closure disruptions. Therefore, by drawing on Tasmanian school attendance rates, the evaluation by Tomaszewski et al. (2022) aims to assess if Covid-19 school closures led to widening gaps in attendance between students from different SES backgrounds, contributing to a deeper understanding of the pandemic's consequences on education inequality, and providing evidence to inform equitable future policy responses.

1. Method of Evaluation

1.1 The Method and its Core Assumptions

The authors leverage Tasmania's short 2020 lockdown as an exogenous policy shock and embed it in a quasi-experimental difference-in-differences (DiD) framework that they extend to a third order 'difference-in-difference-in-difference' (DDD). Two cohorts are constructed: a 'during-Covid-19' treatment cohort that faced 6-8 weeks of remote learning, and a matched 'pre-Covid' control cohort from the year before – identical in schooling stage but never exposed to the pandemic shock. For the 'during-Covid-19' cohort, attendance is measured at two points: immediately after schools reopened in June-July 2020 (T2) and during the same calendar period one year earlier in 2019 (T1). For the 'pre-Covid' control cohort, attendance is similarly measured during corresponding periods but a year prior: June-July 2019 (T2) and June-July 2018 (T1). By observing the divergence between the high–low SES attendance gap's change in the Covid cohort, and the same gap's change in the pre-Covid cohort, the DDD coefficient aims to isolate the causal impact of Covid-19 school closures on SES attendance. Accordingly, the outcome criteria can be formalised with the expression:

$$\Delta\left(Y_{\{highSES\}} - Y_{\{lowSES\}}\right)_{\{COVID\}} - \Delta\left(Y_{\{highSES\}} - Y_{\{lowSES\}}\right)_{\{preCOVID\}} > 0$$

The strength of this approach lies in its ability to control for time-invariant unobserved heterogeneity and group-invariant time effects. By accounting for differences over time that are common to both the Covid and pre-covid groups (such as seasonal trends or broad policy changes), as well as the stable differences over time between the during-Covid and pre-covid groups (such as baseline disparities in parental engagement or learning resources (Morris, 2024; Bhaumik, Duraipandi & Halis, 2025)), the DDD approach nets stable characteristics which

could systematically influence attendance patterns across SES groups. This is critical in a policy context where socioeconomic disadvantage is multifaceted and structurally embedded. By differencing out these influences, the study is able to more credibly attribute observed widening in SES attendance gaps to the pandemic's exogenous variation itself, rather than to underlying structural inequalities or coincident external changes.

However, for results to be causally interpretable, several assumptions must hold. First, the parallel trends assumption requires that, absent Covid-19 school disruptions, attendance trajectories across SES groups would have evolved similarly over time (Huntington-Klein, 2021, p.408). This assumption is foundational to the validity of the DiD approach as it constitutes the unobserved counterfactual used to establish the effect of school closure interventions – and violation renders results biased. Given the similarities between the cohort samples – being only one year apart in the same education system and location – it can plausibly be assumed that the treated and non-treated groups exhibit sufficient covariate balance and contextual similarity, increasing the likelihood that they would follow comparable attendance trajectories in the absence of treatment, thus increasing the creditability of the parallel trends assumption. Moreover, a random effects regression model was used for a comprehensive set of covariates known to correlate both with socioeconomic status and school attendance – including student-level factors (e.g. gender, disability) and school-level Index of Community Socio-Educational Advantage (ICSEA) scores – helping the triple-difference coefficient to capture the pandemic shock rather than latent composition effects which could otherwise impact trends. Together, these choices strengthen (but do not verify) the conditional parallel trends assumption on which the DDD estimator rests.

To establish causal identification, the stable unit treatment value assumption (SUTVA) is required – there must be only one version of the treatment, and potential outcomes for one student are unaffected by the treatment of other students (Angrist, Imbens & Rubin, 1996, p.446). Given that the Tasmanian lockdown was system-wide, all students were exposed to the same treatment, which helps satisfy the single-version condition. The study also makes strong efforts to isolate Covid-19 effects by comparing pre- and during-pandemic cohorts. However, SUTVA presumes that the attendance of a low-SES student was not influenced by the treatment effects on their peers – yet we might reasonably suspect that peer effects could spill over and influence individual attendance, such as low-SES students being embedded in peer networks where others are disengaging, reducing individual motivation (Lin, 2000, pp.786-787). The

estimated DDD coefficient therefore captures both direct, individual-level impact of school closures on attendance and the compounding social effects through peer networks. Such violation of SUTVA does not necessarily undermine the policy relevance of findings; in fact, including these indirect effects arguably strengthens the substantive relevance of the study, as it reflects the total impact of school closures on widening SES attendance gaps. However, the authors do not explicitly address whether the inclusion of these spillover effects was theoretically anticipated or empirically intended, leaving open questions about the precise interpretation of the estimated treatment effect and causal interpretations.

1.2 Methodological Rationale

The DiD / DDD approach is a well-established quasi-experimental method in policy evaluation, suited to examining causal effects in non-experimental settings (Bello-Gomez, Simon & Wing, 2018). Indeed, Covid-19 school closures provide a 'natural experiment' as system-wide school closures affected all students simultaneously, creating an exogenous treatment.

The comparison below highlights that Tomaszewski et al.'s choice of DDD was pragmatic and justifiable: given the absence of randomisation, treatment thresholds, or untreated comparison units, DDD provided a feasible approach to isolate the causal effect of school closures on SES attendance gaps:

Method	Strengths in this policy context	Weaknesses / Limitations in this policy context
Difference-in-Differences (DiD)	Controls for time-invariant differences between SES groups and general time trends (e.g., seasonal effects); feasible using pre-Covid and during-Covid cohorts.	Relies on the parallel trends assumption – but no pre-trend tests were conducted; does not account for unmeasured shocks that differentially affect SES groups over time (e.g., economic or health shocks during Covid).
Difference-in-Difference-in-Difference (DDD)	Adds a third difference (pre/post, high/low SES, Covid/pre-Covid), improving causal identification in the absence of geographic variation; strengthens credibility of causal claims.	Still depends on untested parallel trends; assumes no interaction between time, treatment, and SES beyond the policy shock; may conflate peer spillover effects with direct policy effects; interpreting the DDD coefficient is complex without mediation analysis; ignores time-varying SES shocks (e.g., pandemic job losses) that can bias estimates.
Randomised Controlled Trial (RCT)	Often considered the 'gold standard' for causal inference (Akobeng, 2005; Meldrum, 2000), random allocation of school closures would, in theory, provide strong causal evidence of impact on attendance across SES groups.	Impossible and unethical in this context – school closures were public health mandates; even if feasible, parents' non-compliance and school-level decisions would undermine randomisation, and self-selection risks biases; unscalable in a crisis.
Regression Discontinuity Design (RDD)	Could exploit a cutoff (e.g., age, grade, or policy threshold) if it existed to estimate causal effects around the cutoff.	Not applicable here – closures applied uniformly to all students; no discontinuity or threshold to exploit; SES groups were not assigned treatment based on a cutoff, so RDD is infeasible.
Instrumental Variables (IV)	A valid instrument could isolate exogenous variation in treatment across SES groups.	No clear, valid instrument available; most pandemic factors were correlated with both SES and attendance; risk of weak instrument bias; IV would estimate only a local average treatment effect, limiting generalisability.
Synthetic Control Method (SCM)	Could construct a synthetic Tasmania from other states without closures or with different policies to estimate counterfactual trends.	SCM requires an untreated comparison, which does not exist given 94% of students worldwide were affected by school closures (United Nations, 2020).

Figure 1: Strengths and Limitations of Causal Evaluation Methods for Assessing Covid-19 School Closure Impacts on SES Attendance Gaps in Tasmania (By Author).

Similar studies have relied heavily on DiD frameworks both in Australia and internationally; Gore et al. (2021) used DiD to estimate Covid-19 effects on student achievement in New South Wales and a systematic review of international studies on Covid-19-related school closures and academic achievement demonstrates that DiD is frequently used as a policy evaluation method in this context (Dreisoerner et al. 2021). A key difference is that some studies used geographic variation in lockdown intensity as a treatment contrast (Christrup-Kjeldsen et al., 2024; Gibbons, McNally & Montebruno, 2024), whereas the Tasmanian study relies on pre-pandemic cohorts to establish a counterfactual. This is a strength in the Tasmanian case because it compares temporally separated cohorts within the same geographic and educational context, strengthening SUTVA – thereby providing cleaner identification of the causal effect. However,

in Tasmania Year 10 students had 40 days of remote learning versus 30 for Years 11/12, and this could have been exploited as an additional layer of variation in a dosage-response design.

1.3 Data Quality

The study's reliance on attendance as a proxy for educational engagement is a double-edged sword. There exist many strengths: the use of administrative data from the Tasmanian Department of Education ensures precision and consistency in the measurement of the observed outcome (attendance rate), and enables the use of random effects models with multiple covariates. The dataset also provides extensive coverage across three-year groups (Years 10–12) and multiple cohorts (pre- and during-Covid) enhancing statistical power and supporting subgroup analysis. Moreover, the large sample size (N = 14,312) increases the precision of estimates, and reduces sampling error. However, attendance metrics may not truly reflect educational engagement, motivation, well-being or educational outcomes, limiting the substantive interpretation of the findings as attendance does not necessarily map cleanly onto learning loss or engagement.

Furthermore, the dataset shows non-trivial levels of missing data, particularly at baseline (T1), with 21% of cases excluded from the Year 11 subsample. The authors attribute this to school system transfers and mobility, but provide no formal tests for whether attrition is random with respect to SES or prior attendance. If missingness is systematically patterned – for example, if low-SES or more disengaged students are disproportionately missing – this introduces selection bias, potentially under or overstating the observed SES gaps. Additionally, the SES measure, constructed from parental education and occupation, suffers from 7.2% of cases with missing values. While the creation of an "unknown" category retains sample size, it risks introducing measurement error and obscuring heterogeneity, particularly if missingness is non-random. These data limitations bear directly on the method and findings, as DiD estimates hinge on the assumption that observed groups are comparable over time. Systematic missingness threatens this comparability, undermining internal validity, and without sensitivity analysis or formal attrition tests, confidence in the causal interpretation of widening SES gaps is necessarily tempered.

2. Critical Review of Evaluation Findings

Findings show that Covid-19 related school closures exacerbated existing SES disparities in attendance in Tasmania among Year 10 and 11 students, while no significant widening was detected among Year 12 students. Indeed, for Years 10/11, high-SES students' attendance rates remained stable, while attendance among low-SES students and those from jobless households significantly declined following pandemic-related school closures. These results are broadly consistent with international evidence suggesting that school closures disproportionately affected low-SES students (Dreisoerner, 2021; UNESCO, 2021), yet Tomaszewski et al. (2022) add nuance by demonstrating outcome heterogeneity by year level, suggesting that the high-stakes of final exams motivated sustained educational engagement. However, there exist four key factors which challenge the plausibility of findings: 1) *untested parallel trends*; 2) *contemporaneous factors;* 3) *time-varying SES*; and 4) *indirect measurement of causal pathways*.

2.1 Untested Parallel Trends

As previously discussed, the DiD /DDD design relies on the assumption that absent Covid-19 school disruptions, attendance trends across SES groups would have evolved similarly. While this is inherently unobservable, there exist empirical tests which can strengthen plausibility of the assumption (Bello-Gomez, Simon, & Wing, 2018) – yet Tomaszewski et al. (2022) failed to conduct these checks.

Authors could have tracked attendance rates between SES groups across multiple pre-covid time periods, to establish if trends were indeed parallel prior to Covid-19 (Bello-Gomez, Simon, & Wing, 2018; Cunningham, 2021, pp. 425-461; Huntington-Klein, 2021, pp.409-412). This would have been relatively straightforward given the availability of longitudinal administrative data and the single treatment point. Furthermore, placebo or falsification tests – estimating the DDD model on pre-Covid cohorts with a pseudo-treatment year – could have evaluated whether pseudo-treatment coefficients were statistically indistinguishable from zero, a standard approach to testing pre-treatment balance (Cunningham, 2021, pp. 425-461). Importantly, failure to address the parallel trends assumption leaves open the possibility that widening SES gaps were driven not by Covid-19, but by underlying, time-varying factors unrelated to the pandemic, thus biasing the estimated treatment effect upwards. For policymakers, this matters: interventions based on overstated or misattributed Covid effects risk misallocating resources or

overlooking deeper structural drivers of SES inequality that predated the pandemic. While empirical checks cannot conclusively establish the counterfactual (Kahn-Lang & Lang, 2019, as cited in Cunningham, 2021), their omission weakens the study's causal claims and limits policy relevance.

2.2 Contemporaneous Factors

In policy evaluation, isolating the causal effect of a policy intervention such as school closures requires accounting for other contemporaneous factors that may influence the outcome of interest. While the DDD approach employed by Tomaszewski et al. (2023) controls for pre-treatment group differences and common trends between low- and high-SES students, it does not account for shocks that disproportionately impact SES groups, exposing the study to risks that could bias the estimated impact of Covid-19 school closures on attendance gaps.

Indeed, the pandemic was accompanied by a range of simultaneous disruptions beyond school closures, which likely held different impacts on students' attendance by SES-group. Existing literature consistently shows that financial instability and parental unemployment is negatively associated with attendance (Lee & Romero, 2008, p.6; Berdan, 2018), and, given the disproportionate economic effects of Covid-19 on disadvantaged households in Australia, it is plausible that rising unemployment or household financial stress independently contributed to declining attendance among low-SES students. (Bryson et al., 2021; Parliament of Australia, 2022). Moreover, Covid-19 infection rates were often higher in socioeconomically disadvantaged communities (Athan et al., 2022), potentially leading to health-related absences or risk-avoidant withdrawal from school, unrelated to the closure policy. Last, low prior achievement is strongly correlated with both low-SES and disengagement from school (Productivity Commission, 2022), and, during crises, students with lower achievement levels may disproportionately withdraw from formal education, independent of SES. Accordingly, it is plausible that the DDD estimate overstates the causal effect of school closures on attendance gaps, as the model may attribute to school closures effects what was partly driven by simultaneous economic and health shocks correlated with SES.

Mitigating these risks, however, is difficult. As previously mentioned, synthetic control method (SCM) is well-suited when unobserved confounders vary over time and differentially affect groups, constructing a weighted combination of control units to approximate the treated unit's pre-intervention trajectory (Abadie et al., 2010; Huntington-Klein, 2021, pp. 517–520). In this

context however, school closures were a universal policy and therefore a synthetic control cannot be constructed, as control groups which experienced Covid-19 socioeconomic shocks without the school closures do not exist. Further, the method could have benefitted from controlling for unemployment and Covid-19 infection rates – yet the administrative dataset used likely lacked granular individual-level data on employment and health shocks, limiting the capacity to adjust for these contemporaneous factors. This highlights a broader challenge in policy evaluation: the difficulty of isolating causal effects in real-world contexts where multiple, overlapping disruptions interact with policy changes, particularly in crises like the Covid-19 pandemic.

2.3 Time-varying SES

The treatment of SES as time-invariant raises further concerns for the validity of findings. Tomaszewski et al.'s (2022) evaluation, treated SES as a static characteristic across the study period, operationalised through parental education and occupation, as recorded in school administrative data. However, during Covid-19, widespread economic disruption and job losses substantially altered many households' employment status during the observed time period – with 870,000 Australians losing their jobs in only the first month of the pandemic (Australian Bureau of Statistics, 2021). By failing to account for occupational variation, families are likely misclassified into higher SES groups, having experienced downward social mobility during the study period. This ultimately leads to attenuation bias – whereby the estimated differences between SES groups are inclined towards zero – underestimating the true impact of Covid-19 on low-SES students. From a policy evaluation standpoint, this matters: if the analysis underestimates the extent to which disadvantaged students were affected, policymakers may underestimate the scale of targeted support or recovery efforts needed. While it is methodologically challenging to incorporate SES updates, failure to do so risks blunting the precision and policy relevance of the findings.

2.4 Indirect Measurement of Causal Pathways

The authors' discussion of mechanisms is theoretically compelling but empirically underdeveloped. Tomaszewski et al. propose that digital exclusion, family stress, and reduced academic support may mediate the relationship between SES and attendance decline, but these pathways are not directly tested in the analysis. Without empirical mediation analysis or mixed

methods approaches, the causal pathways remain largely speculative, rather than demonstrated contributors to the SES-attendance relationship.

This matters greatly for policy relevance. Policymakers require evidence not just that disparities exist, but *why* they exist, in order to design targeted and efficient responses; if the widening attendance gap is driven primarily by digital exclusion, for instance, interventions should focus on device access and broadband infrastructure. If family stress or mental health strain is the dominant driver, then psychosocial supports and counselling may be more effective. Accordingly, future research could integrate survey measures on student well-being, family dynamics, or digital access into administrative datasets or apply causal mediation models to estimate the proportion of the treatment effect explained by each mechanism (Imai, Keele & Tingley, 2010). Additionally, qualitative research capturing student and family perspectives could provide lived experiences that numbers alone cannot convey. The absence of this dimension in the present study limits its capacity to inform mechanism-sensitive policy design, risking technocratic policy responses that overlook underlying behavioural and structural drivers.

Implications for Policy Design

The evaluation by Tomaszewski et al. (2022) offers clear evidence that even relatively short school closures can exacerbate educational inequalities in attendance among disadvantaged students, in Years 10 and 11. This finding holds several critical implications.

With regards to policy design, the absence of a Covid-19 effect among Year 12 students suggests that motivation and institutional incentives (such as the stakes attached to final examinations) may improve attendance rates between SES groups, and therefore interventions might include increased importance placed on end-of year exams in non-terminal years, or reward systems for high attendance, particularly in low-SES contexts where re-engagement risks are highest. The study also strengthens the case that digital inclusion as a foundation for educational equity, addressing not only material access (devices, data plans) but also digital literacy among students and their families. Fundamentally, the findings suggest that post-pandemic In terms of post-pandemic response, findings suggest that recovery efforts should not

focus solely on academic catch-up or test performance, but also on rebuilding the relational and behavioural dimensions of schooling; re-establishing school routines, rebuilding student-teacher connections, and restoring a sense of belonging may be particularly critical for low-SES students who are disproportionately likely to become disengaged. Looking to the future, this study supports the many policy recommendations that pandemic responses should prioritise schools staying open, in a balance of safeguarding public health and long-term costs on education and equity (Bowen et al., 2021; Broadbent et al., 2022).

Methodologically, this study shows how administrative data can support policy evaluation and crisis preparedness. The ability to track attendance longitudinally across cohorts allowed the authors to generate policy-relevant insights in the absence of experimental data. However, the study also highlights the limits of administrative data when contemporaneous, group-variant factors and causal pathways remain unmeasured. Future evaluations should combine administrative data with survey, qualitative, or mixed-methods approaches to substantiate causal pathways, ensuring that policies are both evidence-based and mechanism-sensitive. Overall, this evaluation strengthens the case for strengthening equity in education systems – and for ensuring that future policy evaluation design is informed by both causal evidence and a deep understanding of the lived experience of disadvantaged students.

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