EC4305 Group Project Writeup

<u>Research Question</u>

"How does financial aid for low-income families in Singapore affect children's behaviour and life outcomes in the future?"

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1 Research question

"How does financial aid for low-income families in Singapore affect children's behaviour and life outcomes over time?"

This research question was formulated as it is highly relevant to policymakers in Singapore given that the government plays a significant role in social welfare through their financial assistance schemes targeting lower-income families. We are interested in evaluating the impacts of financial aid on low-income families and whether these financial assistance schemes have had a positive impact on these families in the future.

In addition, we are also interested to see what type of financial aid schemes tend to perform better in terms of future outcomes so that the government can allocate resources appropriately to maximise societal welfare.

2 Background information

Singapore is widely regarded as a high-income and highly urbanised nation-state in the world for its political stability, economic performance and successful social development policies since independence in 1965. However, just like many other developed countries, Singapore does face the issue of income inequality and has families that live under relative poverty. To tackle income inequality, the Singapore government actively provides financial aid and support services to low-income families via the relevant statutory boards in collaboration with various non-government organisations.

2.1 How financial aid is distributed in Singapore

By providing financial aid to these families, it helps them offset the burden placed on households by increasing consumption of goods and services that they would otherwise be unable to afford due to their household budget constraint. We are interested to see the impact of these financial aid on children's future outcomes as Singapore prides itself on meritocracy whereby every child in Singapore is entitled to a formal education and social mobility can be achieved through one's capabilities and not their financial background.

In general, financial assistance in Singapore is distributed according to one's household income after being means-tested and verification of one's circumstance has been completed. This is done through the usage of systems such as HOMES which is also known as the Household Means Eligibility System that is a Government system supporting public schemes in their conduct of means-tests as part of their assessment in determining the level of assistance for households.

According to our research, we find that the Singapore government provides support to needy entities based on 9 major categories:

1. Children & Youth
2. Housing & Shelter
3. Disability Support
4. Mental Health
5. Families & Parenting
6. Seniors
7. Financial Support
8. Work & Learning
9. Health & Medical

As of April 2024, there were 86 social support schemes available for needy entities which typically come in the form of monetary assistance such as subsidies and vouchers.

The eligibility of applicants is usually dependent on gross household income and/or household's per capita income. Most of the financial aid schemes are for Singapore citizens, with exceptions made on a case-by-case basis.

2.2 Relevance to policymakers

Through this research design, we aim to identify the causal effects of financial aid on children from low-income households on children's future outcomes in terms of education, health and social behaviours.

For policymakers, we foresee that this will help them in the following ways: 1) Evaluate the effectiveness of financial aid distributed to eligible households, 2) Facilitate proper allocation of government resources to maximise societal welfare, 3) Identify areas in which financial aid policies can be improved.

3 Literature review

Our literature review spans across studies that evaluate the impact of financial aid and other policy changes that affect the future outcomes of treatment groups. Through this literature review, we attempt to find out what empirical studies have been conducted along with their methodologies and key findings to help guide our research design process.

Jacob et. al. (2015) conducted a study on how housing vouchers affected the behaviour and life chances of children from low-income families through the use of a randomised control trial (RCT) research design. This RCT was enabled by the fact that the Chicago Housing Authority Corporation conducted a randomised housing lottery for housing assistance to low-income families. They found that the receipt of a housing voucher had little if any impact on the education, crime or health outcomes over a 14-year follow-up period. The findings are surprising given the generosity of the voucher program but are consistent with the study conducted by Gubits et al. (2008). The study also proposed to look at direct interventions to target poor children in order to improve their long-term outcomes as suggested by Currie (2006).

A relevant study was conducted by Duncan et al. (2011) to investigate how family income impacts the academic achievement and behavioural outcomes of young children. Using data from a set of welfare and anti-poverty experiments conducted in the 1990s, they estimated a $1,000 increase in annual income increases young children's achievement by 5%– 6% of a standard deviation which suggest that family income has a policy-relevant, positive impact on the eventual school achievement of preschool children which is consistent with studies done by Duncan et al. (1997) and Haveman & Wolfe (1995).

We also looked into studies that investigate the effect of government welfare and employment policies on children development (Gennetian et al., 2008). Morris et al. (2005) wanted to find out if there were any points in a child's development that was sensitive to the implementation of welfare and employment policies. Using more than 30,000 observations of children's achievement from 7 randomly-assigned welfare and anti-poverty policies, they found that times of developmental transition are the only periods sensitive to the changes in families' household condition brought about by these policy interventions. This is supported by other research studies which indicate that early education programs aimed directly at children are cost-effective methods of promoting the achievement of young children (Phillips et al., 2000) and that policy interventions focusing on the parents' economic outcomes such as cash-transfer programs can be fruitful in promoting the achievement of young children (Duncan & Brooks-Gunn, 1997; Magnuson & Votruba-Drzal, 2008; Mayer, 1997, 2002) as well.

Our proposed research design has yet to be done in a Singapore context and thus it would be a novel idea to investigate if the outcomes from past academic studies above have external validity in the Singapore context.

Unlike the other studies, we are also including all types of financial aid that are available to eligible low-income households for these children which can help identify which types of policies can best improve the future outcomes of children from low-income households.

4 Ideal dataset

This section will cover the key data sources that will be used in our analysis. We assume that the dataset is ideal and there are no constraints to accessing these data.

To start off, our sample will include all financial aid recipients from low-income families from 2010 to 2020. They would have been studying in Primary 1 to Secondary 5 within the Singapore education system when they were applying for financial aid and are Singaporean citizens.

To retrieve the data required for our research, we can obtain longitudinal administrative data from the databases maintained by the respective Singaporean ministries and statutory boards that are in charge of the various social support schemes. Every Singaporean citizen and permanent resident is given a unique National Registration Identity Card (NRIC) number which can be used by them to access relevant information and conduct transactions with the respective government agencies. Likewise, this means that government agencies are able to access data that has been tagged to each unique individual for the different types of social support schemes that they qualify for as well as hold historical records on what financial aid that have received in the past and what type of future outcomes have they achieved in terms of income, educational qualification and social behaviour.

The extraction of these individual-level data can then be used as part of our research design to determine the impact of financial aid for children from low-income families in Singapore on their future behaviour and life outcomes.

For data that is not available on governmental databases, a survey can be conducted to gather additional data to supplement the existing datasets that we have obtained from governmental sources.

4.1 Variables of interest

We are interested to find out how financial aid for low-income families affect the behaviour of children and their life outcomes in the future. Hence, we use the following variables (or proxies) to measure their future outcomes, extent of financial aid they receive and control for potential confounders.

4.1.1 Dependent Variables

4.1.1.1 Education

NRIC	L1R5 (test score)	EducationalPathway	CCAParticipation	Disciplinary Record	Alcoholic	Conduct	School Attendance
1	20	Polytechnic	20	0	0	Excellent	55%
2	10	Institute of Technical Education	27	0	0	Good	70%
3	6	Junior College	30	0	0	Poor	50%
4	40	Secondary school	10	1	1	Poor	80%
5	16	Polytechnic	16	1	0	Average	70%
6	30	Junior College	25	1	1	Average	60%

Fig 1: Simulation of 1 year's worth of sample data of individual's academic and disciplinary records from MOE

From the Singapore Ministry of Education, we can obtain student-level schools records for the academic years from 2010 to 2020 for individuals in our sample to evaluate what effect does the distribution of financial aid have on their academic performance. This may include their test scores, grades, etc. for each year; but we can also obtain one-time data for variables that would only be received at the end of their secondary schooling, such as L1R5 test scores and their educational pathway after secondary.

4.1.1.2 Health and Social

From the Singapore Ministry of Health, we can obtain individual-level health records for the individuals in our sample to determine their past and present health status and future health outcomes. We can check for past illnesses, number of physical visits to clinics, vaccinations and medical claims from their private insurance or CPF Medical Accounts to capture changes in health status among sample members.

From the Ministry of Education, we can obtain data on their social behaviour in school through their disciplinary records, co-curricular records and class conduct that is updated minimally on an annual basis. This would include their absenteeism from school, participation in co-curricular activities and any reported behavioural issues of concerns such as alcoholism, smoking, teen pregnancy or any criminal offences. This can also be cross-checked with data from the Ministry of Home Affairs and Ministry of Law to see if they were involved in any criminal activities or committed any legal infractions.

4.1.1.3 Financial

From the Inland Revenue Authority of Singapore (IRAS), we are able to obtain individual-level data on the income of the children's working family members through their income tax filings. This would help us verify their household incomes and compare the effects of having financial aid for individuals from our samples.

4.1.2 Independent Variables

4.1.2.1 Demographic and socioeconomic information

When family members apply on behalf of the applicants (children from low-income families), they would need to input their household information to allow the relevant government agencies to conduct means-testing and check whether they qualify for the respective social support schemes. This information includes the number of dependents in the household, number of working adults and non-working individuals, labour income per capita, total household income and per capita household income (PCI), place of residence and other demographic variables. We can then extract this data from the Ministry of Social and Family Development and Ministry of Education as they are usually the main government agencies that will distribute financial aid to low-income families with school-going children.

While it is possible to obtain information about the parents' education level, occupation and employment status from the relevant government agencies that are mentioned above, this would likely only apply for parents who are Singapore citizens or Permanent Residents (PRs) or have taken their education in Singapore. If the parents of these children (individuals in our sample) were not educated in Singapore, then we would need to conduct an additional survey on these individuals to obtain this data.

4.1.2.2 Type of Aid

Data on the type of aid that individuals in our sample received can also be obtained using similar methods as above. We then aggregate the different financial aid received by the household of each individual from the 9 main categories covered in section 2.1: Children & Youth, Housing & Shelter, Disability Support, Mental Health, Families & Parenting, Seniors, Financial Support, Work & Learning and Health & Medical.

4.1.3 Instrumental Variables

We also needed an instrumental variable (IV) to address any potential concerns about endogeneity in estimating the causal effect of financial aid on children's future outcomes. The instrumental variable we have chosen is proximity of Social Service Offices (SSOs) to the place of residences of individuals. The location data for the SSOs can be found from the Ministry of Social and Family Development's website and the distance can be computed using Google Maps or geospatial software with Singapore location data. This IV was selected as we felt that it fulfilled the relevance condition and exclusion restriction that is required for us to conduct an IV regression which will be covered in section 5.3.

This figure below shows a within-cohort analysis for each individual aged between 7 years old and 17 years (primary 1 - secondary 5) and the amount of financial aid they're receiving that will be used in our regression models later on.

Child (i)	Year (t)	Age_{It}	Time to event (k)	$Event_{It}$	$PreEvent_{it}$	$EducationAid_{it}$	$HealthAid_{it}$	Aid_{it}
1	2010	7	-2	2012	1	0	0	0
1	2011	8	-1	2012	1	0	0	0
1	2012	9	0	2012	0	0	100	100
1	2013	10	1	2012	0	50	100	150
1	2014	11	2	2012	0	50	100	150
1	2015	12	3	2012	0	50	100	150
…	…	…	…	…	…	…	…	…
1	2020	17	8	2012	0	50	100	150
2	2010	7	-1	2011	1	0	0	0
2	2011	8	0	2011	0	50	0	50
2	2012	9	1	2011	0	50	100	150
2	2013	10	2	2011	0	50	100	150
2	2014	11	3	2011	0	50	100	150
2	2015	12	4	2011	0	50	100	150
…	…	…	…	…	…	…	…	…
2	2020	17	9	2011	0	50	100	150

Fig 2: Simulated dataset over time

5 Research design

5.1 Baseline regression model

We estimate the intention to treat (ITT) effect of the total amount of financial aid (per capita) that a child receives in a household. For child *i* in year *t*, where *t* denotes the year that the child's household first receive any type of financial aid, we use a difference-in-difference model as such:

$$(1)\quad Outcome_{it} = \alpha + \beta_1 Aid_{it} + \beta_2 PreEvent_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

Where:

Aid_{it} is the total amount of financial aid (per capita) that a child receives in a household;

β_1 is the coefficient of interest;

$Outcome_{it}$ can be $Grades_{it}$, $Alcoholism_{it}$, $Crime_{it}$, $Absenteeism_{it}$, etc.;

$PreEvent_{it} = 1[t < Event_{it}]$, this allows us to capture the average difference between the treatment and control groups before the event occurs;

Vector of controls X'_{it} include $LabourIncome_{it}$, $ParentsEducationLevel_{it}$, etc.;

γ_i is individual fixed effects;

λ_t is time fixed effects;

ε_{it} is the error term;

We can also run an event study regression, as such:

$$(2)\quad Outcome_{it} = \alpha + \sum_{k=-K}^{K} \beta_k Aid^k_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

Where:

k ranges from -*K* to *K*, where *K* is the number of periods before and after the event;

Aid_{it} is the total amount of financial aid (per capita) that a child receives in a household;

β_k is the coefficient of interest;

$Outcome_{it}$ can be $Grades_{it}$, $Alcoholism_{it}$, $Crime_{it}$, $Absenteeism_{it}$, etc.;

Vector of controls X'_{it} include $LabourIncome_{it}$, $ParentsEducationLevel_{it}$, etc.;

γ_i is individual fixed effects;

λ_t is time fixed effects;

ε_{it} is the error term;

5.2 Checking identifying assumptions

5.2.1 Common trend assumption

To satisfy this assumption, for the difference-in-difference regression, we have to check that the coefficient β_2 of $PreEvent_{it}$ is 0. While for the event study regression, we have to verify that the coefficients of the lags ($k < 0$) are 0.

5.2.1 Exogeneity assumption

A key assumption of our regressions is that we assume that the explanatory variables are exogenous. This assumption could be violated if there are endogeneity concerns, be it any unobserved policy/economic shocks that occurred in the same year or reverse causality, among other things.

We can do a placebo/falsification test by either (i) using an outcome variable which is not affected by the potential unobserved shocks; or (ii) exploiting a population that was not affected by financial aid, e.g. running the same regression but on children from high-income households that are not eligible for any financial aid and confirm that the treatment effect is not statistically significant.

5.3 Instrumental variable

In the event that the test reveals endogeneity concerns, we propose the inclusion of an instrumental variable, $Proximity_{it}$, representing the distance of a household's place of residence to Social Service Offices (SSOs).

5.3.1 Relevance condition

Proximity to social service offices should have a direct influence on the amount of financial aid a child receives. This is because children living closer to social service offices should have better access to information about aid programs or are more easily reached by outreach efforts, and therefore, they are more likely to apply and receive financial aid successfully.

To satisfy the relevance condition, we can run a first stage regression to verify that the coefficient of $Proximity_{it}$, π_1 has a high F-statistic (> 10).

First stage:

(3) $Aid_{it} = \pi_0 + \pi_1 Proximity_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + v_{it}$

5.3.2 Exclusion restriction

This requires $Proximity_{it}$ to not be directly related to any other unobserved factors that can influence the outcome, which would mean that it does not directly affect the child's outcomes except through its impact on financial aid.

Theoretically, the placements of the SSOs are driven by long-term planning by the Urban Redevelopment Authority (URA) in conjunction with the Ministry of Social and Family Development to promote community development and have sufficient coverage of the various zones in Singapore, which are independent of individual household characteristics and their children's potential outcomes. Hence, any variation in proximity to these offices would be exogenously given to the individuals and not influenced by their unobserved traits or behaviours (i.e. exclusion restriction has a high likelihood of being satisfied).

As additional supporting evidence, we can do a placebo/falsification test and verify that it is not statistically significant. For example, using a sample of individuals whose households are not eligible for financial aid, we can run a regression of $Outcome_{it}$ against the instrument $Proximity_{it}$ and check that the coefficient is 0.

An overidentification test would not be appropriate in our case since we only have one instrumental variable.

5.3.3 Common trend assumption

After verifying that $Proximity_{it}$ is a valid instrument, we can ensure that the common trend assumption is still satisfied.

DiD with IV pre-trend check:

$$(4) \quad Outcome_{it} = \alpha + \beta_1 (PreEvent_{it} \times \widehat{Aid}_{it}) + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from first stage.

The interaction $PreEvent_{it} \times \widehat{Aid}_{it}$ allows us to check for the instrumented part of financial aid. We will verify that β_1 is not statistically significant.

Event study with IV pre-trend check:

$$(5) \quad Outcome_{it} = \alpha + \sum_{k=-K}^{0} \beta_k \widehat{Aid}^{k}_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from the first stage.

We will also verify that β_k for $k < 0$ is not statistically significant.

5.4 Complete regression with IV

We can run first stage + second stage and/or first stage + reduced form.

5.4.1 Difference-in-difference regression with IV

First stage:

(3) $Aid_{it} = \pi_0 + \pi_1 Proximity_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + v_{it}$

Second stage:

(6) $Outcome_{it} = \alpha + \beta_1 \widehat{Aid}_{it} + \beta_2 PreEvent_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from first stage.

β_1 is the coefficient of interest.

Reduced form:

(7) $Outcome_{it} = \alpha + \theta_1 Proximity_{it} + \beta_2 PreEvent_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \mu_{it}$

θ_1 is the coefficient of interest.

5.4.2 Event study regression with IV

First stage:

(3) $Aid_{it} = \pi_0 + \pi_1 Proximity_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + v_{it}$

Second stage:

(8) $Outcome_{it} = \alpha + \sum_{k=-K}^{K} \beta_k \widehat{Aid}^{k}_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from first stage.

β_k is the coefficient of interest.

Reduced form:

$$(9)\quad Outcome_{it} = \alpha + \sum_{k=-K}^{K} \theta_k Proximity^{k}_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

θ_k is the coefficient of interest.

6 Discussion

6.1 Internal validity

Conditional on the validity of our instrumental variable, the inclusion of time and individual fixed effects in addition to the extensive checks we included to satisfy the identifying assumptions and to address endogeneity concerns should allow us a high likelihood of having internal validity.

The robustness of our study can be explored by conducting sensitivity analyses. We can consider alternative model specifications, such as using different functional forms for key variables. Additionally, we can run permutations by including/excluding sets of control variables.

Furthermore, additional instrumental variables might be beneficial if they are valid and strong. We can conduct an overidentifying test on them in addition to the F-statistic check.

However, a possible concern we have is that households may become ineligible for financial aid due to improving income. Slight income improvements may not be a concern as the government tends to adjust (increase) the income eligibility cap every several years. On one hand, this allows us to achieve stability in our dataset. On the other hand, this eligibility adjustment might pose a challenge to our study.

While it is generally unlikely for low-income families to significantly increase their financial standing quickly due to systematic and structural barriers apart from windfall lottery effects, the possibility that some families do improve their income—and hence no longer qualify for financial aid—does present a challenge to the internal validity of our study, affecting the composition of our groups.

Although, we are confident that the application of fixed effects and instrumental variable will effectively mitigate these concerns, thus preserving the validity of our design.

6.2 External validity

The impact of financial aid observed here may be influenced by Singapore's uniquely integrated financial aid system and policies, which may not be the case in other countries.

However, we can do a heterogeneity test that can help determine whether the financial aid effects are consistent across various individuals' characteristics.

First stage:

(3) $Aid_{it} = \pi_0 + \pi_1 Proximity_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + v_{it}$

DiD second stage:

(10) $Outcome_{it} = \alpha + \beta_1 \widehat{Aid}_{it} + \beta_2 Characteristic_i + \beta_3 (\widehat{Aid}_{it} \times Characteristic_i) + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from first stage;

$Characteristic_i$ can be $Gender_i$, $Ethnicity_i$, etc.

Verify that β_3 is not statistically significant.

Event study second stage:

(11) $Outcome_{it} = \alpha + \sum_{k=-K}^{K} \beta_k \widehat{Aid}^{k}_{it} + \theta_1 Characteristic_i + \sum_{k=-K}^{K} \delta_k (\widehat{Aid}^{k}_{it} \times Characteristic_i) + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$

$\widehat{Aid}_{it}$ is the predicted Aid_{it} from first stage;

$Characteristic_i$ can be $Gender_i$, $Ethnicity_i$, etc.

Verify that δ_k is not statistically significant.

If the coefficients mentioned are not statistically significant, this might increase the likelihood of our study having external validity. Additionally, replications of our studies in different contexts will be very helpful in determining the external validity.

6.3 Extension

We can also extend our baseline difference-in-difference regression to analyze each type of aid specifically.

Extensive DiD regression model:

$$Outcome_{it} = \alpha + \beta_1 ChildAid_{it} + \beta_2 HousingAid_{it} + \ldots + \beta_3 EducationAid_{it} + \theta_1 PreEvent_{it} + X'_{it}\Gamma + \gamma_i + \lambda_t + \varepsilon_{it}$$

Going beyond financial aid, our research design can be applied to other government policies that are designed to improve future outcomes. While this would require more resources and subject expertise due to the broad range of policies that the Singapore government and potentially complicate the attribution of causality between aid and future life outcomes, it would help policymakers in having a holistic evaluation of the combined impact of financial aid coupled with other government policies on low-income families and children.

7 Conclusion

To sum up, financial aid remains a key part of Singapore's social policies to help low-income families and children with their standard of living and improving their future life outcomes. Being able to evaluate the treatment effects of financial aid can help policymakers better allocate resources to policies that have been proven effective and look into potential areas for improvement as part of a whole-of-government approach to supplementing low-income families with income in the form of cash and/or vouchers. We believe that this research design can act as a baseline model for which to measure the performance of the various social support schemes and be enhanced upon to include more sophisticated econometric to more accurately reflect the treatment effects of financial aid.

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