

ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis Economics and Business Economics

The impact of the introduction of the rice subsidy in the Pantawid
Pamilyang Pilipino Program on birth weight

Student: Thomas Jansen

Student ID number: 512043

Supervisor: Anandita Bardia

Second assessor: ?

Date final version: 10/07/2024

Abstract

This thesis investigates the effect of the introduction of the rice subsidy in the Pantawid Pamilyang Pilipino Program on the birth weight of children in the Philippines. Conditional cash transfer programs (CCT) are a fairly new method to address poverty. The goal is to invest in and improve human capital level of participants by providing cash grants to low-income households. These grants are contingent on health and education requirements. The rice subsidy, which was introduced in 2017, aimed to enlarge the food consumption among participants of the CCT. Using data from the 2017 and 2022 Demographic Health Surveys (DHS), this study performs a pre-post comparison to analyze changes in birth weight after the introduction of the rice subsidy. In contradiction with previous studies and literature a negative correlation between birth weight and the rice subsidy is identified. Therefore, the hypothesis that the rice subsidy will on average lead to a higher birth weight is rejected. Potential explanations include the diminishing real value of the CCT's grants due to inflation and limitations in accurately identifying Pantawid participants. Future research should address these data constraints and further investigate the effect of inflation.

Table of contents

Abstract (1)

1.0 Introduction (3)

2.0 Literature review (5)

2.1 Structure of the Pantawid Pamilyang Pilipino Program **(5)**

2.1.1 Goal of the program **(5)**

2.1.2 Eligibility **(5)**

2.1.3 Requirements **(6)**

2.1.4 Cash grants **(6)**

2.2 Structure of Progresa/Oportunidades **(7)**

2.2.1 Start of Progresa/Oportunidades **(7)**

2.2.2 Eligibility and requirements **(7)**

2.3 Impact evaluation of Progresa/Oportunidades **(8)**

2.3.1 Experimental setup **(8)**

2.3.2 Results **(8)**

2.4 Impact evaluation of the Pantawid Pamilyang Pilipino Program **(8)**

2.4.1 Results **(9)**

2.4.2 Methodologies of the impact evaluations **(11)**

2.5 Behavioral biases in CCTs **(13)**

2.6 Contribution to literature **(14)**

2.7 Hypothesis **(15)**

3.0 Data (16)

3.1 Data source **(16)**

3.2 The dependent and independent variable **(16)**

3.3 Control variables **(18)**

4.0 Methodology (20)

4.1 Analysis method **(20)**

4.2 Data preparation **(20)**

4.3 Analysis **(20)**

4.4 Pre-post comparison shortcomings **(21)**

5.0 Results (22)

5.1 Simple regression model **(22)**

5.2 Multiple regression model **(23)**

6.0 Conclusion (26)

7.0 Discussion (27)

8.0 References (28)

9.0 Appendix (32)

1.0 Introduction

Nowadays, poverty is one of the biggest problems the world faces (Huang & Liu, 2022). Especially, the consequences that arise from poverty. Poverty is defined as a lack of economic resources that has negative social consequences (Mood & Jonsson, 2015). Everyone who lives in poverty struggles, but children growing up in poverty suffer life-long consequences. Research has shown that children growing up in poverty are more likely to have lower educational attainment, a higher chance at teen pregnancy and are more likely to have economic problems as an adult (Corcoran, 2009). Furthermore, poverty has a negative effect on mental health. The stress of constantly having to make ends meet can cause depression or other illnesses. These conditions can limit parents in raising their children effectively. Resulting in an environment which does not provide children with the ability to maximize their emotional and cognitive growth. Finally, poor parents can lack the resources to invest in their children's development and health (Duncan et al., 2017).

During the 1990s a new method to address poverty was developed. This method is called the conditional cash transfer program. These programs often provide monetary support to low-income families in low and middle-income countries. In exchange for the monetary support offered by the programs, participating families are required to meet certain conditions. For example, children have to attend school, families have to visit health clinics and are required to participate in nutrition supplementation programs (Fernald et al., 2008). The goal of these programs is to reduce current poverty and also to invest in the human capital levels of the children from these low-income families. Ideally, these increased human capital levels could also lead to a reduction in future poverty. One of the first large-scale conditional cash transfer programs, which was based on human capital accumulation, was called *Progresa* and started in Mexico in 1997 (Parker & Todd, 2017).

During its initial two years results of the program underwent thorough evaluation based on the randomized design of the conditional cash transfer (CCT) program. They concluded the program had a positive contribution towards its goals. Research has shown that CCTs affected a lot of different outcomes, including income, savings, poverty, health, school enrollment and attendance of children, obesity and lots of other outcomes. These conclusions led to an expansion of the CCT program in Mexico. Also, other countries got inspired by the newly designed CCT program based on human capital accumulation, because of its ability to decrease present poverty and at the same time prevent its transfer to the next generations. As of 2017, CCT programs have been adopted by more than sixty countries spread over five continents (Parker & Todd, 2017).

The Philippines is one of the countries that struggles with poverty. After poverty decreased in the early 1990s, it started to increase again in the 2000s. Also, human capital levels in education and health weren't increasing: universal primary education remained elusive, alongside maternal mortality

and child malnutrition rates, which were among the highest in East Asia. As a reaction, the Philippine government also introduced a CCT: *Pantawid Pamilyang Pilipino Program*. This CCT is based on the *Progresá* CCT and inspired by the success of CCTs in Latin America. It started in February 2008, with 320,000 households and has been expanded since. To be eligible, households have to meet certain criteria: living in the program area, being identified as poor and having pregnant women or a child younger than fifteen years old (Velarde & Fernandez, 2011).

A lot of impact evaluations have been performed on these CCT programs. These evaluations show that CCTs can help to reduce current and future poverty (Fiszbein & Schady, 2009). The impact of the Pantawid CCT also has been evaluated in the last few years. The most recent evaluation is the third-wave impact evaluation. The main source of data is a survey, which was conducted between November 2017 and January 2018. The results were published in 2021 and unlike earlier evaluations of the program, they concluded the CCT no longer affected child labor. The evaluation concluded no program impact on the occurrence and duration of paid and unpaid labor among children aged ten to fourteen years old. However, they also concluded 90% of the children, who were working still attended school. That suggests the income is used additionally with the grant to pay for educational costs (Orbeta et al, 2021). Furthermore, Philippine politician Lee pleaded for higher grants in 2023. Because of COVID-19 and inflation costs have risen so much that the relative value of the cash grant has been reduced by half (CNN Philippines, 2023).

Another important problem that was observed before introducing the CCT is that almost two out of three households, from the poorest quintile, live in food poverty. Earlier CCTs have shown that grants are allocated towards putting food on the table. Therefore, the CCT could positively influence food poverty (Delgado & Velarde, 2011). The CCT had a positive impact on food poverty, but the Philippine government introduced an extra rice subsidy to the program in 2017. The goal of the rice subsidy is to increase the food consumption of participants (Orbeta et al., 2021).

This thesis will research the influence of the rice subsidy on the birth weight of children born after the introduction of the rice subsidy in 2017. There hasn't been a evaluation of the CCT since the rice subsidy was introduced. Furthermore, research has shown that a higher maternal weight leads to a higher birth weight of children (Rode et al., 2007). Therefore, the research question of this thesis is:

What influence had the introduction of the rice subsidy on birth weight of children?

2.0 Literature review

The following section will discuss the structure and impact evaluations of the Pantawid Pamilyang Pilipino Program. Furthermore, it will briefly discuss the structure and impact evaluations of Progresa/Oportunidades which the Pantawid program was inspired by. This information will ultimately be used to form an hypothesis for the research question.

2.1 Structure of the Pantawid Pamilyang Pilipino Program

2.1.1 Goal of the program

The Pantawid Pamilyang Pilipino Program is the national CCT of the Philippines. It was implemented in 2007, after the Philippines' economy had been growing for ten years yet poverty was not reduced. The program was designed after the CCTs in South-America, who had proved they could effectively help poor households (Parler & Todd, 2017). Poor families, who do not have enough resources to invest in their children's health and future, are supported with cash grants. The goal of the program is two-fold: in the short-term, poor families get a cash grant so they can meet their basic needs. In the long-term, the goal is to accumulate the human capital levels of the children so they can become productive members of society and therefore, break the cycle of intergenerational poverty. These accumulated levels of human capital are created by making the cash grant conditional on certain health and education behavior (Acosta & Velarde, 2015).

2.1.2 Eligibility

To become eligible for the Pantawid Pamilyang Pilipino program must meet certain demands. Firstly, the household has to be considered as poor. The Philippine government has developed a poverty identification system to make a list of all poor households (Acosta & Velarde, 2015). This list is called the national household targeting system *Listahanan*. *Listahanan* is a proxy means test based statistical program to determine objectively which households are considered as poor. Before the introduction of *Listahanan* there was not an uniform way to determine this, leading to inadequate allocation of the program and therefore, waste of funds. The data for the test is collected through national surveys and contains variables like materials used in housing structures, access to basic utilities like water and electricity, ownership of assets and education of household members (DWSD, 2018). Secondly, participating families must at least have one children or a pregnant mother. Finally, the families must comply with the program's requirements (Acosta & Velarde, 2015).

2.1.3 Requirements

The program has three requirements for households to fulfill: basic maternal and child health services, enrollment and regular attendance in school and attendance to family development sessions. This last condition is unique in CCTs.

The required health services for pregnant women are: at least one visit to a health clinic every two months to receive pre- and postnatal healthcare, during the pregnancy at least one prenatal check-up every trimester, delivery services from a skilled healthcare professional and usage of postnatal care services in the first six weeks after giving birth. Children up to two years should receive vaccination according to the Department of Health vaccination schedule, children aged between two and five have to visit a health clinic every two months for weight tracking and children between six and fourteen have to take deworming pills no less than twice a year.

The educational requirements are: children between three and five should attend Daycare or Kindergarten with a minimum attendance rate of 85% per month. The same attendance rate applies to children between six and eighteen for their enrollment in Elementary or High School.

The last requirement are the family development sessions. These sessions are held once a month and are designed as learning seminars for the parents. During the sessions parents will learn about core principles of family development and active participation in community activities. The goal is to educate the parents so they can fulfill their responsibilities in the human capital accumulation of their children and become active members of the community. The parent, who is authorized to receive the grants, should attend the sessions. Usually this is the mother as they are seen as the caregivers of the household. Sometimes the sessions are mandatory for both of the parents or the whole household (Orbeta et al., 2021).

2.1.4 Cash grants

Beneficiaries of the program receive three types of cash grants. Firstly, the education grant. The amount of the grant depends on whether the child is in daycare, elementary or high school. Children enrolled in daycare or elementary school receive 300 Philippines Pesos (PHP) per month, while children enrolled in high school receive 500 PHP per month. Both grants lasts for a maximum of ten months while children meet the demanded attendance rate. Households can receive the educational grant for a maximum of three children. Secondly, there is a health grant. Beneficiary households receive 500 PHP per month, as long as the required health conditions are met. The health grant last a whole year. Finally, households can receive a rice subsidy. The rice subsidy is set at 600 PHP per month and also last a whole year. This grant was not part of the program from the beginning, but was added

since 2017. To receive the subsidy households must either comply with the education or health requirements.

When households are registered into the program they will receive non-contingent cash grants based on the number of eligible people in the household. The grants after this are based on the compliance of the program's requirements. Grants are paid out every two months. Households have two options to receive the grant. The first option is through bank transfer and the second option is cash through over-the-counter, which is primarily used in rural areas where there is a lack of ATM's (Orbeta et al., 2021).

2.2 Structure of Progesa/Oportunidades

As mentioned in the introduction, the Pantawid program was designed after a successful CCT performed in Mexico. The program was originally called Progesa and later renamed to Oportunidades. This section of the literature review will briefly address the structure of this CCT.

2.2.1 Start of Progesa/Oportunidades

Oportunidades, back then called Progesa, was founded in 1998 in Mexico. 506 different low-income communities were assigned to be part of the program. Some communities started directly with the program, while others joined eighteen months later. This selection was randomly determined. The CCT had the same goal as the Pantawid program: immediate relieve of poverty through cash payments and the reduction of future poverty by investing in human capital (Fernald et al., 2008).

2.2.2 Eligibility and requirements

The poverty program targeted rural and urban communities. Rural applicants were chosen based on surveys, while urban applicants had to apply and be visited to verify their information. Once in the program, families received aid for 3 years with no income checks, but had to comply with program rules. Eligibility was then reassessed (Todd & Parker, 2017).

To stay in the program, families had to meet education and health requirements. Education involved enrolling children in school and maintaining attendance. Missing too many classes led to losing the education grant. Health required using a clinic, attending appointments, and participating in workshops. Failure to meet these requirements meant removal from the program (Dávila Lárraga & Inter-American Development Bank, 2016).

2.3 Impact evaluation of Progesa/Oportunidades

This section of the literature review will briefly discuss the experimental setup and impact evaluations of Progesa/Oportunidades.

2.3.1 Experimental setup

Progesa/Oportunidades was set up as a randomized controlled trial. A part of the initially selected households immediately received cash grants. Other households joined the program eighteen months later.

To evaluate the CCT, the International Food Policy Research Institute designed surveys for participants and non-participants. Some studies focused only on eligible households, but others analyzed all data to identify spillover effects, which could bias the results. Randomization by village provided a more accurate picture of the program's true impact as positive spillovers could weaken the true effect of the program (Angelucci & DiGiorgi, 2009).

2.3.2 Results

Research on Progesa/Oportunidades showed long-term benefits for children's education. School enrollment increased, especially for girls. This was due to initially lower enrollment rates and because girls received higher grants (Schultz, 2004). Children repeated fewer grades, stayed in school longer, dropped out less and the educational attainment gap between poor and nonpoor children was reduced (Todd & Parker, 2017).

Early evaluations of Progesa/Oportunidades showed increased clinic visits, reduced illness, taller children, and lower anemia rates. Importantly, babies born to participating mothers had a significant increase in birth weight by 127.3 grams and the prevalence of low birth weight was reduced (Barber & Gertler, 2008). Child mortality also decreased by 17% (Barham, 2011).

2.4 Impact evaluation of the Pantawid Pamilyang Pilipino Program

This section of the literature review will analyze impact evaluations of the Pantawid CCT. Lastly, it will present the hypothesis linked to the research question.

2.4.1 Results of the Pantawid Pamilyang Pilipino Program

The evaluations of the Pantawid CCT consists of three different papers. The first evaluation was performed by Delgado and Velarde (2011), the second by Acosta and Velarde (2015) and the third by Orbeta et al. (2021).

Delgado and Velarde (2011) established that the CCT had a significant effect on reducing current poverty. It reduced current poverty with 6.2 percent. Furthermore, the program reduced income inequality with 6.6 percent. However, it was also established that the program's impact could be enhanced if more participants would comply to the requirements. For example, around 20 percent of the enrolled children did not attend school or were not enlisted with a health clinic. The article also found that the program increased the household income of participants with 12.6 percent. This number could potentially reach 17% with better compliance rates.

Earlier CCTs evaluations from other countries discovered was that program grants would widely be used for basic necessities. Therefore, Delgado and Velarde (2011) also concluded the grant could reduce food poverty with 13.3 percent among the program's participants. Finally, they conclude the program would expand a lot in the coming years. Therefore, the program would need to strengthen its foundation so they can support the implementation and control the compliance of participants. Compliance is essential as the requirements ensure increased human capital levels, which should reduce future poverty. The last recommendation is to make sure that educational and healthcare services can handle the increased demand due to the program.

The second evaluation of the program was performed by Acosta & Velgarde (2015). Firstly, they found that the program still accurately targeted the poor families despite its rapid expansion since 2011. As of 2015, the program covered 4.4 million households while in 2011 the program covered 700,000 households. 100% of the poor households with children, who were identified so by Listahanan, were included in these 4.4 million households. The government's goal was to broaden Listahanan, which currently holds information on 11 million households, to include an additional 4.3 million, reaching 75% of all households in the Philippines. While expanding the program, the government decided to hold the cash grants at the same value since the start in 2007 to keep the program on a reasonable budget. This decision caused an decrease in real value of 42 percent of the grant due to inflation. Making the Pantawid program the least generous of all other large CCTs.

The program still had positive impacts. With total poverty reduction of 6.5 percent, food poverty reduction of 6.7 percent, reduction of income cap by 7.6 percent and an increase in children's school enrollment. Recommendations for the future entailed updating Listahanan more frequently, this

would ensure a more accurate list of beneficiaries and updating the value of the grant based on the inflation (Acosta & Velarde, 2015).

The last evaluation was performed by Orbeta et al. (2021). This is the biggest evaluation of the Pantawid program. Multiple health effects were established. Pregnant women were more likely to have at least four prenatal checkups, which is the advised minimum. Furthermore, participating women are more often accompanied by a doctor or nurse when giving birth. Surprisingly, there was no effect on postnatal care even though it is a requirement of the program.

Participating children aged up to five years more often receive regular weight monitoring, which is a minimum of once a month. These children also have higher rates of vitamin A supplementation. No positive effect was found on the immunization of children or the amount of times children visited health clinics, even though they are a requirement of the program. This also resulted in no effect in the prevention of vaccine-preventable diseases. A positive effect is found on the amount of children that take deworming pills at least twice a year. However, this group only consists of 32 to 34 percent of the participating children. Again, this is a requirement of the program. Surprisingly, a positive effect was found on stunting of children. This contradicted the effects on nutrition found by earlier evaluations. No significant effects were found on other nutrition indicators besides stunting of growth (Orbeta et al., 2021).

In line with expectations, the program had a positive impact on school enrollment. However, this was only the case for high school as the enrollment rates for primary school already were really high. No significant effect was found on school attendance, with researchers suggesting this was due to the attendance rate already being really high. A significant decrease was found on the dropout rates for children aged between six and fourteen years old. Furthermore, Pantawid children were more likely to participate in extracurricular activities and their spending on school expenditures was 9% higher. There was no longer a significant effect on the decrease of child labor. Researchers also found something new: Pantawid children have more grit than their Philippine counterparts. Meaning, the children would have more determination to reach their goals. This was attributed to the educational and health support, which created a stable environment to focus on long-term goals. Furthermore, the family development sessions and community engagement contributed positively towards this attitude. Due to the program's grants, the basic needs of children are met. Therefore, they can focus long-term goals and potentially leave poverty behind (Orbeta et al., 2021).

One the most important remarks of the evaluation is that still most of the Pantawid grants were not raised since their introduction in 2008. Thus, each year their real value will become lower due to inflation. In 2008, the real value of the grants would be 20% of the poverty threshold while in 2017 it

would only be equal to 15% of the threshold. The grants for high school children were increased, but it is not enough to keep the real value from decreasing. The new rice subsidy is expected to compensate for the lost value. Still researchers recommend to reevaluate the amount of the grants. Furthermore, the importance of good monitoring of the requirements is stressed and finally, further research on nutritional, maternal healthcare and child labor outcomes is recommended (Orbeta et al., 2021).

2.4.2 Methodologies of the impact evaluations

The first paper by Delgado and Velarde (2011) approached the impact evaluation by simulating a predicted income with a proxy means test (PMT). PMT is a method that predicts income through socio-economic conditions of households, education of household members, access to basic necessities, amount of assets and living conditions. With these factors a simulated income is calculated which is considered as the income of a household without receiving the Pantawid grants. The grants are added to this income to create the income with the grants from the program. These incomes are compared with the national threshold of poverty. If a household's income without the grants is below the threshold and the income with the grants is above the threshold the program lifted the household out of poverty. If the income without grants already exceeds the threshold, the program most likely didn't had a positive effect on escaping poverty.

The strength of the method is that it allows for quantitative assessment of the CCT, which makes it easier to interpret the results. The predicted outcomes can be easily compared with the poverty threshold to evaluate the effectiveness of the CCT. Furthermore, PMT is a relatively inexpensive method to collect data compared to directly collecting data through surveys and it is easily expandable for programs with lots of participants. However, the method also has its weaknesses. It is possible that the PMT does not accurately predict outcomes, the national poverty threshold might not include all poverty like access to education or healthcare and households with characteristics, which are not covered by the PMT, could be classified as non-poor while they actually are poor. For example, a household with really high fixed healthcare costs.

The second evaluation paper uses two different methods to address two different time-periods of the CCT. For results in the beginning of the program, up till 2009, the impact is evaluated with a randomized control design. Pantawid was designed after Progresa/Oportunidades and initially implemented the same experimental design. The first round of results were therefore evaluated with a randomized controlled trial (RCT). RCTs are known as the holy grail for impact evaluations, because they allow for clear causal interpretation of the effect. This is achieved due to several reasons: the random assignment to the treatment or control group eliminates selection bias, meaning the characteristics between the treatment and control group are the same. Therefore, the effect can be

considered due to the treatment and not to pre-existing differences between the groups (Webber & Prouse, 2017). In conclusion, the found treatment effect can be considered as causal. Which is However, RCTs do also have drawbacks: the costs of setting up a RCT can be really high. Furthermore, RCTs can raise ethical concerns. Who should be treated and who should be in the control group? The last concern is external validity. Can the results of the study be used for other populations?

Because the program rapidly expanded and no longer had the same experimental set-up. The second time-period of the program was evaluated with a regression discontinuity design (RDD). The same applies for the third paper, which also uses a RDD to evaluate the effect of the CCT. This following paragraph will address the RDD from the paper of Orbeta et al. (2021).

RDD is an evaluation method that compares the outcome of two groups around a cutoff point. The cutoff point determines whether an individual should have gotten the treatment. The reasoning behind RDD is that individuals around the cutoff point should be nearly identical. Therefore assignment of the treatment can be considered as done randomly. Therefore, outcomes without a treatment should roughly follow same trajectory. If individuals below the cutoff point show a big jump in the outcome variable, this can be addressed to the difference in treatment. There are two different RDDs: fuzzy and sharp. Sharp RDDs assume almost perfect compliance to the assignment of the treatment. In this case meaning all households below the poverty threshold should have been treated, while none of the households above the poverty threshold should have been treated. This method calculates the intent-to-treat effect. This effect shows the effect of the treatment among all eligible households whether they did or did not receive the treatment. Fuzzy RDD does not assume perfect compliance. For, example eligible household could have denied to be part of the program and non-eligible households might be able to manipulate their PMT and unjustly obtain treatment. To fix this problem an instrumental variable (IV) approach is used. An IV is variable that affects the treatment and only affects the outcome through the treatment. The paper used administrative information on who actually received the grants as an IV for who received the treatment (Orbeta et al., 2021).

Three assumptions have to be met in order for a RDD function properly: no manipulation around the threshold, clustered observations around the threshold might be a sign of manipulation. No discontinuity of baseline characteristics around the threshold to assure the groups are the same and no difference in outcome variables around the threshold in absence of the program, as this would imply something else than the program already causes difference in outcomes. In this paper only the baseline characteristics assumption was potentially violated. Five out of twenty-one characteristics showed discontinuity. For the evaluation no manipulation is assumed, but recommended is to analyze whether these discontinuities occur (Orbeta et al., 2021).

The weakness of a RDD is that it has low external validity, results only apply to households near the cutoff point. Therefore, the treatment effect is only established for the “richest” group of the poor households. Unlike with a RCT, results cannot be extrapolated to the other participants of the CCT (Orbeta et al., 2021).

2.5 Behavioral biases in CCTs

Researchers have studied how behavioral biases can influence CCTs. This section will address the outcomes of this research.

The first study looked at time-preference parameters. The results of a CCT in Guatemala were analyzed to research the influence of utility curvature, discounting and present bias. Utility curvature is a function which describes the preference of the smoothing of consumption. When a person has a high utility curvature they prefer to consume at a steady rate instead of saving up or investing for future compensation. The discounting factor tells how much value a person attributes to future rewards. A low discount factor means a person does not attribute much value to future rewards. Finally, present bias is the phenomenon that people favor immediate rewards over future rewards, even when the future rewards would relatively be bigger (Aycinena et al., 2019).

The study found that participants had a high utility curvature, thus a preference for consumption smoothing. Furthermore, participants had low discount factors showing their impatience and preference for immediate consumption. Both of these preferences can be troubling for the goal of the CCT, investing in human capital, as this does not provide immediate rewards. Therefore, it could lead to underinvestment in their children’s education or health. The researchers found no evidence for the presence of present bias (Aycinena et al., 2019).

Another study performed on a CCT in Bangladesh studied the effect of loss framing. Loss framing is approach based on loss aversion. Loss aversion is the psychological concept that losing something is more painful than the pleasure of gaining something. In fact, research suggests that the pain of loss is felt about twice as intensely as the pleasure of an equivalent gain. This concept can be used in the set up of CCTs. For example, in the Bangladesh CCT the goal was to increase the school attendance of children. By employing loss framing instead of gain framing, households would lose money for each day a child did not attend school instead of gaining money per attended day of school, the positive impact of the CCT was slightly increased. Since people are more likely to prevent losses, this can be useful information for future CCTs (Fujii et al., 2021).

Gennetian et al. (2021) also studied behavioral insights into cash transfer programs. Firstly, they conclude that humans have the tendency to satisfy immediate needs rather than worrying about

future needs, which is known as present bias. Also, loss aversion is again mentioned as something that influences the parent's decisions. Furthermore, living in poverty puts a lot of stress on parents draining their mental capacity. As a result it limits their ability to make efficient decisions. Gennetian et al. (2021) further elaborate that the conditions of CCTs can increase the amount of stress and further drain their mental capacity. Therefore, they suggest unconditional cash transfers might be better than conditional ones. If conditions are deemed as necessary, they should at least require minimal administrative requirements. Furthermore, cash transfers should be provided on a regular basis instead of a one-time transfer. Lastly, they suggest the use of nudges to encourage the desired behavior from parents. For example, they analyzed an unconditional cash transfer program in Morocco where told the cash grants should be used for their children's education. The program substantially improved the educational outcomes of participating children.

2.6 Contribution to literature

Previous research has shown the positive impacts of the Pantawid CCT. Through the years impact evaluations established positive results in a lot of different areas. The Pantawid program has successfully showed a reduction of poverty rates among participating households. Furthermore, the program showed increased rate of school enrollment and a reduction in dropout rates. Food poverty was decreased and positive health effects were established. Mothers got more prenatal checkups, children more often received deworming pills and participating children showed more grit to reach their long-term goals.

The most concerning issue identified in the evaluations was the reduction of the real value of the grants. The grants had not been raised since the start of the program. Therefore, Acosta & Velarde (2015) concluded the real value of the grant was reduced by 42%. This concern was again highlighted in the latest impact evaluation of Orbeta et al. (2021). Between these two evaluations the rice subsidy was introduced. Which should partly cover the real value reduction.

This thesis will analyze the effect of the rice subsidy on birth weight of children in the Pantawid CCT. This will add to the existing literature because the latest impact evaluation used data from the 2017 DHS program. This thesis will compare the birth weights of the 2017 and 2022 DHS program. Furthermore, it will be interesting to see if the birth weight increased because of the rice subsidy or that the participants might use the rice subsidy to cover the lost real value of the grants. The conclusions of this thesis can create interesting new ideas for follow-up research.

2.7 Hypothesis

As mentioned in the introduction food poverty is a big problem in the Philippines among the target audience of the Pantawid program. The consensus of Delgado and Velarde (2011) was that the program could positively influence food poverty. In the impact evaluations discussed in section 2.4.1 this positive effect was established. Delgado and Velarde (2011) found a decrease of 6.2% in food poverty among the participants. In the second impact evaluation a decrease of 6,7% was established (Acosta & Velarde, 2015) and the third evaluation found that households from the CCT increased their spending on food and suffered less from hunger (Acosta et al., 2021). The research question of this thesis is:

What influence had the introduction of the rice subsidy on birth weight of children?

Multiple studies have been conducted on the relationship between maternal nutrition and the birth weight of children. Low birth weight is something that occurs more often in Asia and it is predominantly due to the maternal nutrition during and before the pregnancy. It is a problem because babies with low birth weight are four times more likely to die during the first month of their life. A randomized controlled trial in Gambia showed an increase in birth weight by increasing the maternal weight. A positive effect of 136 grams was established (Muthayya, 2009). Furthermore, another study established a significant correlation between maternal weight gain and birth weight (Diemert et al., 2016).

As the rice subsidy is created to increase the food consumption of the participants and participants have proven to spend the grants on essential needs and not on vice goods (Acosta et al., 2021). The expectation is that the rice subsidy will led to higher food consumption and therefore a higher maternal weight. Therefore, the hypothesis to the research question is:

H1: Children born after the introduction of the rice subsidy will on average have a higher birth weight

3.0 Data

The following section will address the dataset of the thesis. Firstly, the source will be addressed. Secondly, the dependent and independent variable will be presented. Lastly, the control variables will be discussed.

3.1 Data source

The data used in this thesis is collected from the website of the Demographic Health Survey (DHS) program. The DHS program was created more than thirty years ago by the United States Agency for International Development. During this period the DHS program has run more than 320 surveys in 90 countries across Africa, Latin America, Eastern Europe and Asia. It works together with local governments to perform the surveys and collect information about people and their health. Anyone can request access to the data to perform research. The data is often used to implement policies, health programs or funding priorities (USAID, 2023).

In this thesis we will use two different datasets from the DHS program in the Philippines: the 2017 and the 2022 Standard DHS. The surveys collect data on a wide range of variables. All the respondents are female and between 15 and 49 years old. The 2017 and 2022 mostly contain the same questions and therefore the same variables in their datasets. For this research a merged dataset of the 2017 and 2022 survey will be used.

3.2 The dependent and independent variable

The dependent variable of the research is birth weight. This variable, m19, is included in both surveys and shows the birth weight of babies in grams. The variable m19 is followed by a unique identifier for each child. m19_1 refers to the data for the last-born child, m19_2 refers to the data for the second-to-last-born child, and so on. This research will use m19_1 as its dependent variable for two reasons. Firstly, m19_1 has by far the most observations. Before cleaning the data, m19_1 has 12,385 observations, m19_2 has 2,698 and this quickly further declines till only 2 observations for m19_6. This is important as a larger sample size leads to reduced sampling error and reduced standard errors. Secondly, the rice subsidy is implemented in 2017. By looking at the last born child of the 2022 survey we know their mothers were pregnant after the introduction of the rice subsidy, since the children are a maximum of five years old.

After merging the datasets there are 52,895 observations. However, there are a lot of missing values for the dependent variable which need to be dropped. In this dataset we have ordinary missing values, 9996 for babies who were not weighed and 9998 if mothers do not know the birth weight. All of

these values need to be dropped for our research. This leaves us with 10,538 observations. However, the variable still contains a lot of illogical observations. Which is shown in the boxplot in figure 1. According to the WHO an average baby has a birth weight between 2.5 kg and 4,0 kg. Babies born weighing 4.42 kg are in the top 2%, while those weighing 2.39 kg fall into the bottom 2% (De Pietro CRT, 2024). Furthermore, the values of the upper and lower whisker of the boxplot are: 4350 grams and 1550 grams. Therefore, we will drop the birth weight variables higher than 4500 grams and lower than 1500 grams as this are not plausible birth weights. This leaves the dataset with 10,158 observations.

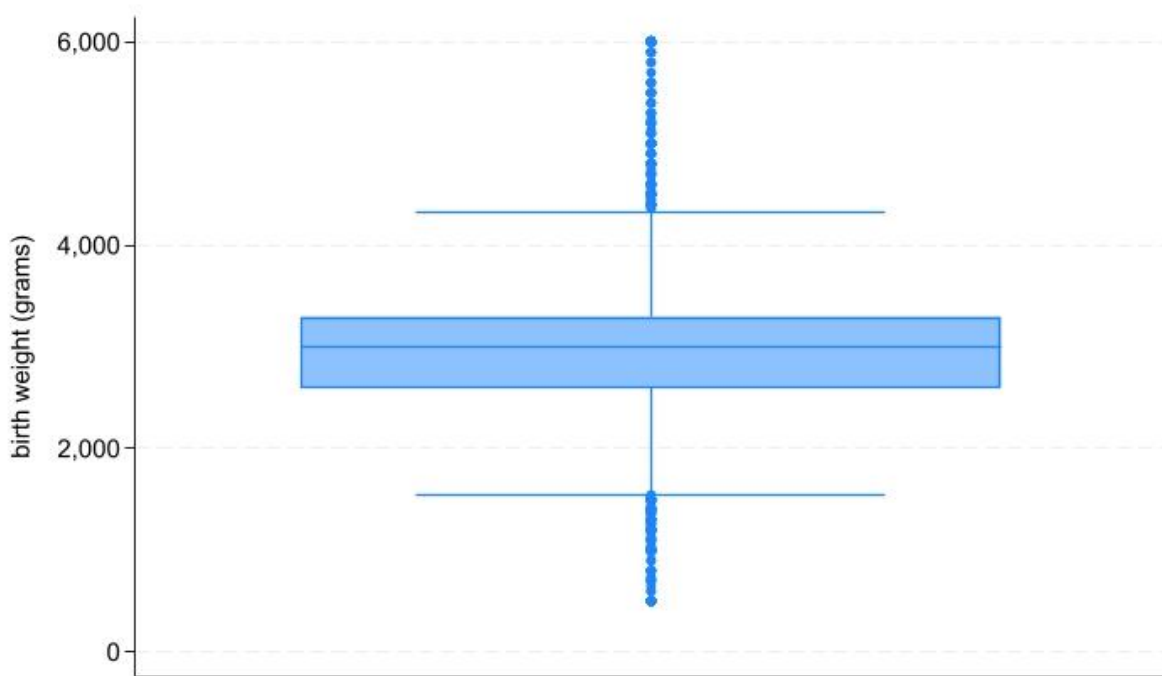


Figure 1: Boxplot of the birth weight variable. This boxplot displays the distribution of birth weights (in grams) among newborns in the study sample. The box represents the interquartile range (IQR), with the median indicated by the line inside the box. Whiskers extend to 1.5 times the IQR, and individual points outside this range are considered outliers.

The ideal dependent variable would be one that indicates whether a respondent participated in the Pantawid CCT. Unfortunately, such a variable is not part of the DHS datasets. Therefore, the dependent variable *postsubsidy* is created by combining other variables of the dataset. In the most recent impact evaluation Orbeta et al. (2021) mentioned the program covered 60% of the households in the poorest quintile. According to the most recent data the CCT now covers 4.4 million households (DSWD). In total there are 26,393,906 households in the Philippines (PSA, 2022). This means roughly 5.3 million households belong to the poorest quintile. Therefore, we will assume in this thesis that people from the poorest quintile belonging to the dataset of 2022 will have participated in the CCT and got the rice subsidy. Finally, only the data of the poorest quintile will be kept as they are the only observations that could have gotten the subsidy. This leaves 2,834 observations.

3.3 Control variables

Control variables are added to the model to reduce omitted variable bias and extract the real effect of the independent variable. A good control variable should affect our variable of interest, birth weight, independent of the effect of the rice subsidy. In this research multiple control variables are added: sex of the baby, fixed region effects, whether a person lived in a rural or urban setting, highest educational attainment and access to electricity.

The sex of the baby is an important determinant of birth weight. Male babies are heavier compared to female babies (Dougherty & Jones, 1982). The sex of the baby does affect the birth weight, but does not decide participation to the CCT. Fixed region effects control for unobserved factors that vary across regions but not over time. With the addition of fixed region effects several factors are accounted for. For example, the difference in access to healthcare and environmental factors like air pollution. It provides the analysis with the effect of the subsidy per region. The variable rural can account for unobserved differences between participants living in cities or in rural areas. Furthermore, a study among Malaysian women found higher rates of low birth weight in rural areas compared to urban areas (Kaur et al., 2019). Dougherty and Jones (1982) also found a significant effect for educational attainment on birth weight. A higher educational attainment of the mother contributed to a higher birth weight of their children. The last control variable added is access to electricity. Access to electricity, provides households with the option to refrigerate food, store medications and improve quality of life in general. This increases the maternal weight, which increases the birth weight (Rode et al., 2007).

An important aspect with control variables is to check for multicollinearity. Normally, the first step would be a correlation matrix. As this research uses categorical variables this is not an option. Therefore, a variance inflation factor (VIF) is performed. The results of the VIF test are shown in table 1. To ensure readability the VIF scores of 17 regions are left out. Their VIF scores vary from 1.39 till 6.46. VIF scores are considered alarming when they have a value which is bigger than 10 (Vittinghof et al., 2005). As shown by the table all the VIF values are lower than 10, except four educational variables. However, this is not a problem in this case as high VIF scores are expected for categorical variables as they reflect the inherent correlation among the dummy variables (Kalnins & Hill, 2023). Furthermore, they are all significant and improve the significance of the subsidy variable. This will be further elaborated in the results section.

VIF values (region left out in table)	
Variable	VIF
Postsubsidy	1.05
Education	
1. Incomplete primary	11.30
3. Complete primary	10.62
3. Incomplete secondary	17.61
4. Complete secondary	18.15
5. Higher	9.45
Rural	1.12
Female	1.01
Electricity	1.04
Mean VIF	5.82

Table 1: VIF test.

4.0 Methodology

4.1 Analysis method

The goal of this thesis is to research the effect of the rice subsidy on the birth weight of children. In an ideal world a randomized controlled trial would be conducted to determine the causal effect. However, that is not the case. As mentioned in the data section, the DHS program does not have a variable to indicate whether an individual was part of the Pantawid CCT. Since eligibility for Pantawid CCT is determined by the proxy means test, there is not a clear threshold in terms of wealth or income. Therefore, a regression discontinuity design was not an option as well. Because of these data limitations, this thesis will try to estimate the effect of the introduction of the rice subsidy by running a pre-post comparison on birth weight.

4.2 Data preparation

For the pre-post comparison two datasets of the DHS program are merged: the 2017 and 2022 surveys. After the datasets are merged, the data has to be prepared for the analysis. Since birth weight is the dependent variable all missing values and outliers are dropped. Thereafter, only the data of people from the poorest quintile are kept since only they could have participated in the Pantawid CCT. Variables also get renamed into clear names. For example, *m19_1* becomes birth weight. Lastly, the control variables are checked for multicollinearity.

4.3 Analysis

To establish the effect of the introduction of the rice subsidy a pre-post comparison is performed. In this comparison, birth weights of babies from the 2017 survey are compared to birth weights of babies in the 2022 survey. If a baby is part of the survey it means the baby was born in the last five years at the moment of the survey. The variable *postsubsidy* is created to enter in the regression on birth weight. This variable equals 1 for babies from the 2022 dataset and 0 for babies from the 2017 dataset. Furthermore, we add the control variables to the regression model to try and reduce omitted variable bias and improve the significance of the *postsubsidy* variable. The basic linear regression model is shown in the formula:

$$\text{birth weight} = \beta_0 + \beta_1 * \text{postsubsidy} + \varepsilon$$

In this model β_0 is called the intercept, which means it shows the average predicted value of birth weight when all independent variables are equal to zero. So in this case, it shows the average predicted value of a baby born from the 2017 dataset. β_1 shows the change in average birth weight when the *postsubsidy* variable equals 1 instead of 0. This variable should tell us the average effect of

the rice subsidy on birth weight. Lastly, the ε is the error term. The error term captures the unexplained variance in birth weight, which is not accounted for by the *postsubsidy* variable. It represents the difference between an actual data point and the predicted birth weight based on the regression model. The final model with control variables is:

$$\begin{aligned} \text{Birth weight} = & \beta_1 * \text{postsubsidy} + \beta_2 * \text{region2} + \beta_3 * \text{region3} + \dots + \beta_{17} * \text{region17} \\ & + \beta_{18} * \text{rural} + \beta_{19} * \text{female} + \beta_{20} * \text{education1} + \dots + \beta_{24} * \text{education5} \\ & + \beta_{25} * \text{electricity} + \varepsilon \end{aligned}$$

The model works the same as the first simple regression, but it now has the addition of control variables. For example, β_{19} shows the average change in birth weight when a baby is a female compared to being male. The variable *female* is a dummy variable, which equals 1 for females and 0 for males. The variable *region* is added as fixed regional effects to the multiple regression model. Regional fixed effects are used to control for unobserved variables that could bias the coefficient of *postsubsidy*. The fixed regional effects control for differences between regions that do not change over time. With the addition of these fixed effects to the model, it considers that each region has unique characteristics that could influence the birth weight independently of the other control variables. For example, the accessibility of healthcare could differ in regions or environmental factors like air quality.

The control variables are added one by one with the first simple regression as starting point. If a control variable tributes to the significancy of the *postsubsidy* variable, improves the overall fit of the model by making R-squared higher or improving the F-statistic the control variable was kept in the model. On the condition, it did not cause multicollinearity and academic articles supported the variable to be a good control variable for birth weight.

The analysis of the data is performed in Stata, which is a statistical software for data science. The regressions are all run with the *robust* command. Adding the robust command makes sure Stata runs the regression with robust standard errors, which can deal with heteroscedasticity. Heteroscedasticity occurs when the variance of the errors is not constant across observations. Without robust standard errors this could lead to biased parameter estimates. Furthermore, robust standard errors compute more reliable p-values for variables.

4.4 Pre-post comparison shortcomings

Ideally, an experimental set up or a quasi-experiment would have been analysed to research the effect of the introduction of the rice subsidy. Unfortunately, due to data limitations, such a set up was not part of the possibilities. The reason these methods would have been preferred compared to

a pre-post comparison is that they provide the ability to try and identify a causal effect of the subsidy. This means the change of birth weight could be fully attributed to the introduction of the rice subsidy. This makes the results really useful to evaluate the subsidy and come up with suggestions for new policies or subsidies.

Unfortunately, a pre-post comparison does not provide a causal effect. The result of the regression analysis shows the correlation between birth weight and the rice subsidy. However, that does not mean the change in birth weight is caused by the introduction of the subsidy. They could be a lot of other reasons why birth weight has changed. For example, changes in external factors, like economic or medical shifts, could influence birth weight. Furthermore, the people from the 2017 survey are not the same people that participated in the 2022 survey. Therefore, they could differ in their characteristics. This could again bias the effect of the subsidy, making it impossible to find a causal effect. A pre-post comparison also have very low external validity. This means that the results of the research can not be generalized towards other populations.

5.0 Results

This section will present the results of the regression analysis. Firstly, the simple regression model will be presented. After this, the final multiple regression model will be presented.

5.1 Simple regression model

To answer the research question regression analysis was performed in Stata. Firstly, a simple regression model, which shows the correlation between the *postsubsidy* and *birth weight* variable, was run. The results of the simple regression model will be presented in table 2 below. The simple regression model is equal to:

$$birth\ weight = \beta_0 + \beta_1 * postsubsidy + \epsilon$$

Dependent variable: birth weight

Postsubsidy	-33.888
	(20.784)
Constant	2961.079
Observations	2834
R ²	.0

Note. Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

Table 2: simple regression model

The results in the table 2 should be interpret as follows. The constant coefficient is the average birthweight of babies which did not receive the rice subsidy treatment. The *postsubsidy* coefficient shows the change of grams in birth weight, when *postsubsidy* is equal to a value of 1 which means the mother of the baby got the rice subsidy. In this simple regression model the subsidy holds a negative effect of 33.888 grams on the birth weight. The coefficient is not significant on a 1%,5% or 10% level. The model is run with 2,834 observations and the value of R-Squared, which measures which proportion of the variance in birth weight is explained by the independent variables of the model, is equal to 0.0009. This is equal to 0.09%, which is very low.

5.2 Multiple regression model

The second regression is run with the control variables, making it a multiple regression model. The results of the regression are shown in table 3. The multiple regression model is equal to:

$$\begin{aligned} \text{Birth weight} = & \beta_1 * \text{postsubsidy} + \beta_2 * \text{region2} + \beta_3 * \text{region3} + \dots + \beta_{17} * \text{region17} \\ & + \beta_{18} * \text{rural} + \beta_{19} * \text{female} + \beta_{20} * \text{education1} + \dots + \beta_{24} * \text{education5} \\ & + \beta_{25} * \text{electricity} + \varepsilon \end{aligned}$$

After adding the control variables, the results in table 3 are different than those of the simple regression in table 2. The coefficient of *postsubsidy* is now equal to -43.719 grams and it is significant at a 5% level. The R-squared value increased to 0.0177, but is still very low. The region fixed effects are left out in table 3, but will be added in the appendix. Only a few regions have significant effects. Furthermore, female babies are on average 65.976 grams lighter than male babies this is significant at a 1% level. Babies whose mothers live in a rural area are 31.15 grams lighter on average, but the result is not significant. Access to electricity has a positive impact of 21.12 grams, but is only significant on a 10% level. All education variables are significant on at least a 5% level. The value of those variables tell us how much the birth weight increases for a education level compared to mothers that followed no education. As mentioned in the data section, the education variables delivered a very high VIF score. Besides the reasons that were mentioned in that section, they were kept in the model because all of them were significant, increased the significancy of the variable of interest and made the model a better overall fit.

Since the p-value of *postsubsidy* is 0.040 and the coefficient is -43.719, we can reject the null hypothesis that there is no difference in birth weight. The results, however, found that on average the subsidy led to a decrease of -43.719 grams in birth weight. Therefore, the hypothesis of the thesis is rejected as it stated that babies born after the introduction of the rice subsidy would on average have a higher birthweight.

It is important to note that the regression model provides an Intent-to-Treat (ITT) effect. An ITT analysis measures the impact of being assigned to a treatment group, regardless of whether an individual actually received the treatment. It does not consider noncompliance, withdrawal or protocol deviations (Gupta, 2011). In this case, the ITT effect, estimates the average effect of the introduction of the rice subsidy on the birth weight of the poorest quintile population. It is assumed that all the individuals from the postsubsidy period are assigned to the treatment condition.

Dependent variable: Birth weight

Postsubsidy	-43.719**
	(21.302)
Rural	-31.154
	(28.655)
Female	-65.976***
	(20.126)
Education	
Incomplete primary	186.532**
	(86.176)
Complete primary	218.936**
	(86.624)
Incomplete secondary	222.209***
	(83.815)
Complete secondary	196.820**
	(83.684)
Higher	210.960**
	(85.754)
Electricity	21.124*
	(12.744)
Constant	2786.71
Observations	2,834
R ²	.0177

Note. Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

Table 3: Multiple regression model. Regions left out for readability.

6.0 Conclusion

CCTs are a relatively new method to address poverty and its consequences. Countries in Latin America started with the experimental set up of these programs and found positive impact on the desired outcomes based on RCTs. This provided scientific evidence that the CCTs had the desired outcome and more countries started to adopt these kind of policies. The Philippines also started a CCT to address problems coming from poverty. This program is called the Pantawid Pamilyang Pilipino Program.

Multiple studies researched the effect of the Pantawid CCT on outcomes like school enrolment and attendance, food poverty, current poverty and many other health or behavior related outcomes. All the three impact evaluations, which were addressed in the literature review section, found positive effects on these outcomes. Therefore, the program was gradually expanded in the Philippines. In 2017 an extra subsidy was introduced to the CCT, called the rice subsidy. It was added to increase the food consumption of the participants and partly to cover the lost real value of the grants.

The goal of this thesis was to research the effect of the introduction of the rice subsidy on birth weight. To gain a more comprehensive understanding of the introduction of the rice subsidy, data from the 2017 and 2022 Philippine Demographic and Health Surveys (DHS) were merged and analyzed. By combining the articles about the impact of the Pantawid CCT and articles about the effect of maternal weight on birth weight, the following hypothesis was formed: *Children born after the introduction of the rice subsidy will on average have a higher birth weight.*

However, the results of the pre-post comparison led to the rejection of the hypothesis. A significant, negative coefficient was found for the subsidy effect on birth weight. On average, a negative effect of 43.72 grams was found for children born after the introduction of the rice subsidy. This was a surprising result as academic articles directed towards a positive outcome, which also feels more logical.

There are two different possible reasons for this unexpected result. Firstly, the grants of the program have never been corrected against inflation. This resulted in the fair value of the grants becoming increasingly lower over the years. The hope was that the rice subsidy could also partially compensate for loss in value, but it might not have been enough. Furthermore, the performed research could not have captured the right relationship. There were a lot of limitations on the data, which therefore also limited the research methods. There was no data on whether a respondent of the survey participated in the CCT. Therefore, a variable was created with assumptions that are

based on scientific articles. However, it is still a small chance that the people who are considered to have participated in the CCT in this research actually have. This could possibly have led to wrong estimations on the impact of the rice subsidy.

7.0 Discussion

In future research, researchers should find a better way to identify participants of the CCT. Ideally, a connection to Listahanan would be available or the question could be added to the DHS survey. This would make the impact evaluation of the CCT on different topics more accessible. This would also allow for different set-up of possible evaluations. Researchers, could use quasi-experimental set-ups compared to the pre-post comparison of this thesis. That would allow them to find causal effects of the CCT, which was not possible in this thesis due to data limitations. Finding causal effects would support better policy suggestions as the results can be fully attributed due to the difference in treatment.

The results of the thesis are contrary to the existing academic articles. Barber and Gertler (2008) found an increase of 127.3 grams in birth weight of children participating in the Oportunidades CCT and a reduction in the prevalence of low birth weight. Additionally, previous impact evaluations of the Pantawid CCT found that the CCT reduced food poverty. This raises the expectation that the introduction of the rice subsidy should at least further reduce food poverty and therefore, increase maternal weight. Especially, since is demonstrated that the participants of Pantawid spend the grants on basic necessities as food instead of vice goods (Acosta et al., 2021). Given that maternal weight is a well-established predictor of birthweight, the expectation was that the introduction of the rice subsidy would lead to, on average, higher birth weights (Acosta et al., 2021; Rode et al., 2007; Muthayya, 2009).

It should be useful to address this topic in future research with better methods to evaluate the impact of the rice subsidy. Furthermore, the effect of inflation on the decreasing real value of the grants is something what should really draw the attention of future research. Previous impact evaluations on the Pantawid CCT all found positive effects on the desired outcomes. However, these effects could possibly become smaller or disappear if the value of the grants do not keep up with the real prices of food, school or healthcare. This really stresses the importance of future research on this topic. Especially, if the Philippine government wishes to continue the positive results of the Pantawid program in the upcoming years.

8.0 References

- Acosta, P. A., & Velarde, R. (2015). "Sa Pantawid, Malapit nang Makatawid!" (With Pantawid, we are closer to getting out of poverty!) of the Philippine Conditional Cash Transfer's. *PHILIPPINE SOCIAL PROTECTION NOTE*. <http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2016/03/24/090224b08422f92b/Rendered/PDF/AnUpdateOfOt0entation0performance.pdf>
- Angelucci, M., & De Giorgi, G. (2009). Indirect Effects of an Aid Program: How Do Cash Transfers Affect Ineligibles' Consumption? *The American Economic Review*, 99(1), 486–508. <https://doi.org/10.1257/aer.99.1.486>
- Aycinena, D., Blazsek, S., Rentschler, L., & Sandoval, B. (2019). Smoothing, discounting, and demand for intra-household control for recipients of conditional cash transfers. *Journal Of Applied Economics*, 22(1), 219–242. <https://doi.org/10.1080/15140326.2019.1596641>
- Barber, S. L., & Gertler, P. J. (2008). The impact of Mexico's conditional cash transfer programme, Oportunidades, on birthweight. *TM & IH. Tropical Medicine And International Health/TM & IH. Tropical Medicine & International Health*, 13(11), 1405–1414. <https://doi.org/10.1111/j.1365-3156.2008.02157.x>
- Barham, T. (2011). A healthier start: The effect of conditional cash transfers on neonatal and infant mortality in rural Mexico. *Journal Of Development Economics*, 94(1), 74–85. <https://doi.org/10.1016/j.jdeveco.2010.01.003>
- Corcoran, M. (2009). Mobility, Persistence, and the Consequences of Poverty for Children: In *Harvard University Press eBooks* (pp. 127–161). <https://doi.org/10.2307/j.ctv1pncqhv.9>
- Dávila Lárraga, L. G. & Inter-American Development Bank. (2016). How Does Prospera Work? Best Practices in the Implementation of Conditional Cash Transfer Programs in Latin America and the Caribbean. In *IDB Technical Note* (report Nr. 971; p. 1). <http://www.iadb.org>
- Delgado, L. P. F., & Velarde, R. B. (2011). Welfare and distributional impacts of the Pantawid Familyang Pilipino Program. *PHILIPPINE SOCIAL PROTECTION NOTE*, 1–12. <http://www->

wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2011/08/04/000333038_20110804015456/Rendered/PDF/634180REVISED0Box361516B00PUBLIC00PSPN03.pdf

De Pietro Crt, M. (2024, June 19). *What is the average baby weight by month?*

<https://www.medicalnewstoday.com/articles/325630>

Diemert, A., Lezius, S., Pagenkemper, M., Hansen, G., Drozdowska, A., Hecher, K., Arck, P., & Zyriax, B. C. (2016). Maternal nutrition, inadequate gestational weight gain and birth weight: results from a prospective birth cohort. *BMC Pregnancy And Childbirth*, 16(1).

<https://doi.org/10.1186/s12884-016-1012-y>

Dougherty, C., & Jones, A. (1982). The determinants of birth weight. *American Journal Of Obstetrics And Gynecology*, 144(2), 190–200. [https://doi.org/10.1016/0002-9378\(82\)90627-5](https://doi.org/10.1016/0002-9378(82)90627-5)

Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2017). Moving Beyond Correlations in Assessing the Consequences of Poverty. *Annual Review Of Psychology*, 68(1), 413–434.

<https://doi.org/10.1146/annurev-psych-010416-044224>

DSWD. (2018). *INTRODUCTION TO LISTAHANAN*. DSWD. Geraadpleegd op 21 mei 2024, van

https://listahanan.dswd.gov.ph/wp-content/uploads/2019/11/listahanan_info_kit_7.pdf

DSWD. (2024, February 28). *Increased 4ps budget to benefit 4.4 million eligible poor households – DSWD spox*. Department of Social Welfare and Development. <https://www.dswd.gov.ph/increased-4ps-budget-to-benefit-4-4-million-eligible-poor-households-dswd-spox/>

Fernald, L. C., Gertler, P. J., & Neufeld, L. M. (2008c). Role of cash in conditional cash transfer programmes for child health, growth, and development: an analysis of Mexico's Oportunidades. *Lancet*, 371(9615), 828–837. [https://doi.org/10.1016/s0140-6736\(08\)60382-7](https://doi.org/10.1016/s0140-6736(08)60382-7)

Fujii, T., Ho, C., Ray, R., & Shonchoy, A. (2021). *Conditional Cash Transfer, Loss Framing, and SMS Nudges: Evidence from a Randomized Field Experiment in Bangladesh* (No. 2109). Florida International University, Department of Economics.

- Gennetian, L. A., Shafi, E., Aber, J. L., & De Hoop, J. (2021). Behavioral insights into cash transfers to families with children. *Behavioral Science & Policy*, 7(1), 71–92.
<https://doi.org/10.1353/bsp.2021.0003>
- Gupta, S. K. (2011). Intention-to-treat concept: A review. *Perspectives in Clinical Research*, 2(3), 109.
<https://doi.org/10.4103/2229-3485.83221>
- Huang, C., & Liu, J. (2022). International Cooperation on Poverty Reduction. In *Research on the Concept and Practice of Poverty Reduction in China* (pp. 147–162).
https://doi.org/10.1007/978-981-16-9519-3_9
- Kalnins, A., & Hill, K. P. (2023). The VIF Score. What is it Good For? Absolutely Nothing. *Organizational Research Methods*. <https://doi.org/10.1177/10944281231216381>
- Kaur, S., Ng, C. M., Badon, S. E., Jalil, R. A., Maykanathan, D., Yim, H. S., & Mohamed, H. J. J. (2019). Risk factors for low birth weight among rural and urban Malaysian women. *BMC Public Health*, 19(S4). <https://doi.org/10.1186/s12889-019-6864-4>
- Mood, C., & Jonsson, J. O. (2015). The Social Consequences of Poverty: An Empirical Test on Longitudinal Data. *Social Indicators Research*, 127(2), 633–652.
<https://doi.org/10.1007/s11205-015-0983-9>
- Muthayya, S. (2009). Maternal nutrition & low birth weight - what is really important? *PubMed*, 130(5), 600–608. <https://pubmed.ncbi.nlm.nih.gov/20090114>
- Orbeta, A. C., Melad, K. A. M., & Araos, N. V. V. (2021). Reassessing the Impact of the Pantawid Pamilyang Pilipino Program: Results of the Third Wave Impact Evaluation. *PHILIPPINE INSTITUTE FOR DEVELOPMENT STUDIES*.
<https://www.econstor.eu/bitstream/10419/241053/1/pidsdps2105.pdf>
- Parker, S. W., & Todd, P. E. (2017). Conditional Cash Transfers: The Case of Progresa/Oportunidades. *Journal Of Economic Literature*, 55(3), 866–915. <https://doi.org/10.1257/jel.20151233>
- PSA. (2022, March 23). *Household population, number of households, and average household size of the Philippines (2020 census of population and housing) | Philippine Statistics Authority | Republic of the Philippines*. Household Population, Number of Households, and Average

Household Size of the Philippines (2020 Census of Population and Housing).
<https://psa.gov.ph/content/household-population-number-households-and-average-household-size-philippines-2020-census>

Rode, L., Hegaard, H. K., Kjærgaard, H., Møller, L. F., Tabor, A., & Ottesen, B. (2007). Association Between Maternal Weight Gain and Birth Weight. *Obstetrics And Gynecology (New York. 1953. Online)/Obstetrics And Gynecology, 109(6)*, 1309–1315.
<https://doi.org/10.1097/01.aog.0000266556.69952.de>

USAID. (2023). *The Demographic and Health Surveys Program*. U.S. Agency For International Development. <https://www.usaid.gov/global-health/demographic-and-health-surveys-program>

Vittinghoff, E., Glidden, D. V., Shiboski, S., & McCulloch, C. E. (2005). *Regression methods in biostatistics: linear, logistic, survival, and repeated measures models*.
https://cds.cern.ch/record/1499230/files/9781461413523_TOC.pdf

Webber, S., & Prouse, C. (2017). The New Gold Standard: The Rise of Randomized Control Trials and Experimental Development. *Economic Geography, 94(2)*, 166–187.
<https://doi.org/10.1080/00130095.2017.1392235>

9.0 Appendix

Dependent variable: Birth weight

Cagayan Valley	-89.365
	(101.835)
Central Luzon	123.603
	(96.861)
Calabarzon	-27.965
	(109.578)
Bicol	99.704
	(87.380)
Western Visayas	12.998
	(88.002)
Central Visayas	99.331
	(94.453)
Eastern Visayas	165.359*
	(87.186)
Zamboanga Peninsula	61.994
	(89.544)
Northern Mindanao	151.330*
	(87.019)
Davao	109.728
	(88.596)
Socccsargen	127.139
	(88.624)
National Capital	85.466
	(157.457)
Cordillera	106.140
	(89.921)

Autonomous region in muslim Mimaropa	208.994***
	(87.702)
Caraga	90.952
	(88.746)
Mimaropa	89.056
	(90.642)

Note. Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

Table 4: Left out regions coefficients from multiple regression model