The Impacts of Conditional Cash Transfers on Labor Markets: Evidence from the Philippines

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Abstract

Although Conditional Cash Transfers (CCTs) programs have been perceived to be widely successful in reducing short-term poverty and improving educational and health outcomes of children, their indirect impacts on the labor market or on the local economy remain uncertain. In fact, there has been rising concerns on the disincentive effects of CCTs, which could negatively affect the labor market by reducing labor supply. Given this context, this paper studies the long-term impacts of the CCTs on the labor market. Specifically, it evaluates the labor market outcome in the Philippines from 2009 and 2014 following the introduction of a national social protection program called the Pantawid Pamilyang Pilipino program in 2008. The main finding of the study is that the CCT has positive, yet weak, impacts on the labor market outcomes. The largest impact found in the study is a change in work hours per week, which increase by 4.2 %, or approximately 1 hour and 12 minutes, 2 years following the treatment. The study also confirms that, while the CCT has a potential to reduce worker incentives, the treatment effects on labor supply remain positive, which leads to a conclusion that the overall positive impacts of the CCT on the labor market are driven by an increase in labor supply among the beneficiaries after the treatment.

0. Introduction

Conditional Cash Transfer (CCT) programs are one of the most successful welfare policies in developing countries over the past two decades. After the success of CCTs in the early 2000s, notably *Bolsa Familia* in Brazil and *PROGRESA* in Mexico, countries across Latin America and Africa have consecutively implemented them with the aim of supporting poor families. In fact, today over 63 countries implement at least one conditional cash transfer program (Smith, 2020).

The concept of CCTs is straightforward. The government provides transfers to poor households on the condition that they meet certain criteria, which include sending children to school, receiving regular health checkups, and meeting nutritional requirements. Many CCT programs in developing countries have been remarkably successful in reducing short-term poverty and improving the well-being of the poor families. For example, *PROGRESA* increases the income level of the poorest households by 22%. The program also contributes to a 10% increase in educational attainment of rural children in Mexico. (Skoufias et al., 2001). Apart from these outcomes, CCTs can promote female empowerment by providing education and health grants directly to the female household head. These positive outcomes of CCTs are observed consistently in other developing countries including *Familias en Acción* in Colombia, *Chile Solidaro* in Chile, and *Red de Protección* Social in Nicaragua.

Despite the well-established success of CCTs on reducing poverty and increasing human capital, there are rising concerns over the long-term impacts of CCTs on labor supply. Some critics of CCT have claimed that offering transfers to poor households can reduce incentives of the workers, which leads to a decline in productivity and labor supply. In fact, some studies presented evidence that the distortion of incentives to work happens among the beneficiaries of the CCT in Latin America (Levy, 2008). Having accurate understandings of the impacts of CCT on labor market is extremely salient as the activities in the labor market directly influence stability and growth of the country's economy. Moreover, the use of means-tested welfare programs tends to increase as the country's economy grows larger (Gerald et al., 2021), suggesting that the impacts of CCT on labor market are also likely to expand in many developing countries in the next decade.

Given this context, this paper aims to explore the impacts of CCTs on the labor market. This paper specifically analyzes the Pantawid Pamilyang Pilipino Program (the Pantawid Pamilya), a national cash transfer program in the Philippines launched in 2007. Like CCTs in many other countries, the program provides cash grants to low-income households to alleviate poverty and improve educational, health, and nutritional outcomes of children. I use the Labor Force Survey between 2009 and 2014 to obtain data on the labor market outcomes—including total work hours, basic salary per day, and number of jobs. I also use 2009 Official Poverty Statistics and 2006 Small Area Estimates (SAE) to identify eligible municipalities of the CCT. With this data, this paper examines the causal effects of the Pantawid Pamilya on the labor market. This study focuses on employment in the formal labor market since the data on informal employment is not available through the Philippine Statistic Authority, where most of the data in this paper is provided from.

This study employs two regression models—difference in differences (DID) model and regression discontinuity (RD) design—to examine data. The main finding of the study is that the Pantawid Pamilya has positive, yet small, impacts on the overall labor market outcomes. Average work hours per week increase by 4.2 % (around 1 hour and 12 minutes) 2 years following the treatment. Although I find no strong evidence of treatment effects on some of the employment outcome variables such as hourly wages and number of jobs, the results suggest that it is unlikely that the Pantawid Pamilya has any significant negative impacts on the labor market outcomes. The second half of the paper focuses on analyzing the impacts of the Pantawid Pamilya, specifically, on labor supply. The results show that the CCT positively influences the labor supply outcomes such as work hours and salary per day despite some negative effects on worker incentives. The study concludes that while the concerns on disincentive effects of the CCTs remain, the impacts of the Pantawid Pamilya on the labor market are positive and are driven by an increase in labor supply among the beneficiaries following the treatment.

This paper contributes to the existing literature by providing insights on the long-term impacts of CCT on the labor market in the Philippines. As discussed earlier, while previous studies have identified the effects of CCTs on reducing poverty and improving educational and health outcomes of children, little is known about the effects of CCTs on employment in the labor market, a factor crucial to the well-beings of the people and a country's economic development. The evidence from this paper is also substantial because the Philippines is a country less studied compared to those in Latin America or Africa in terms of CCT. Moreover, to the extent of my knowledge, there has not been a published scholarly article that evaluates the impacts of CCT on the entire labor market in the Philippines using quantitative methods. Although some countries in Southeast Asia have started to develop CCTs following the examples of Latin America, many of them are still in their preliminary stages of development and have not been thoroughly evaluated. Due to the rising economic powers of ASEAN nations, however, it has become increasingly critical to assess the impacts of CCTs among Southeast Asian countries and develop understandings on their implications to their economic development. Thus, this paper aims to provide insights on the long-term impacts of CCTs on employment that are not only applicable to the Philippines but also to other Southeast Asian countries with similar cash transfer programs.

The rest of this paper is organized as follows. Section I introduces existing literature on CCT and their impacts on the labor markets. Section II describes background and data, and Section III explains the empirical strategy. Section IV provides the results, and Section V conducts robustness checks. Finally, Section VI concludes.

1. Literature Review

Many conditional cash transfer programs in developing countries have grown rapidly over the past 20 years. For example, by 1999, *PROGRESA* already covered 2.6 million families, which is equivalent to 1/3 of all the households in Mexico (Skoufias, 2001). The number of beneficiaries in *Bolsa Familia* has also reached 11 million families in 2010 (Soares et al., 2010), becoming the largest CCT program in the world.

After producing positive outcomes in many developing countries, CCTs are often characterized as "magic bullets" in development. What contributes to this extreme popularity of CCT is several rigorous academic papers and experimental studies proving the impacts of CCTs on alleviating short-term poverty in developing countries. Most of the literature has consistently shown evidence of the positive impacts of CCTs on reducing poverty and improving children's educational and health outcomes. A well-cited journal reveals that the program increases secondary school enrollment by 20% for girls and 10% for boys. The beneficiary children also experience a 12% decrease in the incidence of illness and a 13% increase in food expenditure (Skoufias, 2001). Another study on the long-term effects of Conditional Cash Transfer program in Colombia found that children in the beneficiary households were 4 to 8 times more likely to complete high school compared to non-beneficiary children (Baez & Camacho, 2011).

The effects of CCT have been also observed in Southeast Asia. A study on Cambodian CCT conducted by the scholars from the World Bank and the Inter-American Development Bank (IDB) revealed that an annual scholarship of 45 US dollars led to almost 25% increase in school attendance for primary school children, although the evidence suggested "a sharply diminishing marginal response of school attendance to transfer size" (Filmer & Schady, 2011). The positive impacts of CCT on educational and health outcome of children are also noticeable in an Indonesian case study, where school nonenrolment for children aged between 7 and 15 decreased by half, and the likelihood of stunting dropped by 23 % (Cahyadi et al., 2020). The results of these studies are consistent with many other existing literatures. Thus, the short-term impacts of CCTs on education and health have been proven to be effective, which explains why many developing countries have come to implement these conditional welfare programs over the past two decades.

Unlike the short-term effects, however, the long-term impacts of CCTs remain uncertain. Despite the efforts of many scholars to identify the indirect consequences of CCTs—such as impacts on labor markets, housework time allocation, and child labor—, due to limited data and the complexity of the research subject, the evidence on these causal relationships is still weak and insufficient. Given the increasing scale of CCTs in various developing countries, identifying their long-term indirect effects is becoming increasingly salient and pressing. Thus, among the diverse indirect consequences of these welfare programs, this paper focuses on one of the most crucial consequences of CCT: the impacts on labor market. One of the primary goals of conditional cash transfer program is to reduce poverty sustainably by investing in human capital. While there is an expectation that participation in education and health services improves the chance of getting employed and earning a higher income, after two decades of implementation of

CCT across the world, there is no compelling evidence that this causal relationship exists. Moreover, concerns are rising that providing grants to poor households reduces their incentives to participate in the labor market, thus resulting in a negative impact on labor supply.

While we clearly need more evidence before reaching any conclusions on this subject, a few existing literatures provide us with some hypotheses. Research conducted by Gerald et al. provides insightful evidence on the impacts of *Bolsa Familia* on the labor market. In this study, the researchers conduct panel data analysis using administrative data from the former Brazilian Ministry of Social Development (MDS) and find that *Bolsa Familia*, in fact, creates employment in the formal labor market through multiplier effects. The study also reveals, however, that disincentive effects of cash transfers do exist, suggesting that workers from the poor households that receive conditional cash grants are more reluctant to work. The crucial finding of this study is that despite these disincentive effects, CCT still positively contributes to the labor market and employment as the multiplier effect, which increases labor demand, is larger than the disincentive effect, which decreases labor supply (Gerald et al., 2021). Another highly cited article on the long-term impacts of *PROGRESA*, however, finds almost no correlation or causation between the CCT program and labor force participation or leisure time of adults. Despite some fluctuations in labor force participation in the short run, the study concludes that there is no long-term impact of CCT on labor market (Skoufias, 2008).

Some studies also provide evidence on the long-term impacts of CCT on child labor. A five-year follow up evaluation on *PROGRESA* and *Oportunidades* reveals that the probability of working among children aged 9 to 10 preprogram decreased by 30%, 5 years following the programs, whereas older children aged 13 to 15 experienced either an increase or no change in their labor force participation rate. There was a gender gap in labor force participation, where girls were more likely to increase their working hours after they started to receive the benefits from the cash transfer programs (Behrman et al., 2010). Other studies also confirmed that labor force participation decreases for younger children (de Hoop & Rosati, 2014) and increases or remains unchanged for older children after the implementation of CCT programs (Skoufias et al., 2001). Taken together, the results from the existing literature suggest that the overall impacts of CCT on labor market are determined by the balance between demand-side multiplier effects and supply-side disincentive effects, and that children's labor force participation seem to be negatively influenced by the spread of cash transfer programs. Yet, these hypotheses are based on limited evidence and, thus, we need further data-based research on the effects of CCTs on the labor market.

The purpose of this paper can be divided into three elements. First, it aims to understand the dynamic impact of CCTs on labor market outcomes by using data of Labor Force Surveys from 2009 to 2014. The findings not only capture the impacts of the CCT on the aggregate employment in the Philippines but also identify the dynamic movements in the labor market before and after the treatment in 5 years window. Secondly, this paper analyzes the impacts of the CCT on the municipalities—which consist of both the direct impacts on the beneficiary households and the spillover effects on the non-beneficiary households, which allow us to evaluate the treatment effects on a community level. Finally, this study examines the impacts of CCT on the labor market comprehensively by identifying changes in both aggregate employment and labor supply.

2. Background & Data

a. Introduction to the Pantawid Pamilya

The Pantawid Pamilyang Pilipino program is the largest cash transfer program in Southeast Asia. It provides financial supports to poor Filipino households. The program was launched in 2007 by the Department of Social Welfare and Development (DSWD) to meet the short-term needs of poor households while also investing in human capital to reduce poverty in the long run. After undergoing multiple expansions between 2008 and 2014, it currently operates in 17 regions in the Philippines, including 79 provinces, 143 cities, and 1,484 municipalities. The program provides two types of grants—a health grant of P6,000 (US$107) per year per household and an educational grant of P3,000 (US$53) per school year per child. To receive the cash transfers, eligible households must fulfill certain conditions: (1) children aged 0-5 years old must receive regular health checkups and vaccines (2) children aged 3-18 years old must enroll in pre-school, elementary, or secondary school and attend at least 85% per month (3) Pregnant women must visit their local health centers to receive pre-natal and post-natal care, and their delivery must be assisted by a skilled personnel. If these conditions are strictly met throughout the entire year, households can receive a maximum of P6000 ($109) for health grants and P3000 ($54) for educational grants per child[1].

There are two characteristics of the data that are important for understanding the empirical strategies of this paper—difference-in-differences (DID) and regression discontinuity (RD) designs. First, while the Pantawid Pamilya expanded its scale in almost every single region between 2009 and 2014, the speed of expansion varied among the municipalities. The details of the expansion are illustrated in Table 1. After the pilot experiment in 2007, the Pantawid Pamilya officially began in 2008 with 380,000 households residing in the poorest municipalities within

[1] Basic information on the Pantawid Pamilya is provided in the official website of the Department of Social Welfare and Development (DSWD). https://car.dswd.gov.ph/programs-services/core-programs/pantawid-pamilyang-pilipino-program-4ps/

the 20 poorest provinces (Set 1). In the following year, households located in the municipalities with poverty incidence equal to or above 61.53% became eligible for the cash transfer (Set 2). The program experienced the biggest leap in 2011 when the eligible households increased by around 1,200,000 households. Between 2011 and 2014, the program expanded its scale on an annual basis, reaching 4.4 million households or 16% of the entire population in the Philippines. Due to the variation in poverty incidence across the country, some municipalities obtained eligibility to the program earlier than others, which created variation across households in different municipalities that would have not existed without the Pantawid Pamilya. This study takes advantage of this variation across municipalities to conduct a quasi-experimental analysis using the DID method. Details of the empirical strategy are provided later in the methodology section.

Table 1: Expansion of the Pantawid Pamilya between 2009 and 2014[2]

Year	Set and number of households	Eligibility Criteria
2008	Set 1: 292,464 households	- Poorest 20 provinces based on the 2006 official poverty statistics published by the National Statistical Coordination Board (NSCB) - Poorest municipalities in the selected provinces based on the 2003 small area estimates (SAE) published by the NSCB
2009	Set 2: 249,232 households	- Municipalities with poverty incidence equal to or above 61.23% and not covered in set 1 (based on the 2003 SAE)
2010	Set 3: 383,540 households	- Municipalities with poverty incidence equal to or above 57.13% and not covered in sets 1 and 2 (based on the 2003 SAE)
2011	Set 4: 1,208,788 households	- Municipalities with poverty incidence equal to or above 36.99% not covered in sets 1–3 (based on 2003 SAE)
2012	Set 5: 831,751 households	- Municipalities with poverty incidence equal to or above 26.67% and not covered in sets 1–4 - Cities and municipalities under set 3 with remaining eligible households and with poverty incidence equal to or above 31.19% (based on 2003 SAE)
2013	Set 6: 862,784 households	- All remaining municipalities not covered in the previous sets - Set 1, 2, and 3 areas with remaining eligible households.
2014	Set 7: 378,909 households	- All areas covered by the program with remaining eligible beneficiaries

[2] This table is provided from the Asian Development Bank through *"The Design, Expansion, and Impact of Pantawid"* (2015) https://www.adb.org/sites/default/files/project-documents//43407-014-rrp.pdf

Second is the use of means testing. Provinces and municipalities covered by the Pantawid Pamilya are determined based on several poverty thresholds. As show in Table 1, in 2008, 20 poorest provinces were first identified based on the 2006 Official Poverty Statistics of the Philippine Statistics Authority (PSA). Next, within the selected provinces, the poorest municipalities were chosen based on the 2003 Small Area Estimates (SAE) of the National Statistical Coordination Board (NSCB). Then, to determine the beneficiary households within the poorest municipalities, a poverty targeting system called Listahanan was used to compare annual income per capita of the households based on the Proxy Means Test (PMT). Finally, within the identified households, those that have children between 0-18 years old or a pregnant woman at the time of registration obtained the qualifications to receive benefits. While PMT is a widely used method for targeting welfare programs, it is often criticized for its inaccuracy, particularly pertaining to its inherent exclusion and inclusion errors. This study focuses on one of these eligibility criteria—poverty thresholds for selecting eligible municipalities. With the regression discontinuity design, I study the variation in the labor market outcomes of municipalities created by the treatment by comparing the labor market outcomes of individuals in municipalities with a poverty rate just below and above the cutoff point.

b. Data

Due to a lack of data of beneficiaries at an individual level, this study uses the municipality poverty rate to identify the eligibility to the treatment at a municipality level. Based on the eligibility criteria provided in Table 1 (e.g., in 2010, municipalities with poverty incidence above 57.13% were eligible for the program), I determine the treatment year of each municipality and assign the value to each individual. All the regressions conducted in this study use the treatment year of municipalities as an independent variable. Therefore, the results derived from these regressions will be the estimates of the overall impact of the Pantawid Pamilya, which include the direct impacts on the eligible households and the spillover effects on the non-eligible households within the same municipalities.

There are three different data sets employed this study. First, I use the Labor Force Survey (LFS) between 2009 to 2014 for outcome variables. These data include information on employment status, basic salary, and other employment-related information at the individual levels. LFS is a national survey conducted quarterly by the Philippine Statistics Authority (PSA). The results are collected in January, April, July, and October and are made publicly available through the PSA website. In this study, I only use the survey data of the 4th quarter to analyze the labor market outcomes at the end of each year. The number of sample households varies each year but are approximately between 40,000 to 50,000. Second, I use the 2009 Official Poverty Statistics of the Philippines to identify the 20 poorest provinces that first became eligible for the Pantawid Pamilya in 2008. The poverty statistics are published annually by the National Statistical Coordination Board (NSCB) under the administration of the PSA. Since the 20 poorest provinces are determined based on the Official Poverty Statistics in 2006, I use Table 15 of the publication to obtain data on poverty incidence for each municipality in 2006. Third, I use the 2003 Small Area Estimates (SAE) to identify poverty incidence in each municipality, which is used to determine the eligible municipalities between 2009 and 2014. Data on poverty incidence can be matched with the observations in the Labor Force Surveys by simply linking the municipality variable in the two data sets.

Table 2 illustrates the summary statistics of individuals in the Labor Force Survey between 2009 and 2014. Column (1) provides data on the basic characteristics of the full sample. Column (2) to column (7) represents summary statistics for each survey year from 2009 to 2014.

Based on Table 2, the share of individuals in the eligible municipalities increased from 7% in 2009 to 100 % in 2013 after the program went through multiple reforms in eligibility criteria. In respect to the labor market outcome, there is an upward trend in basic salary per day, increasing from 297 Philippine Pesos (PHP) to 366 PHP between 2009 and 2014. Total work hours and number of jobs remain almost unchanged during the same time period.

Table 2: Summary Statistics of the Labor Market Outcomes in the Philippines

	(1) Full sample	(2) 2009	(3) 2010	(4) 2011	(5) 2012	(6) 2013	(7) 2014
Age	28.33	27.82	28.07	28.28	28.38	28.59	28.84
	(20.22)	(20.03)	(20.08)	(20.16)	(20.28)	(20.34)	(20.42)
Treatment	0.51	0.07	0.10	0.34	0.51	1.00	1.00
	(0.500)	(0.260)	(0.297)	(0.473)	(0.500)	(0)	(0)
Unemployed	0.09	0.09	0.09	0.09	0.09	0.09	0.08
	(0.283)	(0.289)	(0.289)	(0.280)	(0.289)	(0.280)	(0.274)
Total Work Hours per Week (hours > 0)	41.20	41.13	41.40	40.81	41.77	40.89	41.20
	(18.92)	(18.99)	(18.52)	(19.39)	(19.00)	(18.80)	(18.77)
Basic Salary per Day (salary > 0)	331.15	297.72	309.24	315.78	339.02	352.18	366.92
	(338.5)	(316.1)	(269.3)	(272.7)	(487.2)	(313.4)	(310.2)
Hourly Wages (wage > 0)	43.08	37.75	39.25	41.59	44.61	46.42	47.87
	(65.24)	(51.14)	(45.19)	(55.57)	(79.05)	(76.38)	(72.28)
Number of Jobs (job > 0)	1.08	1.07	1.07	1.08	1.09	1.08	1.07
	(0.299)	(0.270)	(0.289)	(0.302)	(0.326)	(0.294)	(0.307)
Worked in the Past Week	0.54	0.56	0.55	0.52	0.55	0.55	0.54
	(0.498)	(0.497)	(0.497)	(0.500)	(0.498)	(0.498)	(0.498)
Poverty Rate	28.61	28.57	28.51	28.62	28.60	28.68	28.71
	(19.72)	(19.67)	(19.66)	(19.73)	(19.68)	(19.69)	(19.88)
N	1199335	197734	197939	199207	202220	203470	198765

sd in parentheses

3. Methodology

To estimate the impacts of the Pantawid Pamilya on the labor market outcome, I use difference-in-differences and regression discontinuity strategies. Both regression models use variation in the treatment year among the municipalities between 2009 and 2014 to create quasi-experimental designs.

A. Difference-in-differences (DID) strategy

I use the rollout across municipalities and over time to estimate the program's impacts on the aggregate employment in the local labor market in the Philippines. I use the following specification to estimate the treatment effect.

$$y_{i,m,t} = \alpha_0 + \beta_1 \cdot Treat_{m,t} + \rho_m \cdot \theta_t + \lambda_m + \varepsilon_{i,m,t} \qquad (1)$$

$y_{i,m,t}$ is an outcome for individual i in municipality m at year t. The outcomes of our interest are unemployment rate, total work hours, basic pay of the day, hourly wages, the number of jobs, and worked in the past week (equals to 1 if an individual worked in the past week and 0 otherwise). The interaction fixed effects $\rho_m \cdot \theta_t$ control for the interaction of the time invariant fixed effect of the poverty rate and time-fixed effect of the survey year t. This accounts for a variation in outcomes among municipalities with different poverty rates in each survey year. The time t varies between 2009 and 2014. This also accounts for any economic upturns or downturns that occurred during the Pantawid interventions. λ_m represents municipality fixed effects. The treatment effect β_1 illustrates the impacts of the Pantawid Pamilya on labor market outcomes of the treatment group in the post-treatment period.

$$\beta_1 = E\big(y_{i,m,t} \mid Treat_{m,t} = 1\big) - E(y_{i,m,t} \mid Treat_{m,t} = 0) \qquad (2)$$

While model (1) is a basic linear estimator often used for evaluating treatment effects, it does not capture the dynamic effects of the Pantawid Pamilya on the labor market during the post and pre-treatment periods. As de Chaisemartin and D'Haultfœuille illustrate, the product of a static linear estimator is a weighted sum of the Average Treatment Effects (ATE), which could either over or underestimate the direct treatment effect on the outcome variable. Moreover, given that the change in the labor market occurs only slowly, evaluating the treatment effects on the market with a single coefficient does not provide us with a full picture of the relationship between the treatment and the labor market. Thus, to evaluate policy interventions more holistically, they introduce an alternative estimator for calculating the cumulative effects of treatments on an outcome (de Chaisemartin & D'Haultfœuille, 2020). This study employs their methods to add a dynamic element to the basic model. The use of a dynamic DID model that tracks the treatment effect over time is particularly salient for this study as the impacts of the Pantawid Pamilya on labor market are expected to be more fluctuating, rather than linear. The equation below illustrates the dynamic DID model, which will be used for the regression analysis.

$$y_{i,m,t} = \alpha_0 + \sum_{\substack{\tau=-2, \\ \tau\neq-1}}^{2} \beta_\tau \cdot 1(years\ since\ treatment = \tau)_{m,t} + \rho_m \cdot \theta_t + \lambda_m + \varepsilon_{i,m,t} \quad (3)$$

$1(years\ since\ treatment = \tau)_{m,t}$ is a dummy variable that equals to 1 if the year t is τ years since the municipality became eligible for the Pantawid Pamilya. If the survey year is either more than 2 years before the treatment or 2 years after the treatment, they are categorized as $\tau \leq -2$ and $2 \leq \tau$ respectively. $\tau = 0$ indicates the year when the municipality became eligible to the program. Other variables in this model are already described in the model (1) above.

B. Regression discontinuity (RD) design

The DID design provides insights into the overall impact of the Pantawid Pamilya on the labor market, analyzing how the variation in program's expansion rate compares to the variation in the employment outcomes across municipalities. However, the question remains on whether the aggregate impacts of the Pantawid Pamilya on the labor market are driven by an increase in labor supply or hindered by the reduced incentives of workers to participate in employment. If there is a positive correlation between the treatment and the labor supply, it indicates that the positive labor market outcome is, in fact, driven by both multiplier effects and supply-side effects following the installation of the Pantawid Pamilya. Contrary, if a negative treatment effect on workers' incentives is revealed, it suggests that the aggregate impacts of the Pantawid Pamilya on employment is hindered by a decrease in labor supply.

Given this context, I use the RD design to evaluate the treatment effects on the labor supply by comparing the change in labor supply and incentives of workers observed in the poor municipalities just above and below the eligibility thresholds. Given a lack of data on individual's eligibility for the program, the study uses the poverty threshold at the municipality level to estimate the difference in the overall labor supply outcomes of the treated and non-treated municipalities. The biggest challenge for implementing the RD analysis in this study is that the poverty threshold for selecting municipalities eligible for the Pantawid Pamilya was updated every year, reducing the variation below and above the cutoff point in the preceding years. To identify the direct impacts of the treatment on individuals' participation in the employment and incentives to work, I focus attention to the immediate impact of the treatment on the labor supply within the year. For example, I compare the labor supply between the groups treated in 2009 and the groups not treated in the year by using the Labor Force Survey data from 2009. The equation below is the empirical model for estimating the change in labor supply and worker incentives just below and above the eligibility threshold for municipalities.

$$y_{i,m,t} = \alpha_0 + \beta_1 \cdot P_m + \beta_2 \cdot Treat_{m,t} + \beta_3 \cdot Treat_{m,t} \cdot P_m + \varepsilon_{i,m,,t} \tag{4}$$

$y_{i,m,p,t}$ in this model is again the outcome for individual i in municipality m in province p at year t. The outcome variables for labor supply are (1) total work hours per week (2) basic salary of the day and (3) willingness to work—variables directly collected through the Labor Force Surveys of the Philippine Statistics Authority (PSA). P_m is the running variable, which is calculated by subtracting the poverty threshold of the treatment year from the poverty rate of municipalities in 2003 —a criteria used for selecting eligible households for the Pantawid Pamilya between 2009 and 2014. $Treat_{m,t}$ represents a dummy variable, which equals to 1 if a municipality m was treated in year t and remains 0 otherwise. The interaction term $Treat_{m,t} \cdot P_m$ accounts for different effects of poverty rate on outcome variables within the treated group.

4. Results

A. Aggregate impacts on the labor market

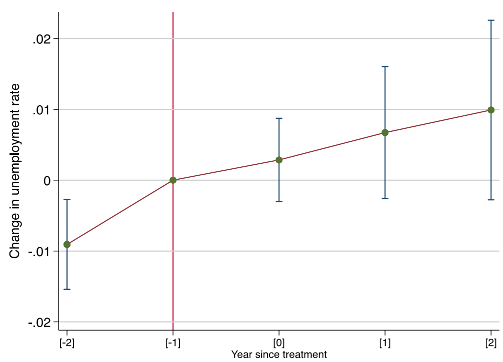
The difference-in-differences model provides evidence on the aggregate impacts of the Pantawid Pamilya on unemployment rate, wages, and other labor market outcomes in the Philippines. Using the dynamic DID model (equation 3), this section of the study not only identifies the overall impacts of the treatment on the labor market but also captures the gradual change in each labor market outcome variable pre and post treatment in the span of 5 years.

Before discussing the treatment effects on the labor market in detail, I present some explanations for the potential pre trends of the outcome variables—whether there is a difference between treated and controlled group other than the treatment itself. The first two rows of the column (1) - (6) evaluate the trends of each dependent variable before the municipalities were treated. Based on the values of coefficients, all the columns except for column (1) provide evidence of the parallel pre-trends, confirming that the changes in the labor market outcome observed in this study were likely caused by the treatment. The coefficient on the first row of column (1) suggests that a non-parallel pre-trend, in fact, exists for unemployment rate, which limits this study's capacity to accurately assess the treatment effects on the variable.

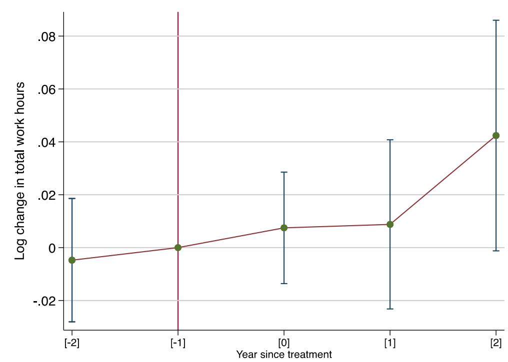
The treatment effects on labor market outcomes are presented in Figure 1. Outcomes of (b) total work hours, (c) basic salary per day and (d) hourly wages are presented in log terms to capture the percentage changes in the variables. Overall, Figure 1 illustrates positive, yet weak, impacts of the treatment on the labor market outcome. While the impacts of the Pantawid Pamilya on work hours and worked in the past week 2 years after treatment (values in the very right side of Figure 1b and f) are statistically significant, their confidence intervals are wide, implying a significant outcome variation among the treated individuals. There is an upward trend in the coefficients of each labor market outcome variable from year 0 to year 2 except for the hourly wages. This trend is consistent with the initial assumption of the study that treatment effects dissolve through the labor market gradually over a few years span.

Figure 1: Dynamic Treatment Effects on Labor Market Outcomes

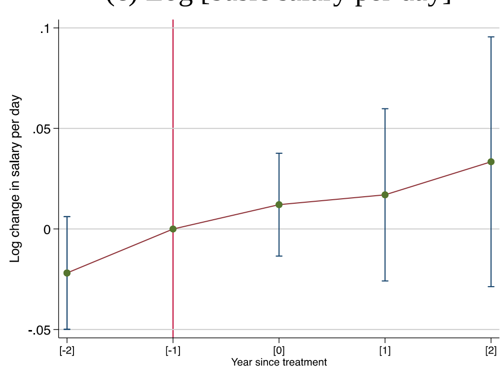
(a) Unemployment rate



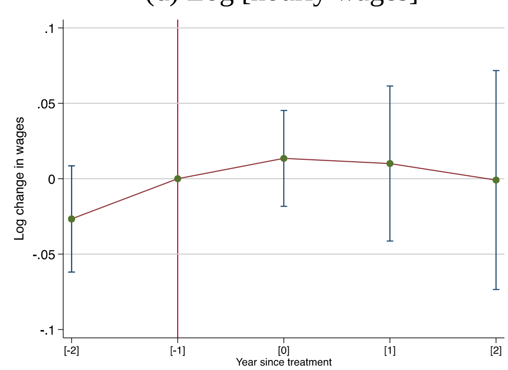
(b) Log [total work hours per week]



(c) Log [basic salary per day]

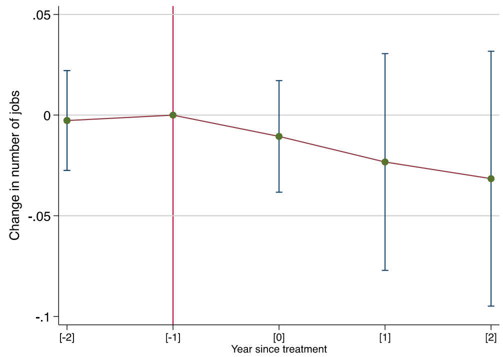


(d) Log [hourly wages]



(e) Number of jobs

(f) Worked in the past week



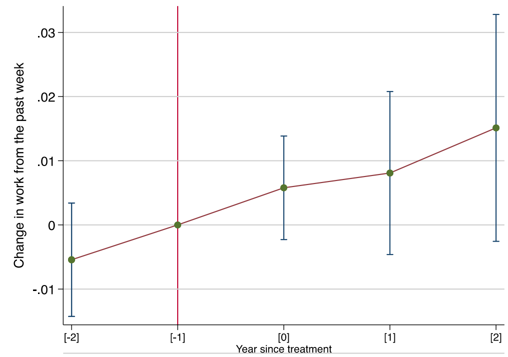


Table 3 summarizes the regression results. Each column represents different labor market outcome variable and reports dynamic treatment effects from 2 years before treatment to 2 years after treatment. The results again show that treatment has positive, yet small, impacts on the labor market outcomes. The coefficient in column (2) illustrates that total work hours per week increases by 4.2 % within 2 years since treatment. Column (3) implies the treatment effects on salary also appear to be positive rather than negative. However, there is no strong evidence of correlation between treatment and higher salary based on the regression results. Column (6) indicates that the percentage of individuals worked in the past week increased by 1.5%, 2 years following the treatment. Although the values of these estimates are extremely small, the lower bounds of their 95% confidence intervals are close to 0, which suggest that treatment is unlikely to have any significant negative impacts on the labor market outcomes in the Philippines. These outcomes are consistent with other existing literature, which argue the overall treatment effect on the labor market is positive despite the potential disincentive effects of CCT on labor supply.

Table 3: Long-Term Impacts of the Pantawid Pamilya on Local Employment

	(1) Unemployment Rate	(2) Log Total Work Hours per Week	(3) Log Basic Salary Per Day	(4) Log Hourly Wages	(5) Number Of Jobs	(6) Worked in the Past Week
2 years before treatment	-0.009***	-0.005	-0.022	-0.027	-0.003	-0.005
	(0.003)	(0.012)	(0.014)	(0.018)	(0.013)	(0.005)
year of treatment	0.003	0.007	0.012	0.013	-0.011	0.006
	(0.003)	(0.011)	(0.013)	(0.016)	(0.014)	(0.004)
A year after treatment	0.007	0.009	0.017	0.010	-0.023	0.008

	(0.005)	(0.016)	(0.022)	(0.026)	(0.027)	(0.006)
2 years after treatment	0.010	0.042*	0.033	-0.001	-0.032	0.015*
	(0.006)	(0.022)	(0.032)	(0.037)	(0.032)	(0.009)
Poverty Rate	-0.001***	-0.006***	-0.008***	-0.004***	0.000	-0.001***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Interactive Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	0.09	3.59	5.52	3.40	1.08	0.55
Number of Observations	526801	475608	215635	213997	43373	1065627
R squared	0.026	0.088	0.177	0.095	0.105	0.016

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table summarizes the main results of the dynamic difference-in-difference model (equation 3). Column (1) to column (6) summarize the treatment effects on 6 labor market outcomes—unemployment rate, total work hours per week, basic salary per day, hourly wages, number of jobs, and worked in the past week—respectively based on the Labor Force Survey Data from 2009 to 2014. Outcome variables from column (2) to column (4) are in log forms.

B. Aggregate Impacts on the non-beneficiaries

Next, I specifically look at the spillover effects on the potential non-beneficiary households by conducting DID analysis on households without children. As cash transfers are only offered to households with children between 0–18-year-old or a pregnant woman, this regression analyzes approximate impacts of the treatment on non-beneficiary households. Table 4 summarizes the results. Based on the coefficients of the table, there is no statistically significant evidence of the treatment effects on the non-beneficiaries. However, this is not to say that there is no spillover effects on the non-beneficiaries.

Table 4: Long-Term Impacts of the Pantawid Pamilya on Non-beneficiaries

	(1) Unemployment Rate	(2) Log Total Work Hours per Week	(3) Log Basic Salary Per Day	(4) Log Hourly Wages	(5) Number Of Jobs	(6) Worked Past Week
2 years before treatment	-0.008	-0.022	-0.023	-0.038	0.035	-0.003
	(0.007)	(0.023)	(0.043)	(0.054)	(0.033)	(0.012)
year of treatment	-0.003	-0.003	-0.024	-0.014	-0.012	-0.011
	(0.007)	(0.022)	(0.044)	(0.052)	(0.035)	(0.011)
A year after treatment	0.006	-0.007	0.030	0.052	0.016	-0.009
	(0.010)	(0.031)	(0.067)	(0.081)	(0.061)	(0.017)
2 years after treatment	0.007	0.040	0.061	0.074	-0.009	0.002
	(0.013)	(0.043)	(0.094)	(0.109)	(0.081)	(0.024)
Poverty Rate	-0.001	-0.008***	-0.004	0.002	0.000	-0.003***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Interactive Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	0.08	3.57	5.55	3.40	1.10	0.40
Number of Observations	53932	49322	21436	21296	4462	82526
R squared	0.042	0.134	0.219	0.142	0.265	0.046

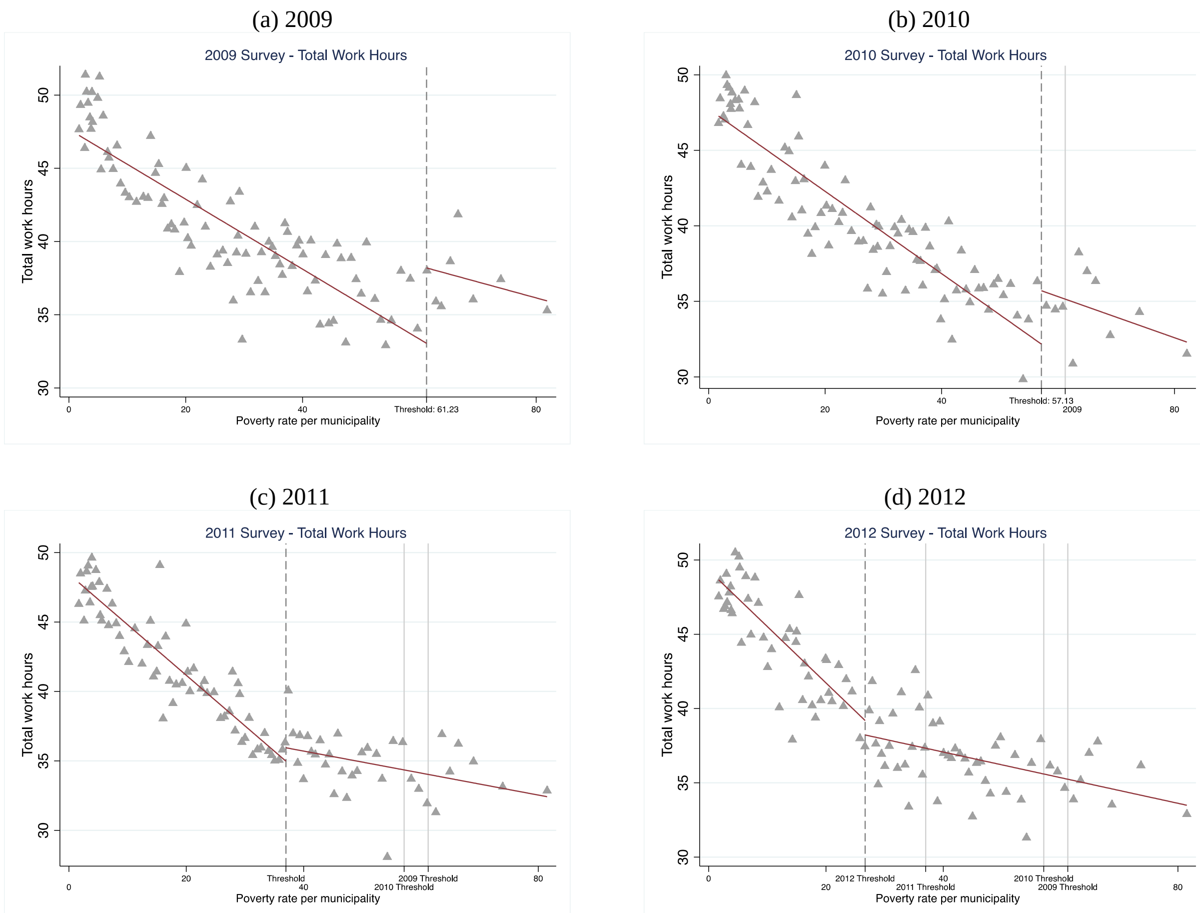
mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C. Treatment effects on labor supply

The previous section has analyzed the impacts of the Pantawid Pamilya on the aggregate employment in the Philippines and found evidence of weak positive treatment effects. However, the concerns regarding the disincentive effects of the CCT still remain. To separate the treatment effects on labor supply from the overall treatment effects on labor market, this section uses regression discontinuity design and provides analysis on how participation in the Pantawid Pamilya could shift labor supply outcomes, particularly through influencing work incentives of individuals.

Figure 2 presents the treatment effects on total work hours per week for each year between 2009 and 2012. As mentioned in the methodology section, this study focuses on analyzing the treatment effect on labor supply within the same year of treatment due to structural limitations. This strategy also allows me to capture the changes in labor supply outcomes immediately after the treatment. Unfortunately, data from 2013 and 2014 cannot be evaluated with this regression discontinuity model as all 1,486 municipalities in the Philippines became eligible for the Pantawid Pamilya by 2013 (view Table 1) and, thus, there were no more arbitrary cutoff points at a municipality level that could be used to estimate the treatment effect. The vertical dashed lines in figure 2 represent poverty thresholds of each treatment year for determining eligible municipalities. Thus, from 2009 to 2012, as the threshold shifted from 61% to 26%, more households from less poor municipalities became eligible for the benefits of the Pantawid Pamilya. In figure 2, while the outcome gap between the treated group and untreated group at the cutoff point for 2009 and 2010 appear to be larger than that of 2011 or 2012, the figure also demonstrates significant variations in outcomes among the observations for 2009 and

Figure 2: Treatment Effects on Total Work Hours per Week (2009 - 2012)



Note: This figure visualizes the treatment effects on total work hours per week from 2009 to 2012. The vertical dashed line represents poverty threshold for each treatment year, and gray lines represent poverty thresholds from the previous years.

2010. Table 5 summarizes the regression results, which are consistent with the outcomes shown in figure 2. In 2009, total work hours per week for the individuals in the treated municipalities were 4.7 hours longer compared to those in the non-treated groups, suggesting that there is no disincentive effect of treatment on the beneficiaries. While I find no statistically significant results for 2011 and 2012, it is unlikely that treatment had significant negative impacts on the total work hours of the beneficiaries based on the 95% confidence interval.

Table 5: Treatment Effects on Total Work Hours per Week (2009 – 2012)

	(1)	(2)	(3)	(4)
	2009	2010	2011	2012
Treatment	4.741***	3.039***	0.840	-0.990
	(1.102)	(0.923)	(0.713)	(0.732)
Poverty Rate	-0.241***	-0.241***	-0.323***	-0.341***
	(0.015)	(0.014)	(0.018)	(0.033)
Poverty Rate × Treatment	0.195**	0.156**	0.267***	0.290***
	(0.085)	(0.075)	(0.035)	(0.039)
Constant	33.508***	34.617***	37.017***	40.676***
	(0.536)	(0.492)	(0.426)	(0.593)
Mean in Control	42.00	42.41	43.40	45.78
Number of Observations	76530	77427	81351	79545
R squared	0.048	0.049	0.049	0.045

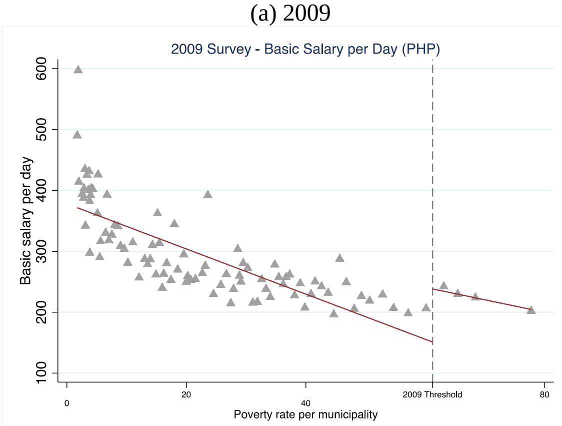
mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents treatment effects on total work hours per week from 2009 to 2012.

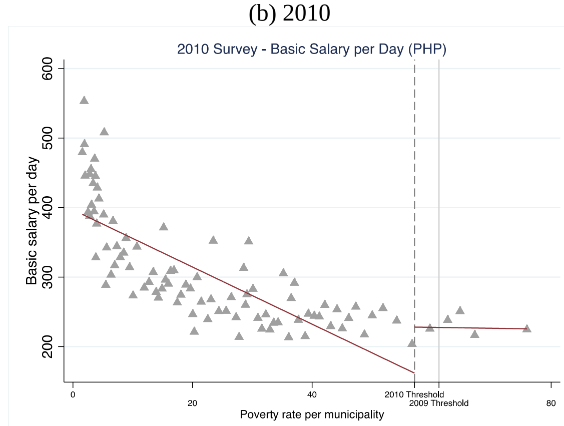
Treatment effects on basic salary per day are provided in figure 3. Based on the values at the cutoff points, I conclude that treatment has overall positive effects on the basic salary per day of the treated population, again questioning the hypothesis on disincentive effects of CCTs.

Figure 3: Treatment Effects on Basic Salary per Day (2009 - 2012)

(a) 2009

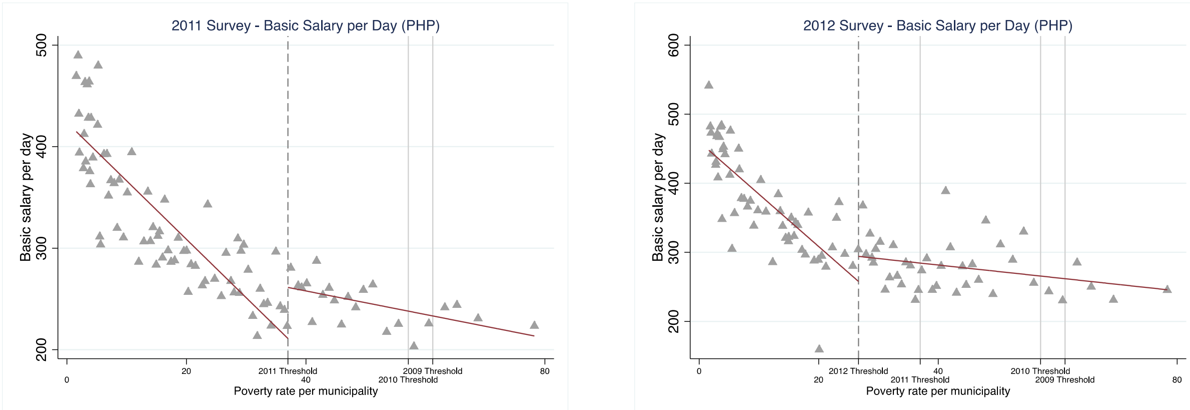


(b) 2010



(c) 2011

(d) 2012



Note: This figure represents the treatment effects on basic salary per day from 2009 to 2012. The vertical dashed line represents poverty threshold for each treatment year, and gray lines represent poverty thresholds from the previous years.

Table 6 provides regression results of the treatment effects on basic salary per day. In 2009, individuals in the treated group experienced an increase in salary of 76 Philippine Pesos (PHP) per day. The results are consistent among other survey years (2010, 2011, and 2012) although there are some variations in the values of coefficients. Based on the outcomes for work hours and salary per day, I conclude that treatment has positive effects on the labor supply of the beneficiaries.

Table 6: Treatment Effects on Basic Salary per Day (2009 – 2012)

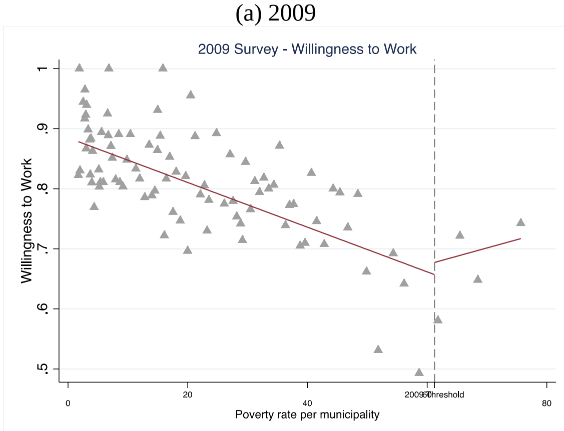
	(1)	(2)	(3)	(4)
	2009	2010	2011	2012
Treatment	76.032***	62.152***	48.741***	36.194**
	(15.537)	(16.877)	(11.567)	(16.300)
Poverty Rate	-3.704***	-4.113***	-5.751***	-7.583***
	(0.314)	(0.368)	(0.461)	(0.758)
Poverty Rate × Treatment	2.791*	4.376***	4.666***	6.652***
	(1.495)	(1.363)	(0.637)	(0.886)
Constant	151.149***	161.809***	211.113***	257.841***
	(9.919)	(10.317)	(8.437)	(12.356)
Mean in Control	301.18	314.01	336.22	379.36
Number of Observations	33175	34204	36295	37087
R squared	0.035	0.056	0.061	0.018

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

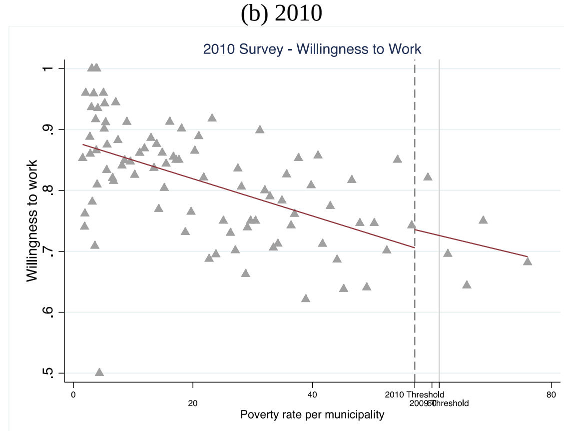
Next, I provide evidence of the treatment effects on the motivations of workers (Figure 4). Again, the vertical dashed line represents the threshold of each year, which declines from 61.23 % in 2009 to 26.67 % in 2012. Unfortunately, only a limited number of observations is available for this variable, which makes it difficult to obtain an accurate estimate of treatment effects on workers' motivations. The rest of the regression results is summarized in Table 7.

Figure 4: Treatment Effects on Workers' Willingness to Work (2009 – 2012)

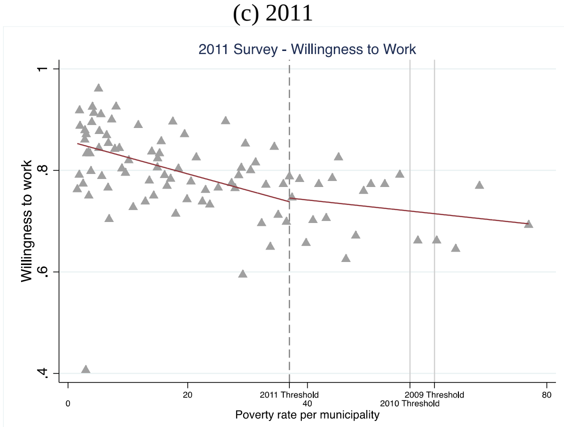
(a) 2009



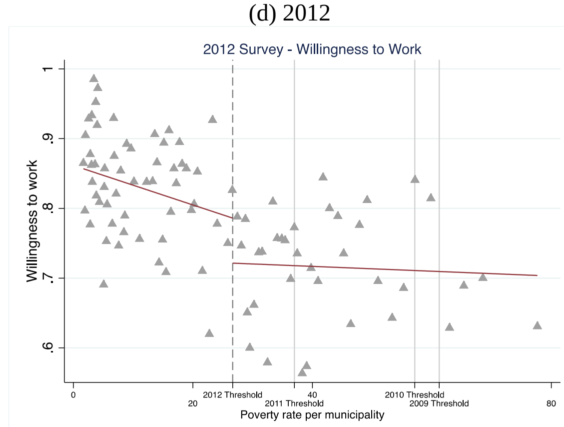
(b) 2010



(c) 2011



(d) 2012



Note: This figure illustrates the treatment effects on workers' willingness to work from 2009 to 2012. The vertical dashed line represents poverty threshold for each treatment year, and gray lines represent poverty thresholds from the previous years.

To estimate the treatment effects on worker incentives, I compare workers' willingness to work between treated group and non-treated group. While the coefficients on table 7 vary among different treatment year, column (4) presents a statistically significant evidence of a negative treatment effect on worker incentives. In 2012, individuals in the treated municipalities experienced a 6.5 % decline in their incentives to work, a result consistent with the evidence from the previous literature.

Table 7: Treatment Effects on Worker Incentives (2009 – 2012)

	(1)	(2)	(3)	(4)
	2009	2010	2011	2012
Treatment	-0.022	0.018	0.014	-0.065*
	(0.054)	(0.049)	(0.032)	(0.033)
Poverty Rate	-0.004***	-0.003***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Poverty Rate × Treatment	0.010**	0.002	0.002	0.002
	(0.005)	(0.004)	(0.002)	(0.002)
Constant	0.662***	0.706***	0.736***	0.786***
	(0.028)	(0.021)	(0.020)	(0.025)
Mean in Control	0.81	0.82	0.81	0.83
Number of Observations	6656	6728	6516	6926
R squared	0.024	0.017	0.013	0.021

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Robustness Checks

This section discusses weaknesses of the findings provided in section 4 and conducts additional regressions to increase internal validity of the analysis. First, the dynamic difference in difference model (equation 3) only identifies the changes in labor market outcomes among the employed individuals, which is a method called “intensive margin”. To understand the treatment effects on the entire labor market, this section uses another method called “extensive margin”, which reflects both the changes in unemployment rate and changes in actual work hours among the employed population. Specifically, I assign a value of 0 to total work hours, basic salary per day, and hourly wages of unemployed individuals in the labor market and calculate the overall changes in the outcome variables. Table 8 summarizes the regression results. Comparing the results from column (1) and column (2), it can be concluded that the impacts of treatment are only positive for intensive margin. Considering the possibilities that some individuals exit the labor market following the treatment, it is possible that there are no significant treatment effects on the work hours in the entire labor market.

Table 8: Treatment Effects on Worker Incentives (2009 – 2012)

	(1) Log Total Work Hours per Week (Employed individuals only)	(2) Log Total Work Hours per Week	(3) Log Basic Salary Per Day (Employed individuals only)	(4) Log Basic Salary Per Day	(5) Log Hourly Wages (Employed individuals only)	(6) Log Hourly Wages
2 years before treatment	-0.005	0.211***	-0.022	-0.124	-0.027	-0.096
	(0.012)	(0.073)	(0.014)	(0.129)	(0.018)	(0.117)
year of treatment	0.007	-0.060	0.012	0.058	0.013	0.059
	(0.011)	(0.067)	(0.013)	(0.133)	(0.016)	(0.120)
A year after treatment	0.009	-0.174	0.017	0.143	0.010	0.130
	(0.016)	(0.108)	(0.022)	(0.214)	(0.026)	(0.191)
2 years after treatment	0.042*	-0.181	0.033	0.110	-0.001	0.103
	(0.022)	(0.149)	(0.032)	(0.299)	(0.037)	(0.268)
Poverty Rate	-0.006***	0.024***	-0.008***	-0.113***	-0.004***	-0.100***
	(0.001)	(0.005)	(0.002)	(0.013)	(0.001)	(0.011)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Interactive Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	3.59	1.66	5.52	-7.28	3.40	-8.20
Number of Observations	475608	526801	215635	526801	213997	526801
R squared	0.088	0.021	0.177	0.094	0.095	0.092

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second, the linear regression discontinuity model (equation 4) could be over or underestimating the treatment effects on labor supply, particularly for 2011 and 2012, due to their large bandwidths. When the bandwidth is too large, an observation that is far from the cutoff point could influence the outcomes of the regression, leading to an over or underestimation of the coefficients. For example, in figure 4d, the slope of the fitted line among the treated group is underestimated due to the presence of an observation at the right edge of the graph. Thus, to reduce these biases, I limit the data to individuals with poverty rate below 60% and rerun the regression on 3 labor supply outcomes—A. total work hours, B. basic salary per day, and C. willingness to work. The results are illustrated in table 9. Based on table 9A, in 2011, total work hours per week increases by 2.3 hours for treated groups compared to the untreated group. Table 9B also suggests that, in 2011, basic salary per day for the treatment group is larger by 53 PHP. Additionally, table 9C illustrates that, in 2012, worker incentives decline for the treatment group by 8.9%. Although these raw numbers are subject to change depending on the functional forms, limiting data to observations that are close to the threshold allows for a more accurate estimation of the treatment effect on labor supply outcomes.

Table 9: Treatment Effects on Labor Supply Outcomes with Narrow Bandwidth

A. Total Work Hours per Week (2011 & 2012)

	(1) 2011	(2) 2011 (Poverty rate < 60)	(3) 2012	(4) 2012 (Poverty rate < 60)
Treatment	0.840	2.326**	-0.990	-0.540
	(0.713)	(0.951)	(0.732)	(0.808)
Poverty Rate	-0.323***	-0.323***	-0.341***	-0.341***
	(0.018)	(0.019)	(0.033)	(0.033)
Poverty Rate × Treatment	0.267***	0.027	0.290***	0.248***
	(0.035)	(0.113)	(0.039)	(0.054)
Constant	37.017***	37.017***	40.676***	40.676***
	(0.426)	(0.426)	(0.593)	(0.593)
Mean in Control	43.40	43.40	45.78	45.78
Number of Observations	81351	68004	79545	66618
R squared	0.049	0.045	0.045	0.042

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. Basic Salary per Day (2011 & 2012)

	(1) 2011	(2) 2011 (Poverty rate < 60)	(3) 2012	(4) 2012 (Poverty rate < 60)
Treatment	48.741***	53.115***	36.194**	35.637*
	(11.567)	(14.502)	(16.300)	(20.247)
Poverty Rate	-5.751***	-5.751***	-7.583***	-7.583***
	(0.461)	(0.461)	(0.758)	(0.759)
Poverty Rate × Treatment	4.666***	4.146**	6.652***	6.550***
	(0.637)	(1.710)	(0.886)	(1.585)
Constant	211.113***	211.113***	257.841***	257.841***
	(8.437)	(8.438)	(12.356)	(12.358)
Mean in Control	336.22	336.22	379.36	379.36
Number of Observations	36295	32967	37087	33467
R squared	0.061	0.055	0.018	0.019

C. Willingness to Work (2011 & 2012)

	(1) 2011	(2) 2011 (Poverty rate < 60)	(3) 2012	(4) 2012 (Poverty rate < 60)
Treatment	0.014	0.027	-0.065*	-0.089**
	(0.032)	(0.042)	(0.033)	(0.038)
Poverty Rate	-0.003***	-0.003***	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)

Poverty Rate × Treatment	0.002	-0.001	0.002	0.005^{*}
	(0.002)	(0.006)	(0.002)	(0.003)
Constant	0.736^{***}	0.736^{***}	0.786^{***}	0.786^{***}
	(0.020)	(0.020)	(0.025)	(0.025)
Mean in Control	0.81	0.81	0.83	0.83
Number of Observations	6516	5995	6926	6308
R squared	0.013	0.011	0.021	0.019

6. Conclusion

This study contributes to the literature on CCTs by analyzing their impacts on the labor markets. Using the Pantawid Pamilya in the Philippines as a case study, this paper provides evidence of positive, yet weak, treatment effects of the cash transfers on the labor market outcomes. It also confirms that while the CCTs could potentially lower worker incentives, the overall treatment effects on labor supply remain positive. The study concludes that the overall treatment effects on aggregate employment are positive and are reinforced by an increase in labor supply among the beneficiaries following the treatment.

Given the limited number of research that investigate the relationship between CCTs and labor markets, researchers should continue their efforts to analyze the treatment effects on the labor markets, conducting micro-level field experiments while understanding macroeconomic implications of the CCTs. While this study focused on the treatment effects on aggregate employment, it will be useful to evaluate the effects in more detail, by analyzing the variation in labor market outcomes among different industries and contract types. Further research is also needed to understand the impacts of CCTs on the Overseas Filipino Workers (OFW), which comprise a large portion of the working population in the Philippines.

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