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Conditional Cash Transfers, Civil Conflict and Insurgent Influence: Experimental Evidence from the Philippines[1]

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HiCN Working Paper 174

April 2014

Abstract: Conditional cash transfer (CCT) programs are an increasingly popular tool for reducing poverty in conflict-affected areas. Despite their growing popularity, there is limited evidence on how CCT programs affect conflict and theoretical predictions are ambiguous. We estimate the effect of conditional cash transfers on civil conflict in the Philippines by exploiting an experiment that randomly assigned eligibility for a CCT program at the village level. We find that cash transfers caused a substantial decrease in conflict-related incidents in treatment villages relative to control villages. Using unique data on local insurgent influence, we also find that the program significantly reduced insurgent influence in treated villages.

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[1] The authors thank Eli Berman, Christian Deloria, Radha Iyengar, Daniel Rees, Jacob Shapiro, and seminar participants at the NBER Economics of National Security meeting for comments on earlier versions. Felter and Johnston acknowledge support from AFOSR Award No. FA9550-09-1-0314. Any opinions, findings, conclusions, and recommendations expressed in this publication are the authors' and do not necessarily reflect AFOSR's views.

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1 Introduction

The rate of extreme poverty in developing countries decreased dramatically over the past two decades, from 43 percent in 1990 to 21 percent in 2010.[1] This reduction in poverty, however, is not equally distributed. One group of countries in particular has seen little improvement: those affected by conflict (World Bank, 2011, p.1). People in conflict-affected countries are substantially more likely to be undernourished, less likely to have access to clean water and education, and face higher rates of childhood mortality than people in peaceful developing countries (World Bank, 2011, p.5). As of 2011, no low-income conflict-affected country had achieved the Millennium Development Goals (World Bank, 2011, p.1). Continued progress against global poverty will therefore require that conflict-affected countries achieve rates of poverty reduction similar to those achieved elsewhere. As a means to this end, governments and donor organizations are giving large and increasing amounts of development aid to countries affected by conflict.

The effects of this influx of aid on conflict are largely unknown. Some experts argue that aid can exacerbate conflict and contribute to a vicious cycle of poverty and violence (Bryer and Cairns, 1997; Goodhand, 2002; Polman, 2010). Recent empirical studies lend support to this argument. Crost et al. (forthcoming) find that government-initiated infrastructure spending disbursed in the form of community-driven development (CDD) projects created incentives for insurgents to retaliate and thus increased conflict in the Philippines. Similarly, Nunn and Qian (forthcoming) find that US food aid increased conflict in recipient countries. An important economic question with significant policy relevance is therefore how aid can be delivered in a manner that reduces poverty without exacerbating conflict.[2]

[1] These numbers are based on the World Bank's definition of extreme poverty as subsisting on an income below $1.25 a day in 2005 dollars purchasing power parity. They were retrieved from the World Bank's website in November 2013 (http://www.worldbank.org/en/topic/poverty/overview).

[2] Evidence for a conflict-reducing effect of aid comes from Berman et al. (2011a), who find that small-scale aid and reconstruction spending disbursed by the US Army in Iraq led to a decrease in violence against US forces and civilians. However, this may have been due to the fact that aid was disbursed in close coordination

This study examines the effect of a different type of program – conditional cash-transfers (CCT) – on civil conflict. CCT programs distribute cash payments to poor households that meet a number of prerequisites and conditions, such as child vaccinations and school attendance. Over the past decade they have become one of the most important modes of delivering development aid and a large literature documents their positive impact on the well being of the poor (Fiszbein and Schady, 2009). However, little is known about the relationship between CCT programs and civil conflict.[3] This issue is both timely and important: CCT programs are currently operating in numerous conflict-affected countries including Colombia, India, Indonesia and the Philippines.

In this paper, we estimate the effect of a large CCT program, the Philippines' *Pantawid Pamilyang Pilipino Program* (hereafter referred to as *Pantawid Pamilya*) on civil conflict. Our analysis exploits a randomized experiment conducted by the World Bank starting in 2009.[4] In this experiment, 130 villages in 8 municipalities of the Philippines were randomly divided into a treatment group and a control group. The treatment group began receiving transfers through the program in 2009, while the control group did not receive transfers until 2011. Using a unique village-level dataset on conflict incidents from the Armed Forces of the Philippines (AFP) – the most comprehensive data source on conflict in the Philippines – we estimate the causal effect of CCTs on conflict by comparing the intensity of violence in treatment and control villages in 2009 and 2010.

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with military security efforts (Berman et al., 2013), making it difficult to extrapolate to the effects of civilian forms of aid.

[3] A recent study found that the Brazilian CCT program *Bolsa Familia* led to a reduction in crime, mostly in the form of robberies and drug-related offenses (Chioda et al., 2012). However, it is difficult to extrapolate from the behavior of individual criminals to the behavior of insurgent organizations that act strategically and pursue political goal on a large scale. For example, Crost et al. (forthcoming) find evidence that CDD projects increased conflict in the Philippines because insurgent groups sabotaged these projects in order to derail their successful implementation and avoid an anticipated shift in popular support towards the government. It is therefore possible that aid programs might reduce crime, perhaps by increasing the opportunity cost of criminal behavior, but increase civil conflict because insurgents have an incentive to sabotage them because successful implementation would undermine their position.

[4] Data from this experiment has been previously used to estimate the effect of *Pantawid Pamilya* on electoral support for incumbent politicians. (Labonne, 2013).

The first part of our analysis finds that CCTs led to a substantial reduction in conflict intensity – measured by the number of conflict-related incidents – in treatment villages. We believe this is the first experimental evidence of the effect of CCTs on conflict. There are several reasons why the effect of CCT programs on the intensity of conflict might differ from the effects of other programs, such as CDD and food aid. For one, CDD programs disburse aid through small infrastructure projects chosen by a participatory democratic process. As a result, they create highly visible targets – the infrastructure itself as well as the community meetings needed to plan and execute the projects – which insurgents can attack in their efforts to derail the program Crost et al. (forthcoming). In contrast, CCT programs target households directly and disburse aid in cash primarily through largely invisible electronic transfers to beneficiaries' bank accounts. This gives insurgents few high-profile targets and makes it more difficult to target CCT programs directly through violence. In support of this hypothesis, there is anecdotal evidence, reported by Crost et al. (forthcoming) that insurgents used violence in attempts to derail the implementation of a major Philippine CDD program in a number of locations, but there is no analogous evidence for the *Pantawid Pamilya* program. A similar reason might also explain the different effects of cash-transfers and food aid on conflict. Food aid needs to be physically transported to its destination and disbursed to recipients, which also creates visible targets for insurgents and incentives for looting food shipments.

Second, we estimate the effect of *Pantawid Pamilya* on local insurgent influence. It is important to understand the effect of different types of aid on insurgent influence because insurgent influence can have substantial negative consequences even in the absence of violence.[5] The presence of insurgents can depress economic activity by eroding the rule of law and creating insecure property rights that may disincentivize investment (Berman et al., 2012). In

[5]For a survey of the qualitative evidence for negative economic and welfare consequences of insurgent influence, see Kalyvas (2006). On insurgent influence and predation, see also Fearon (2008); Berman et al. (2012).

addition, insurgents often levy taxes on the population, imposing an additional burden on economic activity. In the Philippines, rebel extortion activities known as "revolutionary taxes" imposed by the New People's Army (NPA) on businesses discourage investment and permit the rebels to skim profits from resource-rich but impoverished areas where it wields influence (Group, 2011). A program that reduces violence by weakening insurgent influence is therefore likely to have more beneficial long-term effects than a program that merely reduces incentives to commit acts of violence but does not affect the local influence of insurgents.

It is possible that the CCT program's conflict-reducing effect is due to a decline in local insurgent influence – perhaps because the program increased popular support for the government or created economic opportunity and thereby made it more difficult for insurgents to recruit followers Berman et al. (2011a). But there are two reasons why this interpretation may not be correct. First, the program may merely have reduced the incentive for insurgents to draw attention to themselves by committing violent acts, but did nothing to reduce the strength or influence of their forces in local areas. Second, the program may even have increased insurgent strength by giving insurgents access to additional resources from taxing or extorting the cash transfers. A number of well-established theoretical models predict that an increase in insurgent strength can lead to a decrease in violence (Hirshleifer, 1989; Skaperdas, 1996; Kalyvas, 2006). These models predict that areas that are fully controlled by either insurgents or the government see the lowest levels of violence since the other party's forces refrain from entering them. Some of these theories predict that violence is therefore more likely in areas where insurgents and government are of similar strength, since these areas are most strongly contested. If insurgents and government were equally strong in the experimental villages prior to the program, the program's conflict-reducing effect might reflect an increase in insurgent strength that made the treatment villages less contested Fearon (2008); Berman et al. (2012).

Analyzing unique data from comprehensive assessments made by the Philippine military, we find that treated villages experienced a significant decrease in insurgent influence compared to control villages, suggesting that the program reduced conflict by weakening rebel presence. To our knowledge, this is the first empirical evidence of the effect of a CCT program on a direct measure of insurgent influence. Consistent with the hypothesis that the program weakened insurgent support, we also find evidence that conflict intensity decreased in villages in close proximity to treated ones, which may indicate that the *Pantawid Pamilya* program reduced conflict by making it more difficult for insurgents to recruit combatants so that treated villages were able to "export" fewer combatants to carry out attacks in other villages.

Our result that CCT programs reduce conflict on two important dimensions suggests that their effects differ from those of other types of aid interventions, notably CDD programs and food aid, which recent studies have found to increase conflict (Crost et al., forthcoming; Nunn and Qian, forthcoming).[6] We describe several possible reasons why CCT programs might reduce conflict in the concluding section. More broadly, our results imply numerous opportunities for future research to evaluate how, and under what conditions, various types of aid programs might be able to reduce the risk of violent conflict rather than exacerbate it. We discuss these implications in the final section of the paper.

2 Institutional Background

2.1 The *Pantawid Pamilya* Program

This paper studies the *Pantawid Pamilyang Pilipino Program*, a conditional cash-transfer program implemented by the Philippine government's Department of Social Welfare and

[6]However, Beath et al. (2011) found no statistical effect of CDD on insurgent violence in their evaluation of Afghanistan's National Solidarity Program.

Development (DSWD) and partly funded through loans from the World Bank and the Asian Development Bank. Since it began in 2007, the program financed transfers to approximately one million households in 782 cities and municipalities in 81 provinces in all 17 regions of the Philippines.[7] It is currently the country's flagship antipoverty program.

Pantawid Pamilya is similar to numerous other CCT programs, such as Mexico's *Oportunidades* and Brazil's *Bolsa Familia*. Like these programs, *Pantawid Pamilya* is intended to reduce poverty and promote human capital investment by providing grants to poor households on the condition that they satisfy basic health and education requirements. In order to receive transfers, recipient households are required to ensure their children attend school and receive a variety of vaccinations and deworming treatments. Pregnant women are required to receive regular pre- and post-natal health check-ups.

Households are eligible for transfers through the program if their per capita income is below the regional poverty line and they have children aged 0-14. Per capita incomes are estimated by a Proxy-Means Test (PMT) based on the following indicators: household consumption; education of household members; occupation; housing conditions; access to basic services; ownership of assets; tenure status of housing; and regional dummy variables.[8] Finally, the lists of households identified by the PMT are validated through spot-checks and community assemblies. (Usui, 2011). The program was initially targeted to municipalities with a poverty incidence greater than 50%, so that a large share of the population was eligible for the cash transfers. For instance, approximately 52% of all households were eligible for transfers in the villages that made up the experimental sample (Redaelli, 2009).

Pantawid Pamilya transfers amounted to a substantial fraction of the household income of

[7] These statistics were current as of January 2011. See Arulpragasam et al. 2011, p. 1.

[8] The PMT's formula is not disclosed publicly, in order to minimize the chances of strategic reporting of census data. Moreover, instead of asking directly about the income and expenditure of households in collecting local census data, the PMT instead estimates them with household-level socioeconomic indicators.

program participants. The maximum transfer amount corresponded to 23 percent of the national poverty line; households above the poverty line were ineligible for the program. Families with three or more eligible children received the maximum annual grant of PHP 15,000, as long as they meet the program's conditions; the minimum annual grant is PHP 8,000 to families with only one child [9] This transfer size was comparable to CCT programs in Latin America. In the well-known Mexican CCT program *Oportunidades*, the transfer size was approximately 21 percent of total annual household expenditures; in the Colombian CCT program *Familias en Accion*, transfers represented about 15 percent of the minimum wage; and the Nicaraguan CCT program *Red de Proteccion Social*, transfers were about 17 percent of annual household expenditures (Fernandez and Olfindo, 2011, p. 6).

The relatively large size of the transfers created a strong incentive to comply with the program conditions. In the villages covered in "Set 1" of the program, from which the experimental sample was drawn, 87 percent of eligible households complied with the program's conditions and received transfers (Fernandez and Olfindo, 2011, pp. 8-9).

2.2 Civil Conflict in the Philippines

The Philippines is home to multiple long-running insurgencies with distinct motives and characteristics. The main insurgencies in the Philippines are the New People's Army (NPA), the Moro Islamic Liberation Front (MILF), the Abu Sayyaf Group (ASG), and loosely connected criminal organizations referred to by the Armed Forces of the Philippines (AFP) in its reporting as "Lawless Elements" (LE). Table 1 shows the distribution of incidents nationwide in in Pantawid Pamilya experimental villages.

The country's largest and most active insurgent organization during the 2001-2010 period

[9] At current exchange rates, *Pantawid Pamilya* transfers ranged from roughly \$200 to \$370.

of study was the Communist Party of the Philippines (CPP) and its armed wing, the New People's Army (NPA). The NPA's strength averaged approximately 7000 fighters over this period, and the group was active in 63 of the country's 73 provinces.[10] Over 60 percent of the incidents reported by the AFP involved the NPA. In the villages that took part in the *Pantawid Pamilya* experiment, the NPA was involved in 72.1 percent of reported incidents.

The country's second-largest insurgent movement during the period of study was the Moro Islamic Liberation Front (MILF), an Islamist separatist movement active in the southwestern provinces on the island of Mindanao. Between 2001 and 2010, the MILF was involved in 11 percent of security incidents reported by the military nationwide and 9.6 percent of incidents in the villages under study.

The remaining incidents involved insurgent splinter groups and criminal groups that the AFP refers to as Lawless Elements, who were involved in just under 19 percent of nationwide incidents and 18.3 percent of incidents in the villages under study. Finally, the al-Qaeda-affiliated Abu Sayyaf Group (ASG) were involved in 5 percent of the incidents reported by the military nationwide during this period, but were not involved in any of the incidents in the villages under study.[11]

3 Empirical Strategy

We exploit a randomized experiment conducted by the World Bank in 2009 and through 2010 to identify the effect of CCTs on civil conflict. In the experiment, 130 villages were

[10]Estimates based on information maintained by the Armed Forces of the Philippines Deputy Chief of Staff for Intelligence (J2).

[11]The Abu Sayyaf Group operates mainly in remote areas of Basilan and Sulu provinces, which did not take part in the experimental evaluation since *Pantawid Pamilya* was already operating in both provinces by late 2008.

randomly divided into 65 treatment villages and 65 control villages.[12]

The experimental sampling followed a three-step procedure. First, four provinces (Lanao del Norte, Mountain Province, Negros Oriental, and Occidental Mindoro) were selected from a pool of eight provinces that were scheduled to begin receiving the *Pantawid Pamilya* program in 2009. These provinces were non-randomly selected on the basis of geography to ensure that the evaluation would cover areas in each of the country's three major island groups, Luzon, Visayas, and Mindanao (Redaelli, 2009, p. 20). Finally, half of the villages within each of these eight municipalities were randomly assigned to the treatment group and the other half to the control group, leading to a sample of 65 treatment villages and 65 control villages. Table 2 contains information on the treatment assignment of villages in each of the 8 participating municipalities. Overall, the experimental villages contain 47,627 households, out of which 24,651 were eligible for the *Pantawid Pamilya* program (Redaelli, 2009). The four selected provinces are not the most conflict-affected ones in the Philippines, but all of them experience substantial amounts of conflict-related incidents. Summary statistics in Section 4.1 show that the experimental areas experienced on average slightly more conflict-related incidents in the pre-treatment period than the country average. In the second step, two eligible municipalities were randomly selected from each province to participate in the evaluation.

Our empirical strategy allows us to estimate the causal effect of the *Pantawid Pamilya* program by comparing the number of conflict incidents experienced by treatment and control villages in the years 2009 and 2010. Our baseline estimates come from the following regression:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_3 X_i + \lambda_t + \epsilon_{it} \tag{1}$$

[12]Details of the experiment are described in Redaelli (2009); Chaudhury et al. (2013); Labonne (2013).

where Y_i is the number of conflict incidents village i experienced in year t (2009 or 2010), and $Treat_i$ is an indicator variable for villages assigned to the treatment group. The model further controls for a set of observed pre-treatment village characteristics, X_i. The causal effect of the *Pantawid Pamilya* program is captured by the parameter β_1, associated with the treatment indicator.

4 Results

4.1 Data, Summary Statistics and Balance Tests

We use three different sources of data for our empirical analysis. Data on conflict-related incidents were compiled from unclassified portions of the reports submitted by operating units of the AFP deployed to conduct counterinsurgency and other internal security operations in the field. The data includes information on every operational incident recorded by the AFP Joint Operations Center during the period 2001–2010. In total, it contains information on almost 26,000 unique incidents.[13] We use two dependent variables. The first is an annual count of conflict incidents per village. Incident counts are a useful proxy of the intensity of conflict and have been used by previous studies such as Berman et al. (2011a), Beath et al. (2011); Condra and Shapiro (2012); Dube and Vargas (2013). The second is insurgent influence. This variable measures the extent to which villages were influenced by insurgents according to nationwide assessments made by Philippine military in support of their campaign planning.[14] It is coded in four categories. In the order from lowest to highest influence these are: no influence, threatened, influenced, and infiltrated. We have data on

[13]Felter (2005) provides a comprehensive overview of the AFP data. Replication data will be made available through the Empirical Studies of Conflict (ESOC) Project (www.princeton.esoc.edu).

[14]For a description and summation of how communist insurgents in the Philippines exert influence and indicators of this influence at the village level see Felter (2006).

this variable for the years in which the experiment took place, 2009-2010. Out of the 260 village-year observations, 220 are coded by the AFP as not influenced, 31 as threatened, 6 as influenced and 3 as infiltrated. Data on village treatment assignment in the experiment come from *Pantawid Pamilya* program data, which is maintained by the Philippine Department of Social Welfare and Development (DSWD). Finally, data on village characteristics come from the Philippines' 2000 National Census.

Table 3 presents summary statistics and balance tests for village-level control variables. The control variables consist of village population and indicators for the presence of paved streets, electricity, a communal water system, one or more health clinics or hospitals. All variables except for conflict incidents, insurgent influence, and treatment status are from the 2000 National Census of the Philippines.

The first two columns show means for treatment and control villages separately. The last column shows p-values from t-tests for differences in these means. The results show that treated villages had slightly more conflict-related incidents in the pre-treatment period. They also suggest that treated villages have slightly worse infrastructure than control villages, as they are less likely to have paved streets, electricity and stores, and more likely to have a communal water system.[15] However, these differences are not statistically significant at conventional levels, which add to our confidence that the randomization was successful.

Figure 2 shows graphical evidence of the effect of the *Pantawid Pamilya* program on conflict. The top panel compares the trends in the average number of incidents experienced by treatment and control villages over the period 2001–2010, while the bottom panel plots the differences between the groups. The figure shows that the treatment and control group had relatively steady and almost identical levels of conflict in the period 2001–2006. In 2007–

[15] Communal water systems are more likely to be present in poorer villages, while richer villages are likely to have piped water access to individual household.

2008, both groups experienced an upward trend, which was slightly steeper for the treatment group. To test whether the difference in conflict levels in the late pre-treatment period constitutes evidence of non-random assignment, we conduct a robustness test for its statistical significance, which we report together with the main results in the next subsection. In 2009, when the program was implemented in treatment villages, the number of conflict incidents in these villages dropped sharply. In contrast, conflict continued on the same upward trend that it had followed during the previous years in control villages. In 2010, the second year of the experiment, the program's effect appears to be smaller, as conflict increased in the treatment villages and decreases in the control villages. We explore possible changes in the program's effect over time in Section 4.3.

The summary statistics show that the average number of conflict incidents per village in the study area is relatively low. In the pre-treatment period 2001–2008, villages experienced on average approximately 0.1 conflict incidents per year. This is slightly more than the average for the entire country of 0.064 incidents per village per year. While this might seem like a small number of incidents it does not necessarily indicate an unusually low intensity of conflict. For comparison, Beath et al. (2011) report that the villages in their experimental study of aid and conflict in Afghanistan experienced an average of only 0.02 conflict incidents within 1 km of the village in the entire period of observation, 2004–2007 (and an average of only 0.2 incidents within 10km of the village). The average yearly number of incidents per village in our study areas is therefore higher than in certain regions of Afghanistan before US troop surge began in 2009.[16]

[16]Furthermore, a low level of violence does not mean that a conflict is economically insignificant (Abadie and Gardeazabal, 2003; Murdoch and Sandler, 2004). Apart from the lives and resources lost to violence, the mere presence of insurgents distorts economic incentives, by increasing entrepreneurial risks and/or imposing an implicit tax from extortion and bribes paid to insurgents for protection.

4.2 Conditional Cash Transfers and Conflict Intensity

As explained in Section 3, we identify the causal effect of *Pantawid Pamilya* on conflict using data from a randomized control trial of 130 villages in eight randomly-selected municipalities in four provinces that took place in 2009 and 2010. Since the dependent variable is a count of the number of incidents, we use Poisson estimators.

Columns 1 and 2 of Table 4 display the results of equation 1 in section 3. To make interpretation easier, we report marginal effects instead of coefficients for the Poisson models. Standard errors are adjusted for clustering at the village level. The marginal effect associated with the treatment indicator can be interpreted as the causal effect of the *Pantawid Pamilya* program. The results show that the effect of the program is negative, large, statistically significant and robust to the inclusion of control variables (Column 2) and municipality fixed effects (Column 3). The point estimates suggest that the program reduced conflict by between 1.2 and 1.4 incidents per village per year.

4.3 Timing of the Effect

Figure 2 suggests that the program's effect was concentrated in the first year of its operation and decreased in the second year. A possible explanation for this temporal pattern is that the program caused a short-lived increase in support for the government that faded once people were used to receiving transfers. To further explore this possibility, we test whether the difference in the program's effects between the two years is statistically significant. Specifically, we estimate the following regression:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Treat_i \times Y2010_t + \beta_3 X_i + \lambda_t + \epsilon_{it} \tag{2}$$

where $Y2010_t$ is an indicator for the year 2010 and λ_t is a year fixed effect. The parameter β_2 corresponds to the difference in the program's effect between the first and second year of operation.

The results reported in columns 3 and 4 of Table 4 show that while the point estimate of this difference is substantial, it is not statistically significant, so that we cannot rule out the possibility that the program's effect was equally large in both years.

4.4 Tests for Pre-Treatment Differences

Table 5 reports balance tests for the pre-treatment outcome. Columns 1-3 show that there is no statistically significant difference in the number of conflict incidents over the entire pre-treatment period 2001-2008, which suggests that the randomization was successful and treatment and control villages did not differ with respect to unobserved variables that affect conflict. However, the steeper increase in incidents in treatment groups between 2007 and 2008 raises the possibility that treatment and control villages may have experienced unobserved shocks in the late pre-treatment period. To test this hypothesis, columns 4-6 of Table 5 report the difference in conflict between treatment and control villages in the immediate pre-treatment year, 2008. The results show that, while the number of incidents was higher in treatment villages in 2008, this difference was not statistically significant.

4.5 Conditional Cash Transfers and Insurgent Influence

As additional evidence, we present an analysis of the CCT program's effect on the extent of insurgent influence. As described in Section 4.1, the insurgent influence variable comes from assessments by the AFP in support of its counterinsurgency campaign planning. It is coded in four categories, from lowest to highest level of influence: not influenced, threatened, influenced and infiltrated. To estimate the effect of *Pantawid Pamilya* on insurgent influence, Table 7 reports ordered probit regressions of the insurgent influence variable on the treatment indicator. To account for serial correlation of the error term, standard errors are clustered at the village level. The results show that insurgent influence is significantly lower in treated villages during the experimental period 2009-2010. This suggests that the program not only reduced violence but also led to a decrease in local insurgent influence.

4.6 Were There Spillover Effects?

One possible explanation for our results is that the *Pantawid Pamilya* program caused conflict to shift from treated villages to other nearby villages. Insurgents may, for example, have moved their combatants out of treated villages, perhaps because of increased presence of government troops or media scrutiny. It is therefore possible that the program did not decrease aggregate conflict in the country as a whole but merely shifted it from one location to another, as insurgents who moved out of treated villages initiated attacks in their new locations.

To estimate the size and sign of a possible spillover effect, we follow an approach similar to that of Miguel and Kremer (2004) and estimate the effect of being in spatial proximity to treated villages, regardless of own treatment status. To do this, we include the number of treated villages within a certain radius (5 and 10 kilometers) to the explanatory variables on the right-hand side of a regression. Of course, this variable is no longer randomly assigned since it depends on the total number of villages within the radius, so that it will be negatively correlated with the remoteness of the village. Following Miguel and Kremer (2004), we therefore adopt a panel approach that controls for unobserved time-invariant village characteristics that are correlated with the total number of villages within the radius. Specifically, we estimate the following equation: using data from the period 2001-2010:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Treat_i * Prog_t + \beta_3 X_{it} + \gamma_d N^T_{dit} * Prog_t + \phi_d N^T_{dit} + \lambda_t + \epsilon_{it} \quad (3)$$

where N^T_{dit} is the number treatment villages within d kilometers of village i and $Prog_t$ is an indicator for the treatment years 2009 and 2010. The spillover effect is captured by the parameter γ_d, which is associated with the number of villages within d kilometers that were receiving transfers through the *Pantawid Pamilya* program (the interaction of N^T_{dit} and the treatment time-period). The parameter ϕ_d, which is associated with the uninteracted variable N^T_{dit}, captures time-fixed village characteristics, such as remoteness, that are correlated with proximity to treatment villages.

The results reported in Table 6 suggest that villages within 5 kilometers of a treated village experienced between 0.028 and 0.04 fewer incidents (only statistically significant in the specification with control variables). In other words, we find no evidence that the program's effect came from insurgents shifting their operations from treated villages to nearby villages. Rather, the estimates are consistent with the hypothesis that the *Pantawid Pamilya* program reduces conflict by making it more difficult for insurgents to recruit combatants in treated villages, so that these villages can "export" fewer combatants to carry out attacks in other villages.

5 Conclusion

This paper presented an experimental evaluation of the effect of a large conditional cash transfer (CCT) program – the Philippines' *Pantawid Pamilya* – on the intensity of violence and local insurgent influence in civil conflict. In the last decade CCT programs have become one of the most popular tools for delivering development aid and a large literature documents their positive impacts on the well being of the poor. CCT programs are currently operating in numerous conflict-affected countries including Colombia, India, Indonesia and the Philippines. The present study provided novel experimental evidence of how CCT programs can affect civil conflict.

The results of our analysis indicate two key findings. First, the *Pantawid Pamilya* program caused a substantial reduction in the number of conflict-related incidents in the program area. Second, the program reduced insurgent influence in treated villages. This effect is important from a program-evaluation perspective, because insurgent influence can have negative consequences even in the absence of overt violence, for example by eroding the rule of law and restricting civilians' access to markets and employment (Berman et al., 2011b). A program that reduces violence by weakening insurgent influence is therefore likely to have more beneficial long-term effects than a program whose impact is limited to reducing insurgents' incentives to commit acts of violence but does not affect their influence. This finding makes an important contribution as the extant literature on development and conflict focuses almost entirely on measures of violence as the outcome of interest (e.g Miguel et al., 2004; Berman et al., 2011a; Dube and Vargas, 2013; Crost et al., forthcoming; Nunn and Qian, forthcoming) . To our knowledge, this paper provides the first empirical evidence of the effect of an aid program on a direct measure of insurgent influence.

Our results are consistent with previous findings that positive economic shocks reduce civil conflict (Miguel et al., 2004; Dube and Vargas, 2013). There are two potential mechanisms through which this effect might operate. First, CCT programs may increase popular support for the government by "winning hearts and minds." As a result, the population is more likely to provide information on insurgents to government forces, better enabling them to capture or kill insurgents and reduce insurgent attack rates (Berman et al., 2011a). This mechanism is consistent with the finding that the *Pantawid Pamilya* program increased support for incumbent politicians (Labonne, 2013).[17] Second, CCT programs may increase the opportunity cost of joining an insurgency. This could be either because the transfers boost the local economy and create higher incomes from peaceful activities or because the conditions imposed on program participants make it difficult to receive transfers while being active in the insurgency.[18] In either case, an increase in the opportunity cost of joining an insurgency would likely reduce conflict by making insurgent recruiting more difficult.

The available data limits our ability to distinguish between these two mechanisms. However, we do provide clear evidence that he effect of CCTs differs from the effect of other types of aid interventions, like community-driven development (CDD) and food aid programs, which have been found to increase the lethality and incidence of conflict (Crost et al., forthcoming; Nunn and Qian, forthcoming).

Of particular interest is a comparison with the results of Crost et al. (forthcoming), who found that a large-scale CDD program, KALAHI-CIDSS, increased local conflict in the Philippines. KALAHI-CIDSS took place at a similar time (2003-2009) and in similar geographic regions as the *Pantawid Pamilya* experiment studied in the present paper. Furthermore, both programs

[17](Manacorda et al., 2011) found similar evidence that a CCT programs increased popular support for the incumbent president in Uruguay.

[18]The conditions for receiving transfers through the *Pantawid Pamilya* program, for example, created incentives for families to insure none of their members were – or appeared to be – active in an armed insurgency. A senior government official responsible for the program's implementation recounted a case from the volatile Basilan province in the south of the country where spouses pressured their husbands to turn in their firearms lest they be considered incriminating evidence of affiliation with a rebel group and threaten their continued eligibility for cash transfers. (Interview with DSWD officials in Quezon City, Philippines April 2012).

were implemented by the same agency, the Philippine government's Department of Social Welfare and Development. It is therefore unlikely that the opposite effects of these two programs are entirely due to institutional differences or differences in the local intensity or characteristics of the conflict.

Crost et al. (forthcoming) cited two possible explanations for their finding that the KALAHI-CIDSS program increased local conflict in the Philippines. First, if successful aid programs increased popular support for the government as suggested by the "hearts-and-minds" hypothesis, insurgents would consequently have an incentive to sabotage the programs in order to prevent such a shift in public opinion, and this could exacerbate conflict at least in the short run.[19] Second, aid programs might increase conflict by increasing the amount of resources that the conflicting parties fight over (Hirshleifer, 1989; Grossman, 1991; Skaperdas, 1992).

There are several reasons to expect CCTs to have the opposite effect. For one, CDD programs disburse aid through small infrastructure projects chosen by a participatory democratic process. As a result, they create highly visible targets – the infrastructure itself as well as the community meetings needed to carry out the project – which insurgents can attack in their efforts to derail the program. In contrast, CCT programs such as *Pantawid Pamilya* target households directly and disburse aid in cash primarily through electronic transfers to beneficiaries' bank accounts. This gives insurgents fewer visible targets and makes derailing the program more difficult. In support of this hypothesis, there is anecdotal evidence, reported by Crost et al. (forthcoming) that insurgents were able to derail implementation of the KALAHI-CIDSS program in a number of areas, but no analogous evidence for the *Pantawid Pamilya* program. A similar reason might explain the different effects of cash-transfers and food aid, which needs to be physically delivered to its destination, which also creates visible targets and incentives for looting them.

[19] See Powell (2012) for a theoretical discussion of how shifts in power can cause conflict.

While we cannot say precisely which features of conditional cash-transfer programs are responsible for their conflict-reducing effect, our findings provide evidence that the mechanism in which aid is disbursed can determine its impact on civil conflict. Going forward, this suggests opportunities for future research on how and under what conditions various means of targeting and delivering aid can reduce rather than exacerbate the risk violent conflict.

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Figures and Tables

Figure 1: Map of *Pantawid Pamilya* Study Areas

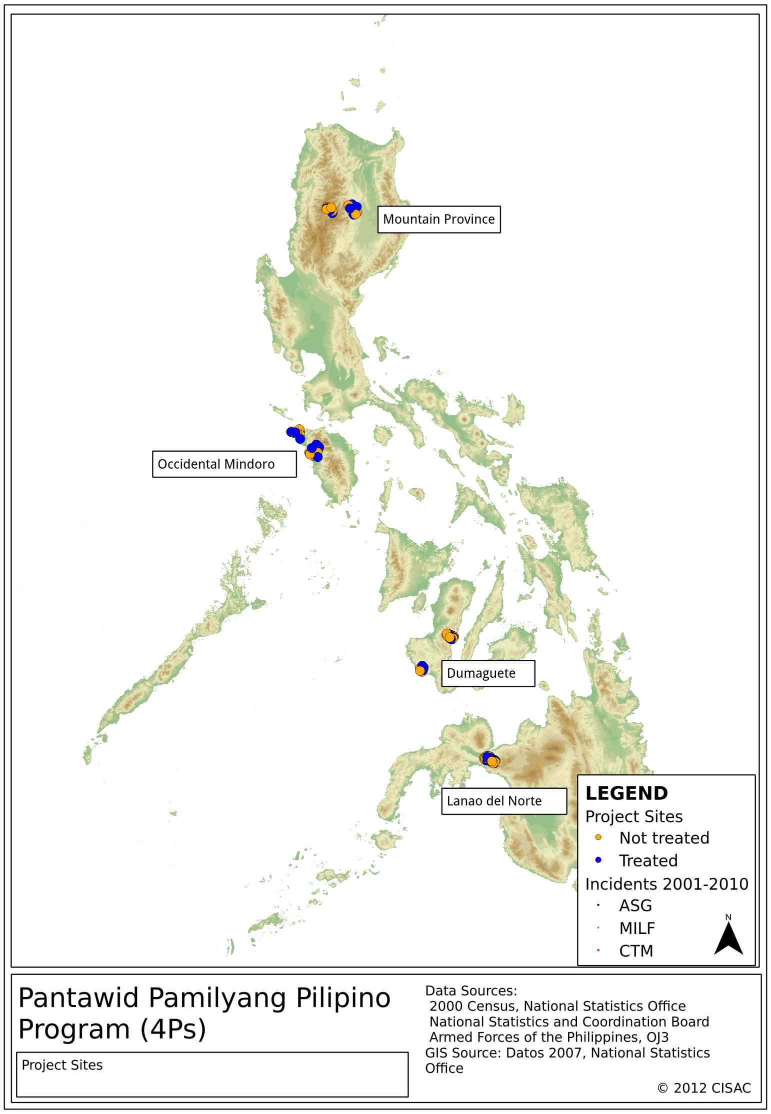

Figure 2: Time Trends of Conflict in Treatment and Control Villages

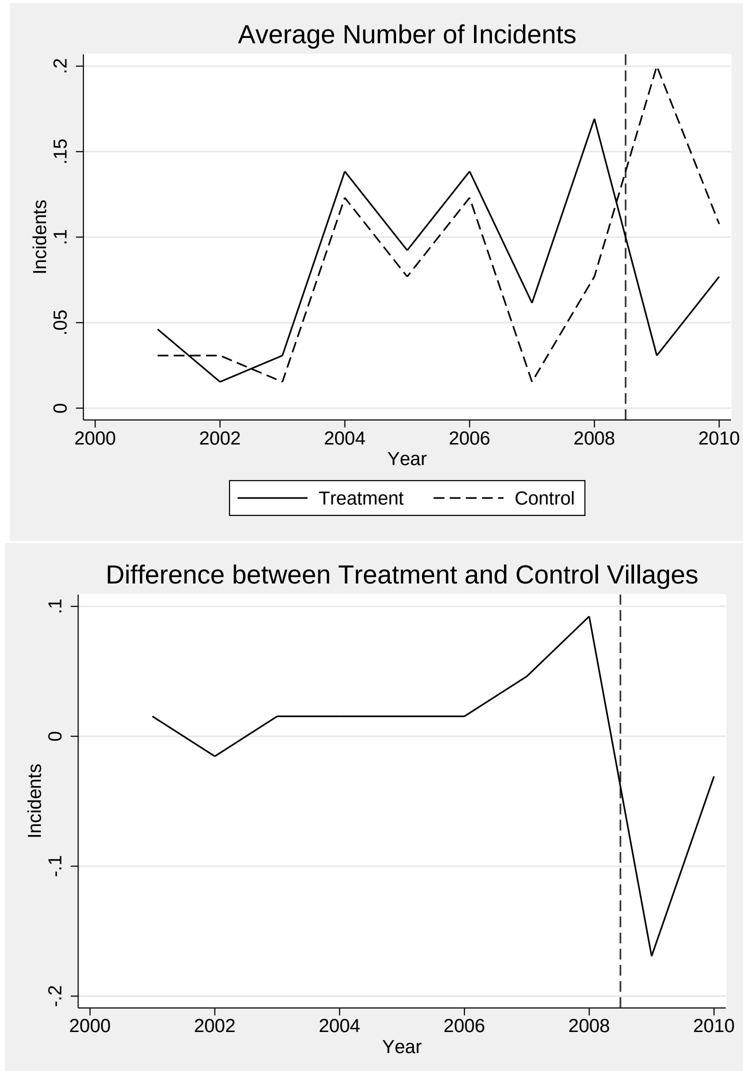

Table 1: Prevalence of Armed Groups in the Philippines, 2001-2010

Group	Nationwide	Experimental
NPA	60%	72%
MILF	11%	10%
LE	19%	18%
ASG	5%	0%
Other	5%	0%
Total	100%	100%

Data come from incident reports by AFP troops, 2001-2010.

Table 2: 4Ps Experimental Sample

Region	**Province**	**Municipality**	**Treatments**	**Controls**
CAR	Mountain Province	Paracelis	4	5
CAR	Mountain Province	Sadanga	4	4
Region IV-B	Occidental Mindoro	Paluan	6	6
Region IV-B	Occidental Mindoro	Santa Cruz	5	6
Region VII	Negros Oriental	Jimalalud	15	13
Region VII	Negros Oriental	Basay	5	5
Region X	Lanao del Norte	Lala	13	14
Region X	Lanao del Norte	Salvador	13	12

Table 3: Summary Statistics and Balance Tests

Variable	Treatment	Control	Difference	P-Value
Conflict Incidents	0.087	0.063	0.023	0.52
Population	1475	1419	55	0.81
Paved Streets	0.215	0.323	-0.108	0.17
Highway Access	0.477	0.508	-0.031	0.73
Communal Water System	0.169	0.154	0.015	0.81
Electricity	0.55	0.66	-0.108	0.21
Health Clinic	0.492	0.462	0.031	0.73
Hospital	0.031	0.046	-0.015	0.65
Observations	65	65	130	130

Summary statistics and balance tests of conflict incidents and village level control variables. The conflict incidents variable is the annual average over the pre-treatment period 2001-2008. All other variables are from the 2000 National Census of the Philippines.

Table 4: The Causal Effect of the 4Ps Program on Civil Conflict: Experimental Estimates

	Dependent Variable: Number of Incidents, 2009-2010			
	Poisson QMLE			
	(1)	(2)	(3)	(4)
Treatment	-0.102*	-0.121***	-0.169	-0.187**
	(0.061)	(0.047)	(0.108)	(0.088)
Treatment × (Year = 2010)			0.095	0.095
			(0.091)	(0.089)
Population (1000)		0.038		0.038
		(0.050)		(0.050)
Paved Streets		-0.33**		-0.33**
		(0.13)		(0.13)
Highway Access		-0.057		-0.057
		(0.061)		(0.061)
Electricity		0.010		-0.010
		(0.051)		(0.051)
Communal Water System		0.158		0.158
		(0.100)		(0.100)
Health Clinic		-0.006		-0.006
		(0.065)		(0.065)
Hospital		-1.51***		-1.50***
		(0.44)		(0.43)
Observations	260	260	260	260
Villages	130	130	130	130

Reported values are marginal effects. The unit of observation is the village-year. All specifications include municipality fixed effects. Standard errors are clustered at the village level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Table 5: Robustness Test for Failure of Randomization: Pre-Treatment Difference in Conflict

	Dependent Variable: Number of Incidents in 2008	
	Poisson QMLE	
	(1)	(2)
Treatment	0.065	0.042
	(0.057)	(0.078)
Population (1000)		-0.0019
		(0.0064)
Paved Streets		-0.058
		(0.073)
Highway Access		0.045
		(0.045)
Electricity		-0.042
		(0.078)
Communal Water System		0.034
		(0.032)
Store		0.013
		(0.036)
Health Clinic		0.034
		(0.033)
Hospital		0.034
		(0.033)
Observations	130	130

Reported values are marginal effects. All specifications include municipality fixed effects. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Table 6: Spillover Effects to Nearby Villages

	Dependent Variable: Number of Incidents	
	Poisson QMLE	
	(1)	(2)
Treatment x Program (2009-2010)	-0.184**	-0.198***
	(0.081)	(0.063)
# of treated villages within 5 miles x Program (2009-2010)	-0.028	-0.040**
	(0.019)	(0.019)
Treatment	0.049	0.056
	(0.049)	(0.039)
# of treated villages within 5 miles	0.008	0.024
	(0.019)	(0.016)
[1em] Total # of villages within 5 miles	-0.010	-0.004
	(0.009)	(0.007)
Mean # of villages within 5 miles of a treated village	16.9	16.9
	[11.7]	[11.7]
Control variables	No	Yes
Observations	780	780
Villages	130	130

Results are based on data for the period 2005-2010. The 4Ps experiment took place in the period 2009-2010. The unit of observation is the village-year. Reported values are marginal effects. Standard errors, clustered at the village level, are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. All specifications include municipality-by-year fixed effects. Standard deviations of means are reported in square brackets.

Table 7: Conditional Cash Transfers and Insurgent Influence

	Dependent Variable: Insurgent Influence, 2009-2010	
	Ordered Probit	
	(1)	(2)
Treatment	-0.40*	-0.54**
	(0.24)	(0.25)
Population (1000)		0.18
		(0.014)
Paved Streets		-0.57
		(0.38)
Highway Access		-0.22
		(0.40)
Electricity		-0.35
		(0.35)
Communal Water System		-0.24
		(0.71)
Health Clinic		-1.09***
		(0.38)
Hospital		0.22
		(0.40)
Observations	260	260
Municipalities	130	130

The dependent variable is an ordered categorical measure of insurgent influence that btakes the values (from lowest to highest influence): not influenced, threatened, influenced, infiltrated. The unit of observation is the village-year. All specifications include municipality and year fixed effects. Standard errors are clustered at the village level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.