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Essays on Weather Indexed Insurance and Energy Use in Mexico

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Essays on Weather Indexed Insurance and Energy Use in Mexico

by

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Abstract

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This dissertation consists of three chapters that analyze the effects of social development programs on productivity, risk management strategies, and energy consumption among the poorest population in Mexico. Weather shocks have important negative impacts on poor rural households' livelihood as they are not only closer to subsistence and more vulnerable but also depend on the weather for survival. Nonetheless, due to high administrative costs and information problems insurance markets tend to leave this part of the population unprotected. Similarly, poor rural households usually make use of cheap yet inefficient and potentially harmful sources of energy for cooking, lighting, and heating their homes. This situation does not only affect their health and daily activities, but also keeps them trapped in poverty. In the following chapters I discuss several ways in which government action can in fact improve this population's wellbeing.

The first chapter entitled "Drought and Retribution: Evidence from a large scale Rainfall-Indexed Insurance Program in Mexico" studies the effects of the recently introduced rainfall-indexed insurance on farmers' productivity, risk management strategies, and per capita income and expenditures in Mexico. Weather shocks are a major source of income fluctuation and most of the world's poor lack insurance coverage against them. In addition, the absence of formal insurance contributes to poverty traps as investment decisions are conflicted with risk management decisions: risk-averse farmers tend to under-invest and concentrate in the production of lower yielding yet safer crops. Recently, weather-indexed insurance has gained increased attention as an effective tool providing small-scale farmers coverage against aggregate shocks. However, there is little empirical evidence about its effectiveness. According to the Ministry of Agriculture, 80 percent of agricultural catastrophic risk in Mexico stems from droughts. Therefore, in 2003 it implemented weather-indexed insurance as a pilot in five counties in the Mexican State of Guanajuato, and by 2008 it already covered almost 1.9 million hectares representing 15 percent of rain-fed agricultural land. The main identification strategy takes advantage of the variation across counties and across time in which the insurance was rolled-out. We find that

insurance presence in treated counties has significant and positive effects on maize productivity. In fact, we find that insurance presence at the county level increases maize yields by more than 5 percent. Similarly, we find that insurance presence at the county level has had a positive effect on rural households' per capita expenditure and income of a magnitude close to 8 percent. However, we find no significant relation between insurance presence and the number of hectares destined to maize production.

The second chapter entitled “Voters Response to Natural Disasters Aid: Quasi-Experimental Evidence from Drought Relief Payment in Mexico” estimates the effect of a government climatic contingency transfer allocated through the recently introduced rainfall indexed insurance on the 2006 Presidential election returns in Mexico. Using the discontinuity in payment based on rainfall accumulation measured on local weather stations that slightly deviate from a pre-established threshold, we show that voters reward the incumbent presidential party for delivering drought relief compensation. We find that receiving indemnity payments leads to a significant increase in average electoral support for the incumbent party of approximately 7.6 percentage points. Our analysis suggests that the incumbent party is rewarded by disaster aid recipients and punished by non-recipients. This chapter provides evidence that voters evaluate government actions and respond to disaster spending contributing to the literature on retrospective voting.

The third and final chapter entitled “Conditional Cash Transfers schemes and Households' Energy Response in Mexico” analyzes the relationship between income and energy use in poor households in Mexico using household expenditure surveys that were collected to evaluate the poverty alleviation program “Oportunidades”. We argue that Oportunidades cash transfers provide an income shock that is exogenous to a household’s energy demand, allowing us to estimate short-run and long-run income elasticities for energy use. Short-run estimates hold household’s appliance stock constant and long-run estimates model the household’s decision to acquire new appliances. As a general estimation strategy households' fixed-effects are included. We also use instrumental variable estimation and a matching difference-in-differences estimator to check for robustness and correct for pre-selection unbalances between treatment and control groups. Results suggest significant differences between long-run and short-run elasticities as households emerging from poverty become first-time purchasers of energy-using appliances. In particular, we find small and not significant effects of cash-transfers on short-run energy consumption expenditure, but find significant and important effects of cumulative conditional cash-transfers on appliance acquisition (i.e. refrigerators and gas stoves). This has important policy implication since poverty alleviation programs like Oportunidades conditional cash transfers program, although not evident in the short run, have significant effects on energy demand.

a Carolina

y a la memoria de mi mamá

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Table of Contents

	Dedication	i
	Acknowledgements	ii
	List of Figures	iv
	List of Tables	v
1	**Drought and Retribution: Evidence from a large scale Rainfall-Indexed Insurance Program in Mexico**	**1**
	1.1 Introduction……………………………………………………..	1
	1.2 Weather-Indexed Insurance………………………………..	3
	1.3 Theoretical Framework…………………………………….	6
	1.4 Empirical Analysis…………………………………………	9
	1.5 Results………………………………………………………..	15
	1.6 Context and magnitude of the effects……………………...	16
	1.7 Robustness……………………………………………………	21
	1.8 Discussion…………………………………………………….	23
	1.9 References……………………………………………………	26
	1.10 Tables…………………………………………………………	30
	1.11 Figures………………………………………………………..	44
2	**Voters Response to Natural Disasters Aid: Quasi-Experimental Evidence from Drought Relief Payment in Mexico**	**49**
	2.1 Introduction……………………………………………………..	49
	2.2 The Context……………………………………………………..	51
	2.3 Data………………………………………………………………..	53
	2.4 Empirical Strategy and Results……………………………….	55
	2.5 Discussion…………………………………………………….	59
	2.6 References……………………………………………………	61
	2.7 Tables…………………………………………………………	63
	2.8 Figures………………………………………………………..	70
3	**Conditional Cash Transfers schemes and Households' Energy Response in Mexico**	**74**
	3.1 Introduction……………………………………………………	74
	3.2 The Model and Empirical Strategy………………………….....	75
	3.3 Oportunidades program and the data………………………….	82
	3.4 Results…………………………………………………………	85
	3.5 Robustness Checks: Matching difference-in-differences……..	87
	3.6 Discussion……………………………………………………..	90
	3.7 References…………………………………………………….	92
	3.8 Tables………………………………………………………….	94
	3.9 Figures…………………………………………………………	102

List of Figures

1.1.a	Weather Insurance Thresholds and Actual Rainfall……………………...	44
1.1.1	Insurance National Expansion (2003-2008)……………………………...	46
1.2.a	Procampo Beneficiaries (2002-2008)……………………………………	47
1.2.c	Average Rainfall (1990-2008)…………………………………………...	47
1.3.a	Maize Productivity Yield Growth………………………………………..	48
2.1.a	Example of a county where no payments where disbursed……………...	70
2.1.b	Example of a county where payments were disbursed…………………..	70
2.2.a	Map of municipalities covered by the WII……………………………….	71
2.2.b	Map of electoral sections included……………………………………….	71
2.3	Drought Relief, electoral sections with insurance coverage in 2005…….	72
2.4	Non-parametric graphic analysis share of votes for the incumbent in electoral sections with insurance coverage in 2005……………………...	72
2.5	Non-parametric graphic analysis, total number of votes casted in electoral sections with insurance coverage in 2005……………………...	73
3.1	Potential and Actual Oportunidades Transfers…………………………...	102
3.2	Lowess Smoother Refrigerator Acquisition……………………………...	102
3.3	Households with Refrigerator……………………………………………	103
3.4	Households with Gas Stove………………………………………………	103
3.5	Histogram of Propensity Score (Beneficiaries)…………………………..	104
3.6	Histogram of Propensity Score (Non Beneficiaries)……………………..	104

List of Tables

1.1.a	Agricultural Production in Mexico by Source and Product……………………	30
1.1.b	WII's Coverage by Crop, Year, Municipio, Extension, Production Value, Premium and Indemnity Payments…………………………………………	31
1.1.c	PROCAMPO Beneficiaries that produce Maize under Rain-Fed Agriculture..	32
1.1.d	Pre-Weather-Indexed Insurance County Characteristics………………………	33
1.1.e	Pre-Weather-Insurance Insurance Household Level Characteristics…………	33
1.2.a	WII's Insurance Effect on Log of Maize Yield at the County Level…………	34
1.2.b	WII's Insurance Effect on Maize Cultivated Hectares at the County Level…..	35
1.3.a	WII's Presence and Real Per Capita Household Expenditure…………………	36
1.3.b	WII's Coverage and Real Per Capita Household Income……………………..	37
1.4	WII's Effect on Log of Maize Yield at the County Level: Income Effect…….	38
1.5	Exogeneity of the Weather Indexed Insurance rollout………………………	39
1.6	Matching using CONAPO's Marginalty Index at the County Level 2000…….	40
1.6.b	WII's Insurance Effect on Log of Fruit Yield………………………………	41
1.6.c	WII's Insurance Effect on Log of Vegetables Yield………………………….	42
1.6.d	WII's Insurance Effect on Log of Pod Vegetables Yield……………………..	43
2.1	Descriptive Statistics, electoral sections with insurance coverage in 2005……	63
2.2	Drought Relief Compensation on Share of Votes for the Incumbent…………	64
2.3	Validity check using the pre-treatment elections of 2000…………………….	65
2.4	Estimates using a polynomial function of rainfall…………………………….	66
2.5	Robustness check, varying the window around the discontinuity…………….	67
2.6	Effect of Drought Relief Compensation on Turnout 2006…………………….	68
2.7	Effect of Drought Relief on the Share of Votes for other Parties……………..	69
3.1	Oportunidades Maximum Support Levels in 2003…………………………….	94
3.2.a	Basic Descriptive Statistics (Urban)…………………………………………...	95
3.2.b	Basic Descriptive Statistics (Rural)……………………………………………	96
3.3	Short-Run Income Elasticities for Energy Demand…………………………..	97
3.4	Income Elasticities Gas Stove and Refrigerator Adoption……………………	97
3.5	Refrigerator Ownership Rates: Beneficiaries versus Non-Beneficiaries………	98
3.6	Short-Run Income Elasticities for Energy Demand……………………………	98
3.7	Income Elasticities Gas Stove and Refrigerator Adoption……………………	99
3.8	Matched Diff-in-Diffs…………………………………………………………	99
3.9	Diff-in-Diffs and Matched Diff-in-Diffs……………………………………..	100
A1	Household asset holding by Income………………………………………….	101
A2	First Stage Regressions for IV estimations…………………………………..	101

Chapter 1

Drought and Retribution: Evidence from a large scale Rainfall-Indexed Insurance Program in Mexico

1.1 Introduction[1]

Weather shocks are a major source of income fluctuation usually translating into consumption interruptions and destroying accumulated assets through years of limited consumption (Barnett and Mahul 2007). These can be catastrophic, triggering famine, displacing families, and transmitting poverty across generations by introducing malnutrition and school dropout (Alderman and Haque 2008). This particular situation is accentuated in rural settings where survival depends on stochastic factors like weather, crop disease, and personal illness. Insurance could alleviate some of weather shocks negative effects. Yet, the majority of the world's poor have limited access to formal insurance.

As a result, numerous informal mechanisms have developed to prevent or mitigate the effects of weather shocks on consumption. Some of these successfully reduce risk exposure, though frequently do so by imposing trade-offs. For example, farmers may choose low-risk yet low-profit investments as alternatives to riskier yet higher-yielding ones (Rosenzweig and Binswanger 1993), keeping producers trapped in extreme poverty (Barnett, Barrett and Skees 2008). Additionally, risk coping mechanisms such as asset depletion and risk sharing arrangements are mainly effective to mitigate idiosyncratic risks. Since generalized shocks --such as those caused by weather-- usually enhance correlated individual losses within a geographical area, risk sharing is partially obstructed and durable assets lose their value in case of massive sales (Barnett and Skees 2009).

Recently, weather-indexed insurance (WII) has gained attention as an effective tool for providing coverage against climatic shocks to a large numbers of farmers. In agriculture, these contracts provide indemnity payments if the realization of a weather event that is highly correlated with material losses exceeds a pre-established threshold. There is neither need for actual loss estimation or individual visits for verification as these contracts rely on publicly available information from weather stations. Similarly, they potentially reduce information problems like adverse selection and moral hazard (Ginè et al. 2005). Moreover, it has been argued that WII could be useful to address some insurance market failures that contribute to the persistence of poverty among rural households (i.e. poverty

[1] This paper is co-authored with Hendrik Wolff. Permission was received from the coauthor to use it on this dissertation.

traps (Barnett, Barrett and Skees, 2008)). For example, WII could lead to increased investments in fertilizers and higher quality seeds or production of cash crops, though it could also lead to specialization or monoculture, depending on the insured crop (Fuchs and Wolff, forthcoming). Nonetheless, there is still little empirical evidence of their effects. Despite the recent increase in the number of studies related to WII, the vast majority focuses on small sample sizes and reduced geographic locations. For example, Ginè and Yang (2009) implement a randomized field experiment to test whether drought insurance in Malawi induces farmers to take loans for investment in new crop varieties, but their sample consists on roughly 800 maize and groundnut farmers. Similarly, Ginè, Townsend and Vickery (2007) study drought insurance implications on farmers in the Indian state of Andhra Pradesh using a sample of 752 households.

With this article, we intend to fill this gap in the literature by analyzing the effect of a large-scale WII. In 2008, the Mexican WII covered over 1.9 million hectares in 656 counties, corresponding to more than 15% of rain-fed agricultural land. Introduced in 2003, it takes advantage of existing weather stations to measure rainfall on insured regions. If precipitation within a certain period of time is below a pre-established threshold, the insurance disburses the corresponding indemnity payments. It is supplied by Agroasemex --a national insurance company-- and co-financed by the Ministry of Agriculture and state governments. Moreover, it provides coverage for production of four of Mexico's main crops of which maize is by far the most important. In 2008, total Mexican agricultural production reached 20.5 million hectares, and 73.6% of these depended exclusively on rain (Ministry of Agriculture 2009).[2] Maize production covered 7.8 million hectares of which more than 6.9 million was produced on non-irrigated land.

It has been argued that recent empirical development literature has relatively little to say about the possible effect of risk on behavior (Fafchamps 2009, page 4). Instead, most empirical studies have focused on measuring the effects of shocks on outcomes and behavior. A possible explanation for this phenomenon is that the impact of shocks on behavior is relatively easy to measure since most shocks are considered 'exogenous' or beyond the control of the agents (Fafchamps 2009). In this paper, we take advantage of the placement of a large scale government risk management tool considered 'exogenous' to individual farmers to identify the effect of risk (or the reduction of risk exposure) on farmers' behavior and overcome this empirical difficulty. In other words, the paper studies the link between the recently introduced WII on farmers' productivity and risk management strategies in Mexico. We use a unique panel dataset that we collected and constructed, combining county level agricultural production (for more than 300 different crop species in more than 2,300 counties from 2002 to 2008) with WII administrative data, weather data (daily rainfall and minimum and maximum temperatures from 1990 to 2008) and the full set of PROCAMPO beneficiaries from 1994 to 2008 (a Federal Government's program that provides cash transfers to farmers). In our identification strategy we take advantage of the variation across time and space in which WII was introduced and

[2] http://www.siap.sagarpa.gob.mx/

expanded. WII's treatment effect on yield is identified through the time and space in which it was rolled-out. We use county fixed effects to control for time invariant characteristics, year fixed effects to control for possible generalized shocks, and control for annual rainfall and temperature deviations. We measure changes in maize yields and hectares sown in counties that received insurance treatment earlier with respect to those who were later treated and those who were not treated at all. As a complementary empirical analysis, we measure weather-indexed insurance's effect at the household level using the National Household Expenditure and Income Surveys (ENIGH) for the rounds of 2002 to 2008.

We find that insurance presence at the county level positively and significantly affects insured counties' maize yield with respect to uninsured counties'. In particular, we find that WII presence has a positive and significant effect of 6% on yield, which compared to the premium that the government paid per hectare in 2008, translates into a substantial yield-increase to paid-premium ratio of a magnitude of 340%. Nevertheless, the effect is insignificantly related to the number of hectares devoted to maize production. Thus, although we cannot rule out off-setting effects, there does not seem to be evidence towards diversification or specialization. Conversely, we find that insurance presence and relative coverage --with respect to total land sowed-- are positively and significantly associated with a higher average per capita household real expenditure and income. In particular, insurance presence in the county is associated with a significantly higher real per capita household expenditure (and income) of around 8 percent with respect to counties without coverage.

The rest of the paper is organized as follows: section II describes weather-indexed insurance and the Mexican case in more detail. Section III presents a simple theoretical framework and Section IV the data and empirical strategy and models we estimate. Section V discusses the results. Section VI discusses a few implications and context of the results, section VII the robustness checks and finally, section VIII concludes.

1.2 Weather-Indexed Insurance

In agriculture, WII contracts provide indemnity payments if the realization of an easily verifiable weather event highly correlated with agricultural losses exceed a pre-established threshold. However, indemnity payments do not directly depend on agricultural losses. These have several advantages relative to traditional crop insurance. First, they are simple in terms of implementation, sales and marketing (Barnett and Mahul 2007). Second, they represent low administrative and implementation costs since there is no need to estimate actual losses experienced by the policyholder; measuring the value of the underlying weather index is sufficient. Also, insurers no longer have to visit individual plots to verify losses as they rely on publicly available information from weather stations. Third, WII reduces potential information problems (i.e. adverse selection and moral hazard) since it is unlikely that policyholders have more information about the underlying index, and policyholders cannot influence its realization (Ginè et al. 2005).

Nevertheless, WII faces some challenges. First, it is expensive to get started. A substantial amount of reliable information is required such as weather and agricultural production information, as well as detailed studies of the relation between soil type, inputs, and production.[3] Consequently, since weather data has public goods characteristics (Barnett and Mahul 2007), they are unlikely to be collected, cleaned, archived and made publicly available by the private sector. Government meteorological bureaus provide these services. In addition, since WII design is easy to copy as it uses publicly available information, few insurance companies will have an incentive to incur development costs. Therefore, governments or non-governmental organizations need to provide incentives to develop products of this nature. However, one of WII's main critiques is that despite its coverage, policyholders are still subject to substantial "basis risk" or the imperfect correlation between the index and the actual experienced losses (Barnett and Mahul 2009). In other words, if the weather index and the agricultural losses are not perfectly correlated, there could be cases in which policyholders receive indemnity payments without having suffered any loss, and there could also be cases in which policyholders suffer losses and still not receive indemnity payments. Similarly, WII could also have unintended consequences, such as potentially providing disincentives to invest in alternative agricultural technology: such as irrigation or research and development of drought resisting seeds. Additionally, depending on the insured crop, it could lead to specialization or monoculture causing the associated economic and environmental consequences (Fuchs and Wolff forthcoming).

The Case of the Mexican WII

In Mexico, small-scale farmers lack access to private production insurance because land fragmentation, large administrative costs and systemic risk discourage private insurers. Consequently, the Mexican Federal Government, through the Ministry of Agriculture, introduced WII in 2003. The program's main objective is to support small-scale agricultural producers (i.e. owning no more than 20 hectares) that "suffer atypical climatic contingencies --in particular droughts-- get reincorporated into their productive activities". Individual producers pay nothing to get coverage since it is jointly contracted by federal and state governments who provide resources from their annual budgets to purchase insurance premiums. Individual farmers become automatically enrolled if they live within the insured regions.

WII's coverage is exclusively provided by Agroasemex, a decentralized governmental agency that was formed in 2001. The design of WII acknowledges the relation between agricultural production, soil quality, crop and cumulative rain during the plant's growth cycle periods. Agroasemex tailors insurance policies for specific crops and regions to maximize the correlation between drought-induced harvest failure and indemnity payments. This is intended to effectively hedge weather risk associated with rain (Giné et al. 2005).[4]

[3] This information must have international quality standards, be collected by a reliable and trusted institution, and be made publicly available.

[4] In other words, weather coverage is characterized at a regional scale to minimize basis risk.

WII's coverage universe consists of crops that use rain as the main humidity input, and indemnity payments are provided if rainfall at any stage of the season is below the pre-established threshold measured in millimeters through local weather stations. As an example, we use three counties of the state of Guanajuato in Figures 1.1.a to 1.1.h. Agroasemex offers the following contract for insuring maize in the selected counties (Apaseo el Alto, Leon and Salamanca): the first period, also known as the sowing period, runs from May 15 to July 5; the second period --referred to as the flowering or growing period-- from July 6 to August 20; and the third --or harvesting period-- from August 21 to October 31. The minimum amount of cumulative rainfall above which Agroasemex does not provide indemnity payments --known as the trigger threshold-- equals 43, 80 and 60 millimeters for the first, second and third periods, respectively.[5] There were no indemnity payments in Apaseo el Alto, since cumulative rainfall was higher than the minimum thresholds in every period from 2003 to 2008. However, indemnity payments were provided in 2005 for maize production in the counties of Leon and Salamanca as cumulative rainfall was lower than the sowing period's minimum threshold.[6] To get this information, Agroasemex takes advantage of existing and publicly available rainfall information. Although there are more than 5 thousand weather stations in the country, WII only uses a subset since only few attain international standards and have more than 25 years of daily information, necessary to predict rain patterns.

Provided that Agroasemex has sufficient information to insure production regions (historical rainfall patterns, soil type, crops' humidity sensibility), state level officials suggest their federal counterparts the area to be insured (number of hectares and counties considered) within the first three months of the year (i.e. before the beginning of the season). For insurance policies' purchase, federal government pays 70% of the cost and the state governments cover the remaining 30%. However, for counties that have high poverty levels (defined by the National Population Council), costs are split 90%-10% between the federal and state governments, respectively.

Although WII was designed as individual producer insurance for small-scale farmers, it could be argued that Agroasemex in fact insures federal and state governments' budgets. In other words, Agroasemex's WII serves as a state governments' budget risk management tool since it allows annual budget planning minimizing the risk of catastrophic expenditure should severe droughts occur. Nevertheless, Agroasemex's WII affects individual producer's behavior. Even when farmers pay nothing to get insurance coverage (premiums are paid through a direct government subsidy), they become automatically insured and get informed about their coverage status through officials at the Program for Direct Assistance

[5] In this case, there was no payment since cumulative rainfall was higher than the minimum thresholds.

[6] We confirmed this information using daily rainfall data from the National Water Commission. Also, note that in 2005 Apaseo el Alto insured 6,885 hectares for maize production and paid premiums of $35 thousand US dollars ($344 thousand Mexican Pesos) for an insured production of $400 thousand US dollars ($3.9 million MXP). Conversely, the same year Leon and Salamanca insured 6,874 and 1,621 hectares for maize production, paid premiums of $46 and $13 thousand (for insured production of $380 thousand and $100 thousand dollars) and received indemnity payments of $380 thousand and $100 thousand dollars, respectively.

in Agriculture (PROCAMPO) regional offices (Centros de Apoyo al Desarrollo Rural (CADER) or in the "Ventanillas Autorizadas" depending on plots location and county).

Evidence of individual farmer's program awareness is provided by the Ministry of Agriculture 2009 through WII's program external evaluation written by a local based University (University of Chapingo). The document describes that a subset of randomly selected farmers were surveyed and asked about their awareness and knowledge of WII. Among those who were interviewed, 98% knew about WII's existence, and over 80% said they would be willing to pay in order to get insurance against droughts if the government did not provide it. This could be used as anecdotal evidence that farmers not only have knowledge of the insurance's existence, but that they also believe it is a valuable product.

1.3 Theoretical Framework

In this section we provide a simple theoretical framework to understand producer behavior under uncertainty. It adapts Sandmo's (1971) competitive firm behavior under price uncertainty to the case of agricultural production under yield uncertainty as suggested by Fafchamps (1999 and 2009). It is divided in three parts. The first part shows that as a consequence of uncertainty, risk-averse farmers tend to under-invest in riskier though potentially more profitable activities (i.e. risk-averse farmers invest a lower than optimum amount of inputs). The second part shows that if perfect insurance were to exist -- cancelling out the complete source of uncertainty-- risk-averse farmers would invest optimal input amounts for each alternative activity (i.e. where marginal products of both risky and safe activities are equalized). Finally, the last subsection introduces the case of weather-indexed insurance. As proposed by Mahul (2001), we divide the risk component of the stochastic production function into an insurable random weather variable and an uninsurable aggregate production shock. The presence of the uninsurable aggregate production shock could be directly associated to the concept of basis risk. In this case, the model predicts that although input investment and productivity are not optimal given the presence of aggregate production shock, risk-averse farmers' input investment in risky activities is higher than the case in which no insurance exists at all. The theoretical predictions from the model are in line with our testable hypotheses.

Agricultural Production under Uncertainty[7]

Assume a risk-averse farmer lives two periods (though it can be generalized to *n* periods). In the first period, also assume our farmer has an initial endowment of Y_1, which can be consumed (C), invested in a 'risky' asset (x), or invested in a 'safe' asset (z). That is, $Y_1 = C + x + z$ or $C = Y_1 - x - z$. In the second period, income depends on the output realization of both the safe and the risky assets. The value of the former is assumed deterministically ($\pi(z)$), but the value of the latter is stochastic ($\pi(x)\theta$) where θ is a multiplicative yield risk. Production functions are assumed to be increasing and concave ($\pi'(x) > 0$ & $\pi''(x) < 0$). Therefore, $Y_2 = \pi(x)\theta + \pi(z)$. In addition, we assume for the

[7] Based on Fafchamps (2009) and Sandmo (1971)

moment that our farmer is in a state of autarky, that is, she has no access to credits, loans, savings, or any other type of income or aid from peers.
The farmer faces an inter-temporal discount factor of δ, and optimizes the following indirect utility function:

$$\max_{x,z} V(Y_1 - x - z) + \delta EV(\pi(x)\theta + \pi(z))$$

We will assume that: $V'(Y) > 0$ & $V''(Y) < 0$.

From the first order conditions we get: $E[V'\theta]\pi'(x) = E[V']\pi'(z)$, which implies that

$$\pi'(x) = \frac{E[V']}{E[V'\theta]}\pi'(z)$$

According to Fafchamps (2009), if the farmer were risk neutral then $\pi'(x)E[\theta] = \pi'(z)$. This implies that the marginal productivity of investing in the 'safe activity' is equal to the marginal productivity of investing in the 'risky activity' weighted by the expected value of the multiplicative output risk. However, if the farmer is risk-averse, then there are two possible cases:

(1) $\frac{E[V']}{E[V'\theta]} > 1 => \pi'(x) > \pi'(z)$, and since $\pi''(x) < 0 => x < z$

(2) $\frac{E[V']}{E[V'\theta]} < 1 => \pi'(x) < \pi'(z)$, and since $\pi''(x) < 0 => x > z$

When farmers are risk averse, both Sandmo (1971) and Fafchamps (2009) show that (1) is true (see appendix for sketch of the proof). Therefore, given that $E[V'\theta] < E[V']$, we can then see that risk-averse farmers without insurance will under-invest in the 'risky activity' with respect to the 'safe activity' and in terms of what a risk neutral individual would invest. Consequently, we can conclude that risk aversion and lack of insurance lead farmers to allocate resources in an inefficient manner and possibly keep them 'trapped' in poverty.

Agricultural Production with Full Insurance

In this section we will assume farmers can acquire --either by purchasing at fair price or through direct government support-- full insurance against production risk (*I*) for a price of γ. Therefore, the farmer's optimization problem becomes:

$$\max_{x,z,I} V(Y_1 - x - z - I) + \delta EV(\pi(x)\theta + \pi(z) + I\gamma\theta)$$

The first order conditions lead to $E[V'\theta]\pi'(x) = E[V'\theta]\gamma$, which implies that $\pi'(x) = \gamma$, meaning that marginal productivity of the 'risky activity' is equal to the price of the insurance. In other words, the farmer will invest in the 'risky' activity (x) until the marginal product is equal to the price of full coverage. Conversely, if insurance were provided by the government for free, for example, then risk-averse farmers would invest on the 'risky' activity until $\pi'(x) = 0$, which is an efficient level of investment.

Insurance against Climatic Experience

In this section we follow Mahul (2001) to analyze the effect of coverage of a partial insurance --such as weather-indexed insurance-- on risk-averse farmers. However, we depart from his model by using Sandmo (1971) and Fafchamps (2009) as a basis to show efficiency gains from partially insuring risk (as opposed to the first case), but still show the inefficiency effects of uncorrelated but uninsurable risk (as opposed to the second). The uninsurable and uncorrelated risk could be related to what is known in the literature as 'basis risk' (Barnett and Mahul 2007, Barnett, Barrett and Skees 2008).

In a similar fashion to the two cases already described, assume the farmer observes a decreasing marginal indirect utility function of consumption. Also assume farmers face a stochastic production function of a 'risky activity' (x) which models the yield impact of an insurable random weather variable, and an uninsurable aggregate production shock, and as before, the input level is selected by the producer. The feature of this production function is that it allows yield in the second period to depend linearly on three sources:

$$Y_2 = \pi(x)\omega + \pi(x)\varepsilon + \pi(z)$$

Where $\pi(x)$ and $\pi(z)$ are defined above, ω is the insurable random weather variable and ε is the uninsurable aggregate production shock which could include basis risk or other non-correlated production shocks. We link this production function with the one faced by uninsured farmers through the following relation: $\pi(x)\theta = \pi(x)\omega + \pi(x)\varepsilon$.

According to Mahul (2001), if the insurable and the uninsurable aggregate production shock are independent, i.e. $\Psi_\omega(\varepsilon|\tilde{\omega} = \omega) = 0$ for all ε and ω, then the design of an optimal insurance contract against a climatic experience in the presence of independent background risk contains a trigger level such that indemnity payments are made if the realized weather index falls below the trigger level.[8] We will assume the two risks are independent.[9]

Consequently, farmers under this scheme solve the following optimization problem:

[8] When the two sources of risk are correlated, however, Mahul argues that the indemnity schedule can take any form without further restrictions on stochastic dependence and on producer's behavior.

[9] This is likely to be the case since one of weather-indexed main critiques is that the basis risk that farmers must bear is still present and important in magnitude. Basis risk is generated by the negative or non correlation between measured weather variable (at the weather station) and actual weather occurrence (at the place of production).

$$\max_{x,z,I_w} V(Y_1 - x - z - I_w) + \delta EV(\pi(x)\varepsilon + \pi(x)\omega + \pi(z) + I_w\gamma\omega)$$

From the first order conditions we get that $E[V'\varepsilon]\pi'(x) + E[V']\omega\pi'(x) = E[V']\pi'(z)$ which implies that

$$\pi'(x) = \frac{E[V']}{E[V'\varepsilon] + E[V']\omega}\pi'(z)$$

As in the case where no insurance is available, there are two possible cases:

(3) $\frac{E[V']}{E[V'\varepsilon]+E[V']\omega} > 1 => \pi'(x) > \pi'(z)$, and since $\pi''(x) < 0 => x < z$

(4) $\frac{E[V']}{E[V'\varepsilon]+E[V']\omega} < 1 => \pi'(x) < \pi'(z)$, and since $\pi''(x) < 0 => x > z$

Since farmers are risk averse, the first case is true. Therefore, we can argue that:

$$E[V'\theta] < E[V'\varepsilon] + E[V']\omega < E[V']$$

Therefore, we conclude that given the presence of the insurable random weather variable covered by WII, input allocation on the ‘risky activity’ is higher or more efficient than in the case where no insurance exists at all. However, due to the presence of the uninsurable aggregate production risk, input allocation on the ‘risky’ activity is suboptimal compared to the case of full insurance. This means that when farmers are risk averse, WII presence could lead to productivity gains due to a more efficient allocation of inputs. In other words, WII helps alleviate a market failure, which is what we empirically test in the following sections.

1.4 Empirical Analysis

Data

We collected, combined and used data from six sources. The first one consists of rain-fed agricultural production by county, year and crop type from 2002 to 2008 reported by the Mexican Ministry of Agriculture. Although we mainly focus our analysis on maize, this dataset has more than 270 crops, and provides the number of hectares sowed and harvested per year, as well as tons of production at the county level. In 2008, Mexican agricultural production reached more than 20.5 million hectares. However, close to 73.6% were produced without irrigation systems, depending exclusively on rain (Ministry of Agriculture 2009).[10] Maize is the most important crop since its production covers over 7.8 million hectares. Moreover, maize's relative importance is higher still for rain-fed

[10] http://www.siap.sagarpa.gob.mx/

agriculture as it covers more than 6.9 million hectares or 42% of sowed land as opposed to 28.3% of irrigated land. Table 1.1.a provides some descriptive statistics.

As noted, 2008 average annual maize yield under rain-fed production in Mexico was 3.2 tons per hectare, which is equal to almost 51 bushels per acre.[11] The same year, the average maize yield in the US state of Iowa was close to 154 bushels per acre (or 9.2 tons per hectare). Similarly, maize yields in Mexico are over 3 times higher under irrigated land than under rain-fed production (over 10 tons per hectare).

The second source consists of administrative data from the Ministry of Agriculture regarding WII's coverage. It includes county level coverage information in terms of weather stations used, insured crops (maize, beans, sorghum and barley), number of hectares insured, value of insured production, value of the premiums paid, and indemnity payments (in case a drought occurred). WII was first piloted in five counties of the Mexican state of Guanajuato in 2003. In the following years, it expanded to other counties and states reaching more than 15% of the country's rain-fed production land in 24 states in 2008.[12] Table 1.b. presents information of insured crops as well as the number of hectares insured, value of production, premiums paid by federal and state governments and indemnity payments. In 2003 WII had presence in only 5 counties, covering just over 107.5 thousand hectares. Conversely, by 2008 WII covered almost 2 million hectares in 656 counties. The first year in which Agroasemex made indemnity payments was 2005. Indemnity payments in 2005 paid by Agroasemex corresponded to 15.6% of the value of insured production. However, indemnity payments in 2005 corresponded to a larger amount than the premiums paid by the state governments that year. Figure 1.1.1 shows the geographic location of the 5 counties in the state of Guanajuato in which the insurance first started in 2003, and figure 1.1.2 shows that it covered 41 municipalities in both states of Guanajuato and Puebla. Figure 1.1.3 shows the program's rapid expansion in 2005 and figure 1.1.4 the coverage in 2007.

The third dataset comes from the Program for Direct Assistance in Agriculture (PROCAMPO). It consists of the program's full beneficiary census from 1994 to 2008. For our analysis, we only use a subset --farmers that produce under rain-fed agriculture from 2002 to 2008-- and take advantage of producer level information of total number of hectares used for production, total assistance amount received, whether the beneficiary produces in private or communal land and total land size (in hectares). We divided farmers in two groups: large (with 20 hectares or more) and small (less than 20 hectares) using WII's criteria for beneficiary selection. As there is no annual agricultural census in Mexico, and PROCAMPO program provides coverage to almost 70% of rain-fed agricultural land, having the full set of beneficiaries is the best approximation we can have to farm size and ownership at the county level. Figures 1.2.a and 1.2.b describe the number

[11] 1 Bushel of corn/maize is equal to 0.0254 tons, and 1 acre is equal to 0.4047 hectares.

[12] http://www.agroasemex.gob.mx. The states are Aguascalientes, Campeche, Chiapas, Chihuahua, Colima, Durango, Estado de Mexico, Guanajuato, Guerrero, Jalisco, Michoacan, Morelos, Nayarit, Oaxaca, Puebla, Queretaro, San Luis Potosi, Sinaloa, Tabasco, Tamaulipas, Tlaxcala, Veracruz, Yucatan and Zacatecas.

of rain-fed farmers that received support of the PROCAMPO program between 2002 and 2008, as well as the number of hectares destined for maize production and other crops. Between 2002 and 2008 PROCAMPO provided support to more than 2 million beneficiaries per year that produced rain-fed agriculture on almost 10 million hectares. Moreover, close to 75% of these received subsidies for maize production. However, if we analyze the extension in hectares that received PROCAMPO support, we notice that the extension destined for rain-fed maize production is close to 50%. In addition, table 1.1.c shows more information on rain-fed maize producers that received benefits from PROCAMPO between 2002 and 2008. In particular, the first column shows the total number of beneficiaries (and column 4 the total number of hectares supported), the second shows the number of "large" rain-fed maize producing beneficiaries (i.e. that own more than 20 hectares), and the third, the number of rain-fed maize producers that sow and harvest in private land. It is worth noting that although large maize producing beneficiaries are a little over 1% of the total number of beneficiaries, they produce in more than 11% of the land (measured in hectares).

The fourth source of data comes from the National Water Commission. The data consists of daily rainfall measures in millimeters for every weather station in the country from January 1990 until December 2008. Figure 1.2.c presents county average rainfall for the agricultural production season (months of April to November) for the years between 1990 and 2008. We also use temperature information of the same source since studies have shown that temperature is highly correlated with agricultural productivity, and in particular, extremely high temperatures negatively affect maize yields (Schlenker and Roberts 2006).

The fifth source comes from the National Population Council (CONAPO in Spanish) and consists of the denominated County Level Poverty Index (a poverty indicator) for 2000. The poverty index is calculated by CONAPO for each county using the method of principal components. Based on the 2000 census, it uses 10 indicators[13] and takes continuous values from 3.4 (poorest county) to -2.5 (richest county). Moreover, CONAPO divides counties into groups depending on the value of their index. For example, they define counties with high poverty as those whose index goes from 3.4 to 1, poor counties as those who have indices from 1 to -0.1, and so on. The index allows us to measure possible heterogeneous impacts of WII on groups of counties with respect to others.

Finally, we use household level information from the 2002, 2004, 2005, 2006 and 2008 National Household Expenditure and Income Survey (ENIGH).[14] ENIGH is a repeated

[13] Total county population, % of illiterate older than 15 years, % without primary school older than 15 years, houses without sewage, houses without electricity, houses without running water, houses with overcrowding, houses with dirt floor, % of rural population and % of people earning less than 2 minimum wages per month.

[14] According to its methodological synthesis, the ENIGH is a cross-section survey that reports information about the "structure, volume and distribution of the Mexican household's income and expenditure". It was surveyed for the first time in 1984, but it was until 1992 that its periodicity was established for every two years. Furthermore, according to INEGI, the ENIGH has maintained the same conceptual framework, unit of analysis, geographic coverage and sample design in order to maintain time comparability. The "household" is its basic unit of analysis, defined as the "space

cross section that contains a rich set of data ranging from socioeconomic characteristics, family structure, monthly reported income and expenditure, among others. Table 1.1.e provides descriptive statistics of rural households on counties that would be covered by WII in later years and those that we use as controls (not treated) in 2002 (a year before WII was introduced). As we can see, in 2002 there does not seem to be significant differences between households located in counties that will later be covered with respect to those that later will serve as controls.

Empirical Strategy

To measure WII's treatment effect on yields, we would ideally compare insured counties' yields with respect to their counterfactual. In other words, we would compare agricultural productivity of the same county had it not been covered by the insurance. Since the counterfactual is never observed, we take advantage of WII's staggered entry to compare treated counties with respect to counties to be covered in future years --and those not covered at all-- as comparison. Consequently, the identifying assumption is that, conditional on county characteristics and other shocks, changes in productivity would have been the same in treatment and control counties had WII not been implemented.

The results may be biased if insured counties were different from those that do not get insurance coverage. For example, if land quality differed among insured and uninsured counties. Further, it could be argued that weather stations were not randomly allocated in terms of land quality. If weather stations are located in more productive land, the difference in yields could be attributed to land quality instead of insurance's effect. Fortunately, most of the weather stations used by the program were built long before WII was introduced.[15] Moreover, Mexico's weather stations are located in places of strategic importance for the National Water Commission (i.e. close to dams and rivers), not based on agricultural productivity criteria.[16] In addition, we include county fixed effects to control for time invariant characteristics, such as land quality. Also, we control for annual rainfall deviation with respect to county rainfall average from 1990 to 2008, monthly average maximum temperature deviation from monthly 1990-2008 average, and include year fixed effects in order to control for common shocks. Finally, as additional robustness, we test for counties' WII rollout exogeneity.

Yield Models

In this section we present the empirical models we estimate. In particular, we start by testing the hypothesis that the introduction of WII had a positive effect on maize yields. Since we do not observe yield data at the farm or individual producer level, we base our

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delimited by roof and walls of any kind of material, in which one or more people live, sleep, cook, eat and protect themselves from the weather".

[15] As mentioned above, one of Agroasemex's requirements to insure a certain crop in a given area is to have at least 25 years of daily rainfall data of good quality (i.e. more than 90% of observations).

[16] This was confirmed by members of SAGARPA that work for the weather indexed insurance in a personal interview in February 2009.

productivity analysis at the minimum aggregation level we can observe: county level productivity.

In the following, we measure WII's presence with a dummy variable that takes the value of one if at least one hectare is insured in a given county, and zero otherwise. Also, we repeat the analysis using land covered by WII as a proportion of total land used for maize production in the county.

The left hand side variable included in the model is

$$(1) \qquad Y_{ct} = \frac{\Pi_{ct}}{H_{ct}}$$

where Π_{ct} represents total maize production (in tons) in county *c* and year *t*, and H_{ct} is the extension of maize harvested land (in hectares) in county *c* in year *t*.
The equation we estimate is the following:

$$(2) \qquad \text{Ln}(Y_{ct}) = \alpha_c + \beta_1 RainDev_{ct} + \beta_2 TempDev_{ct} + \gamma Insurance_{ct} + \sum_{t=1}^{T} \delta_t \, Year_t + \mu X_{ct} + u_{ct}$$

where $Insurance_{ct}$ is an indicator variable that takes the value of one if WII has presence on county *c* in year *t*. Moreover, we also estimate the equations using the proportion of land within each county dedicated to maize production (hectares of maize sowed land) covered by WII in each year. That is, $Insurance_{ct} = \frac{(Hectares\ covered)_{ct}}{(Hectares\ sowed)_{ct}}$.

Similarly, the $RainDev_{ct}$ and $TempDev_{ct}$ variables measure average annual county rainfall and maximum temperature deviation using the available historic rainfall and temperature data (from 1990 to 2008) from annual rainfall and average maximum temperature for the same county over the growing cycle (for the months of May to November). Thus, rainfall deviation is measured as follows:

$$RainDev_{ct} = \ln(AnnualRain_{ct}) - \ln\left(\frac{\sum_{t=1990}^{T=2008}[AnnualRain_c]}{(T-t)}\right)$$

$$RainDev_{ct} = \ln(AnnualRain_{ct}) - \ln\left(\overline{AnnualRain_c}\right)$$

where $\overline{AnnualRain_c}$ is average annual rainfall of county *c* for the 1990-2008 period, and $AnnualRain_{ct}$ is average annual rainfall of county *c* for year *t* (where *t* is 2002 to 2008). Maximum temperature deviation is measured the same way.

Also, in addition to including county and year fixed effects, we control for county level characteristics that change over time, X_{ct}, like the number of PROCAMPO beneficiaries, number of PROCAMPO beneficiaries that produce in private land, number of

PROCAMPO beneficiaries that are small (i.e. less than 20 hectares), and PROCAMPO per beneficiary subsidy in each county. Finally, we include the error term u_{ct}, and to correct for serial correlation, we cluster the standard errors at the state level and we use robust standard errors.

To test our second hypothesis (i.e., risk management or movements towards specialization/diversification), we follow a similar exercise but use the number of maize hectares sowed as left hand side variable. With this exercise we aim to test whether WII presence and coverage lead towards diversification (decrease the number of sowed hectares for maize production) or specialization (the opposite).

Household level analysis using ENIGH data

In this section we describe the empirical strategy and models used to estimate the relationship between WII's presence at the county and household level variables such as per capita (adult equivalent) real income and expenditure.[17] To achieve the latter, we combined WII's administrative data, PROCAMPO beneficiary data aggregated at the county level and county level weather information. Although ENIGH is a household survey conformed by a series of repeated cross sections, we take advantage of detailed household level information to identify correlations between WII presence at the county level and rural households characteristics. The identifying assumption is that conditional on rainfall and maximum temperature deviation, government transfers --such as PROCAMPO and Oportunidades programs-- at the county level, and household level characteristics, the difference in the variables of interests (i.e. poor rural household real per capita income and expenditure) should be negligible had WII not been introduced in the county. In addition to controlling for rainfall and maximum temperature deviation, PROCAMPO and household characteristics, on our most complete estimation we include year and county fixed effects.

The main equation we estimate is the following:

$$(3) \qquad \ln(Y_{ict}) = \alpha_c + \beta_1 RainDev_{ct} + \beta_2 TempDev_{ct} + \gamma Insurance_{ct} + \\ + \sum_{t=1}^{T} \delta_t \, Year_t + \mu X_{ct} + \tau H_{ict} + \varepsilon_{ict}$$

Where $\ln(Y_{ict})$ is the log of either real per capita household income or expenditure for household i in county c in year t. α_c and $\sum_{t=1}^{T} \delta_t \, Year_t$ are county and year fixed effects, respectively. $RainDev_{ct}$ and $TempDev_{ct}$ are rain and maximum temperature deviation (as defined above) in county c at year t. $Insurance_{ct}$ is either a dummy variable that takes the value of one if WII is present in county c at year t, zero otherwise, or it is the proportion of land destined for agricultural production covered by WII in county c in year t. Similarly,

[17] We calculate adult equivalent expenditure and income by weighting household members younger than 12 years as 0.5, and older than 12 years as 1. In addition, we deflate income and expenditure values by the national consumer price index (where 2002=100).

X_{ct} are county level characteristics, such as those obtained from the PROCAMPO beneficiaries' dataset. Finally, H_{ict} are household level characteristics such as household head's years of formal education, and whether the household receives Oportunidades and PROCAMPO benefits.[18]

1.5 Results

Table 1.2.a shows estimates of the relation between the log of maize yield on WII insurance presence (in the odd numbered columns) and WII coverage (in the even numbered columns), as well as county level PROCAMPO variables, rain deviation, maximum temperature deviation, county and year fixed effects from equation (2). The first two columns present estimates of the simplest specifications, and then we add more controls as we move towards the end of the table from left to right (columns (7) and (8)). Thus, the first two columns show the effect of WII (presence in column (1) and coverage in column (2)) on the log of maize yield using only county fixed effects. The coefficient is significant (at the 10% level) and positive in magnitude (5.9% and 6.6% for presence and coverage variables, respectively).

Columns (3) and (4), in addition to county fixed effects, include rain deviation and maximum temperature as controls. The coefficients on WII presence and coverage are still significant, with similar orders of magnitude. Moreover, the coefficient on rain deviation is positive and significant, implying that good rainfall (above average) will be positively associated with higher yield, and bad rainfall will be associated with lower yields. Similarly, the coefficient on maximum temperature deviation is also significant, negative and important in magnitude. This would imply that maximum temperatures above average will have a negative effect on yields. This finding is in line with Schlenker and Roberts' (2006), not only with higher temperatures being negatively related to maize yields, but also on the relative importance of temperature on yields.

Columns (5) and (6) include year dummies, excluding 2008. Finally, columns (7) and (8) present the most complete estimation, including county fixed effects, year dummies, rainfall and maximum temperature deviation and PROCAMPO variables at the county level. According to these estimates, WII's presence has a positive and statistically significant relation with maize yields once we control for county fixed effects, year dummies, precipitation, temperature and the set of controls. Similarly, the coverage variable is also significant (though at the 10% level) and of similar magnitude as before. It is worth noting that having a larger proportion of PROCAMPO beneficiaries that produce in private land is strongly and significantly associated with higher maize yields. This could be related to the literature of property rights and agricultural productivity. For example, Besley (1995 bis) finds a link between property rights and investment incentives in Ghana.

[18] This information is from ENIGH. The survey asks the household whether they are Oportunidades, PROCAMPO and or other government program's beneficiaries.

Similarly, Jacoby and Mansuri (2008) use detailed plot level data from rural Pakistan to show that non-contractible investment is underprovided on tenanted land.

Table 1.2.b show results of the relation between the log of maize cultivated hectares and WII presence and coverage in the county following similar specifications as that of table 1.2.a. The hypothesis behind these models is that WII presence at the county level could have an effect on farmers' decision towards diversification (in which case we would expect a negative coefficient) or towards specialization (positive coefficient). Although we cannot rule out that there might have been a combination of both effects, we argue that overall there is not a clear pattern in reference to WII presence (the coefficients of WII presence go from negative and significant to statistically insignificantly different from zero and small in magnitude as we include the full set of covariates). WII coverage seemed to have had a negative and significant effect in the log of maize hectares sowed, though fairly small in magnitude. Moreover, it is worth noting that as the proportion of PROCAMPO small maize producing beneficiaries increase, the log of maize cultivated hectares decrease. Similarly, the coefficient maize production sowed land covered by PROCAMPO is negative significantly different from zero.

Tables 1.3.a and 1.3.b show household-level cross-sectional relationships between WII presence and coverage at the county level and the log of real per capita household expenditure and income, respectively. The odd numbered columns show the relationship between the variable of interest and the insurance presence at the county as well as the full set of covariates, and the even numbered columns show the relation between the variable of interest and the insurance coverage as a proportion of land sowed in each county. Both tables show that the relationship between the insurance presence/coverage and both the log of real per capita expenditure and income is positive and significantly different from zero and robust to the inclusion of the full set of county and household level covariates. Moreover, the coefficients of the insurance presence on household expenditure and income are similar in magnitude. In these estimations, we are only considering the rural subset of the survey (towns or villages with 10,000 people or less). Insurance presence at the county is associated with an 8.73% higher real per capita household expenditure and 8.32% higher real per capita household income. Similarly, insurance coverage at the county level is associated with an 8.07% higher real per capita household expenditure and a 7.93% higher real per capita household income.

1.6 Context and magnitude of the effects and insurance premium

Context and magnitude of the effects

Most of the recent empirical literature has focused on the effect of shocks on outcomes and behavior rather than the effects of risk and risk management (Fafchamps 2009). Since shocks are usually considered exogenous to individuals' actions, identification follows directly from shock to behavior without much debate. Identifying the effect of risk on individual behavior is much harder. Still, the last few years have seen an increasing number of studies related to weather-indexed insurance projects, mainly in developing countries. Nevertheless, there is little consensus on their effectiveness on farmers' income smoothing, investments decisions and access to credits. This particular situation has inclined many donor organizations to reduce support on weather-indexed insurance. For example, the Bill and Melinda Gates Foundation, through the program for Agricultural Development and Financial Services for the Poor, decided that "it is unlikely that they will increase investment in this area until after assessing the outcomes of current efforts" (Gates Foundation, Summary of Insurance Convening, September 21, 2009). In other words, they will not invest in these projects until they accumulate enough evidence of their effectiveness. Our study contributes value to this debate by providing evidence of WII's effectiveness. We showed that large scale Mexican rainfall-indexed insurance has had a positive impact on maize yields and a positive association between insurance presence and per capita income and expenditure. In particular, we found that WII presence at the county level leads to a 6% increase in maize yield. In this section we provide a framework to measure the magnitude of the effects in terms of the resources invested as well as possible spillover and second order effects.

Treatment Effect on the Treated (TOT)

According to Table 1.1.c, approximately 99% of PROCAMPO's rain-fed maize producers have less than 20 hectares, and their share of total land destined for maize production is equivalent to 88% of the total. Thus, since the average effect of WII presence found was a 5.04% increase in maize yields (and 6.72% of WII coverage), it could be argued that the average treatment effect on the treated (TOT) ranges somewhere between 5.04% and 7.63%. Similarly, considering that the average PROCAMPO maize producer owns 3 hectares, and that rain-fed agriculture maize production yields are around 3 tons per hectare, we can then argue that the 6% increase in yields found due to WII's presence translates into an increase in production of about half a ton of maize per farmer per year. Schlegel and Havlin (1995) document that the use of an optimal amount of nitrogen fertilization in corn fields close to Tribune, Kansas, lead to yield increases of 46% between 1961 and 1991. Although we do not have county level fertilizer use information, having found a positive effect on county level maize yields on the range of 5 to 7.6% in a six years period is suggestive evidence that some kind of investment increase could be happening.

Premium to Value of Increase in Yields Ratio

The average price per ton for Mexican maize in 2008 was $230 US dollars (Ministry of Agriculture). Considering that average annual rain-fed maize production is 3 tons per hectare, we could argue that a 6% increase leads to an average increase of $41.4 dollars per hectare. This may not appear to be a substantial increase in production, but if we compare this number to the premium that the government paid per hectare in 2008 --$11.9 dollars per hectare-- the relative premium paid to increased value ratio is on the magnitude of 350%.[19] Nevertheless, if we compare the Mexican average treatment effect of a 6%

[19] Nevertheless, maize yield under irrigated farm land is closer to 10 tons per hectare. Thus, even acknowledging that irrigated and non-irrigated agricultural land are not directly comparable, the striking difference in yields may induce reconsidering the overall evaluation of irrigation projects. Moreover, agricultural insurance programs such as WII may

increase in maize yields with the Malawi tobacco index insurance, we can say that the impact in Mexico was still relatively small. In Malawi, 2 years after the program started, yields for farmers increased from 650 kg/hectare to 1480 kg/hectare (Grusczynski and Jaisinghani 2009). This implies an increase in yields of almost 130% in two years, though the authors acknowledge that these numbers reflect a good rain season, an important caveat to take into account.

Income versus Insurance and Potential Multiplying Effects

Finally, we address two issues related to the effects of the insurance at the rural household level. The first one is concerned with the possibility that an "income effect" --and not an "insurance effect"-- is driving our results. In other words, it could be the case that maize yields and household per capita expenditure increases result from the direct subsidy provided by the government (income effect through the premium) instead of a change in behavior due to the knowledge of being insured (insurance effect). In any event, we argue that the effect found should be attributed to the insurance for at least two reasons. On the one hand, farmers never receive the government subsidy directly as the government pays the premiums to Agroasemex. Farmers only receive compensation in case of severe drought. On the other hand, according to 2008 ENIGH monthly adult equivalent rural income was $312.2 dollars (or $3,746.4 per annum). Thus, we believe it is highly unlikely that $11.9 dollars per hectare per annum (corresponding to the premium paid by the government) could induce much of an income effect. In addition, we test for potential income effects related to indemnity payments by running yield models (similar to equation (2)) with the difference that we drop observations (counties) after they receive indemnity payments. If the effect found in the results section is in fact an "income effect", we should expect to observe no effect on yields once we drop counties that received indemnity payments. Table 1.4 shows the results of this experiment. Both WII presence and coverage are still positively and statistically significantly related to positive maize yields at the county level after dropping counties that received payments. This could be taken as an indication that what we are finding is in fact an insurance effect.

The second issue is related to the magnitude of the effect of the insurance on adult-equivalent income and expenditure. We found that WII presence is associated with an 8.07% increase in adult equivalent expenditure. According to ENIGH, average per capita monthly expenditure in 2002 was about $209.3, which implies an annual per capita expenditure of $2,512 dollars. Consequently, an 8.07% increase in annual per capita expenditure adds to $202.7 dollars, which compared to the $11.9 dollars paid for as premium, implies that WII is associated to an even larger effect on per capita expenditure than on maize yields. This may be explained through possible WII multiplying effects: for example, Barnett, Barrett and Skees (2008) underline the link between WII and credit markets, and Boucher, Carter and Guirkinger (2008) propose that WII alleviates what they call "risk constraints", thus unleashing the possibility of further credit uptake. Though we

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disincentive investments on irrigation projects (Fuchs and Wolff, forthcoming). It is important to consider second order effects when evaluating the effectiveness of any program to avoid getting biased results.

present weak evidence of the link between WII presence and higher per capita income and expenditure in rural settings, further research is needed to understand the mechanisms under which this relation is channeled.

Pure Premium vs. Actual Premium

If the market for agricultural insurance were competitive, the price of the insurance --or premium-- would be determined by the interaction between the demand and the supply of insurance. However, as already noted, market and regulatory imperfections affect the cost and the price of agricultural insurance.[20] Moreover, the price of the insurance is driven by three components: expected loss, expense load and catastrophe load (Mahul and Stutely 2010). The expected loss (also called pure premium) refers to actuarially calculated frequency and severity of the loss. The expense load is the part of the actual premium intended to compensate for administrative and operating costs. Finally, the catastrophe load, which is defined as “the amount charged to compensate the insurer for bearing risk since in any given year the actual loss can be much larger than the average loss” (Mahul and Stutley 2010 pp. 43), tends to be high in agricultural insurance since actual losses can be many times the expected loss.

To get a sense of the relative magnitude of the premium paid for the Mexican Weather Indexed Insurance, we used administrative data (in particular the trigger thresholds, premiums paid and value of insured production) as well as weather information (cumulative rainfall reported through weather stations used by Agroasemex). We calculate annual expected loss to get an idea of the difference between the “pure premium” and the “actual premium” paid to Agroasemex in 2008. Using the 2008 weather stations’ thresholds and daily rainfall data from 1990 to 2008, we calculated cumulative rainfall for each period-year and constructed the following “drought” variable D_{it}:

$$D_{it} = \begin{cases} 1 \; if \; C_{it} < T_{it} \\ 0 \; if \; C_{it} \geq T_{it} \end{cases}$$

Where C_{it} is cumulative rainfall in weather station *i* and year *t*, and T_{it} is trigger threshold set for weather station *i* and year *t*, below which indemnity payment is triggered.[21] After obtaining the values of the “drought” variable, we calculated the pure premium (*PP)*:

$$PP = \frac{\sum_{t=1}^{T} \sum_{i=1}^{I} D_{it}}{(T-t)*(I-i)} = \frac{\sum_{n=1}^{N} D_n}{N}$$

[20] Mahul and Stutely (2010) enumerate a series of market imperfections that justify public intervention in the provision of agricultural insurance, among which we recall systemic risk, information asymmetries, post-disaster assistance programs, limited access to international reinsurance markets, lack of infrastructure, low risk awareness.

[21] Given that the trigger thresholds and the time periods did not change between 2003 and 2008, we used the same thresholds and periods for the prior years (from 1990 to 2002) in order to calculate the variable.

In this case, $\sum_{t=1}^{T}\sum_{i=1}^{I} D_{it}$ is the sum of actual drought cases (in each station-year) over the total number of cases, N.[22] The calculated pure premium *(PP)* for the case of maize is 6.71%.

In addition, if we further assume that the value of the insured maize production *(VP)* corresponding to each weather station is the same as the one corresponding to 2008 for each year prior to the latter (i.e. from 1990 to 2007) we can calculate the following pure premium "2" *(PP_2)*:

$$PP_2 = \frac{\sum_{t=1}^{T}\sum_{i=1}^{I}(D_{it} * VP)}{(T-t)*(I-i)*VP} = \frac{\sum_{n=1}^{N}(D_n * VP)}{(N * VP)}$$

The calculated PP_2 for the case of maize is equivalent to 8.04%.

The "actual" premium *(AP)* for 2008 can be directly obtained from the 2008 administrative data. From table 1.1.b we know that in 2008 the government paid $18.33 million US dollars (MXP 192.45 million) in premiums for insuring maize. Also, the same table shows that the value of the maize insured production was $114.06 million dollars (MXP 1.2 billion). Thus, the actual premium *(AP)* paid by the government for insuring maize production through Agroasemex's WII was about 16.07%.

Therefore, we can argue that by charging a little over 16% for premium, Agroasemex covers the expected loss (about 6.7% for *PP* or 8% for PP_2) and has enough to cover the expense and catastrophe loads (roughly between 8 and 9.4 percentage points). As mentioned above, WII is relatively expensive to get started, but once running operation cost are relatively low compared to other types of agricultural insurance as their operation is based on publicly available weather information and insures zones of similar agro-climatic conditions instead of individual farmers (plus, there is no need for individual visits for risk estimation and loss verification). Thus, we think that the expense load should not take a large chunk of the remaining 8 to 9.4 percentage points. On the other hand, we also believe that the catastrophe load should not absorb a large part of the actual premium either since Agroasemex reinsures risk in international markets in which individual countries' risk (even those of the size of Mexico) are handled as idiosyncratic and are pooled with other countries and regions. Consequently, we believe the Mexican Government might be overpaying for rainfall-indexed insurance. Even when comparing the Mexican case with the premium paid by farmers in the context of BASIX's weather index insurance in South India we come to the same conclusion. In the Indian case, farmers purchase BASIX's insurance coverage in units of approximately one hectare. According to Grusczynski and Jaisinghani (2009), the premium paid for one unit is approximately $5.50 dollars (Rs270) which corresponds to a maximum indemnity payment of approximately $60 dollars (Rs3,000) should a catastrophic weather event occur. This implies an actual premium *(AP)*

[22] In this case N represents the combination of i and t, that is, $n = 1$ if station $i = 1$ and $t = 1990$, $n = 2$ if $i = 2$ and $t = 1990$, and so on.

of 9.2%, much lower than the *AP* of 16% corresponding to Mexico, even when it is acknowledged to be high by some authors (see Grusczynski and Jaisinghani 2009).

1.7 Robustness

Test of WII's rollout exogeneity

In this section, we will show that WII's introduction into particular counties was not correlated with observable 'pre-intervention' characteristics. In other words, we want to show that counties that acquired insurance coverage earlier than others were not selected due to atypically low qualifications in the immediate past: the 'Ashenfelter dip' story. If counties that received insurance coverage earlier were also suffering atypically low productivity, then yield increases after coverage could not necessarily be attributed to WII. It could well be a case of mean reversal. Therefore, we perform the following tests.

Let y_{ct} be an outcome of interest, such as maize yield, for county c in year *t*. To test that WII's rollout was not correlated with pre-intervention characteristics, we first calculated county level changes in outcomes from the previous year, Δy_{ct}, for all counties (that would eventually get the insurance by 2008, i.e. we exclude from the sample counties that are never treated by WII). In other words, we calculated maize yield growth for each year relative to the last one. Then, we use county/year changes in outcomes for all years prior to PACC's entry, Δy_{ct}, and regress on a set of year dummies δ_t and a variable T_c which gives the numerical year in which the insurance was introduced in county *c*:

$$(1) \qquad \Delta y_{ct} = \delta_t + \beta T_c + u_{ct}$$

This tests whether outcomes were changing at different rates in counties that received insurance earlier relative to those that received it later, which is the identifying assumption of an impact regression using county fixed effect. The results of this regression for both maize and beans yields can be seen in panel A of table 5.

Then, we analyze county productivity more closely over periods of time before and after being insured. This can be seen in Figure 1.2.a. for maize productivity and 1.2.b. for the case of beans. In these figures we show county level performance before and after WII's entry.

There is no particular pattern in the years prior to entry, which would concern with a potential endogenous sequence in the rollout, either in response to lower productivity problems (i.e. Ashenfelter dip), or following an ongoing improvement in performance. The 'Ashenfelter dip' has been discussed in previous non-experimental evaluations of public programs. For example, Rouse (1998) describes this problem in the context of a public sector training program evaluation in which individuals who participate in training programs are observed to have unusually low earnings in the period in which they are selected for the program. If potential beneficiary households that actually applied for the program were having an unusually low income in the time that they were selected, then the fixed effects estimates might be biased. In our particular case, the 'Ashenfelter dip' would bias our results if WII was introduced into counties that were particularly affected by droughts in previous years.

These results can be confirmed by regressing the average county outcome y_{ct} on a set of year dummies δ_t, county fixed effects γ_c, and variables c_{-n} that denote the year before WII's entry

$$(2) \qquad y_{ct} = \delta_t + \gamma_c + \beta_1 c_{-1,ct} + \beta_2 c_{-2,ct} + \beta_3 c_{-3,ct} + \beta_4 c_{-4,ct} + u_{ct}$$

The results of these regressions for maize and beans' yields are presented in panel B of Table 1.5. None of the explanatory variables turned out to be statistically significantly different from zero, which provides suggestive evidence that WI's expansion was not correlated with maize and beans' yield in previous years.

Group Matching Estimations

In this subsection, we use CONAPO's 2000 Poverty Index to measure heterogeneous maize yield's effects among county groups by WII presence and coverage. Based on the 2000 national population census, the poverty index is calculated using the method of principal components for each county. It uses 10 indicators[23] and takes continuous values from 3.4 (poorest county) to -2.5 (richest county in Mexico). Moreover, CONAPO divides counties in groups depending on their poverty index. For example, CONAPO defines counties under extreme poverty as those whose index goes from 3.4 to 1, poor counties as those who have indices from 1 to -0.1, and so on. Although CONAPO's poverty index is available for 2005 (calculated using the 'short census' or Conteo), we use the 2000 information since it is the most recent one we can get before WII was introduced.

We use county fixed effects models (similar to those used in section 3, equation (2)) with log maize yield as the variable of interest, but restricting to county-subsamples that have similar pre-intervention characteristics (matched counties) based on CONAPO's categories. Results are reported in table 1.6.a. The first two columns show estimation results for the full set of counties (which correspond to columns (7) and (8) of table 1.2.a.). Columns (3) and (4) use the same specification restricting the sample to extreme poor counties, (5) and (6) include poor counties only, (7) and (8) medium income counties and finally, (9) and (10) wealthier counties.

The highest effect (positive and significant) seems to be on medium income counties. Insurance presence and coverage seem to lack a significant effect on the extreme poor, poor and wealthy counties. Thus, medium income counties appear to concentrate the

[23] Total county population, % of illiterate older than 15 years, % without primary school older than 15 years, houses without sewage, houses without electricity, houses without running water, houses with overcrowding, houses with dirt floor, % of rural population and % of people earning less than 2 minimum wages per month.

largest number of farmers that are on the margin of changing behavior (increasing investment) and consequently, where WII has a larger impact.

Fruits and other vegetables' yields

As a final exercise, through similar specifications, but instead of using maize yields as interest variable, we used fruits yields, vegetables yields and pod-vegetables yields (produced under rain-fed agriculture) to look for possible WII spillover effects. The results are reported in tables 1.6.b, 1.6.c and 1.6.d for fruits, vegetables and pod-vegetables, respectively. As expected, the effect was positive although small in magnitude and statistically insignificant for fruits and vegetables. However, WII presence had a positive effect on pod-vegetables yields on the order of 4.5%, implying that there might be evidence of spillover effects in terms of increased investment or fertilizer use.

1.8 Discussion

In the last few years, weather index insurance has gained increasing attention as a useful tool to manage and cope with aggregate risk. Much has been said about its advantages over other traditional agricultural insurance contracts regarding low costs and reduction of information problems. Some have argued that it could be used as an effective tool to overcome "poverty traps" by allowing low income farmers produce higher profit yet riskier crops or increase investment in fertilizer and higher yielding crops. Conversely, others have argued that WII may induce specialization or monoculture and even divert investment in R&D of drought resistant seeds or other agricultural technology such as irrigation. Nonetheless, there is still little empirical evidence of its effects on risk taking behavior and farmers' decision making.

Using a unique dataset that combines information of Mexican agricultural production at the county level between 2002 and 2008, rainfall information and administrative data, and taking advantage of the Mexican WII introduction and staggered expansion over time, we identified the insurance's effect on yields and household level variables such as per capita income and expenditure. The paper provides evidence that WII's presence and coverage in treated counties was significant and positively associated with maize productivity. In particular, our results indicate that WII presence (and coverage) at the county level increase maize yields by approximately 6%. Using household level information from the National Household Income and Expenditure Survey (ENIGH) for the rounds of 2002 to 2008, we found that WII presence and coverage at the county level is positively and significantly associated with real per capita household expenditure and income. Moreover, the effects found were around the magnitude of 8%, underlying the possibility of a multiplying effect. Finally, we found that rainfall indexed insurance presence and coverage in Mexican counties was not significantly related with the number of hectares destined to sow maize. Thus, although we cannot argue that there has been a clear pattern towards specialization or diversification, we cannot rule out offsetting effects.

Although our results concentrate on a particular case --i.e. the Mexican WII-- we hope that this study contributes to understand the implications of this type of risk management instruments by studying one of the largest weather index insurance yet implemented. There are many questions left unanswered, but we hope that this paper leaves the door open for answering them in future research.

Appendix

We need to show that $E[V^{'}\theta] < E[V^{'}]$. Following Fafchamps (2009), for ease of notation write $V^{'}(\pi(x)\theta + \pi(z)) = V^{'}(\theta)$. We have two cases:

- If $\theta > E[\theta] => V^{'}(\theta) < V^{'}(E[\theta])$
- If $\theta < E[\theta] => V^{'}(\theta) > V^{'}(E[\theta])$

Taking the first case and multiplying both sides by $(\theta - E[\theta])$ we have:

$$V^{'}(\theta)\ (\theta - E[\theta]) \leq V^{'}(E[\theta])(\theta - E[\theta]) \text{ for all } \theta$$

Since this is true for all θ, then it is also true for averages. Taking expectations from both sides:

$$E[V^{'}(\theta)(\theta - E[\theta])] \leq E[V^{'}(E[\theta])(\theta - E[\theta])]$$

$$E[V^{'}(\theta)\theta - V^{'}(\theta)E[\theta]] \leq V^{'}[(E[\theta])(E[\theta] - E[\theta])]$$

$$E[V^{'}(\theta)\theta] - E[V^{'}(\theta)]E[\theta] \leq 0$$

$$E[V^{'}(\theta)\theta] \leq E[V^{'}(\theta)]E[\theta] => E[V'\theta] \leq E[V']$$

Thus, $\frac{E[V^{'}]}{E[V^{'}\theta]} \geq 1$ which implies that $\pi^{'}(x) > \pi^{'}(z)$ and $x < z$ since $\pi^{''}(x) < 0$.

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Table 1.1.a Agricultural Production in Mexico by Source and Product (2008)[1/]

	Irrigation			Rain-fed			Total		
	(a) Maize	**(b) Total**	**(a)/(b) %**	**(c) Maize**	**(d) Total**	**(c)/(d) %**	**(e) Maize**	**(f) Total**	**(e)/(f) %**
Sowed (Hectares)	1,590,111.2	5,612,662.3	28.33%	6,853,725.7	16,289,910.4	42.07%	8,443,836.9	21,902,572.7	38.55%
Harvest (Hectares)	1,541,559.9	5,413,056.9	28.48%	6,288,549.7	15,089,776.8	41.67%	7,830,109.6	20,502,833.7	38.19%
Production (Tons)	15,835,037.6	355,037,345.1	4.46%	20,022,737.6	118,791,025.7	16.86%	35,857,775.2	473,828,370.9	7.57%
Yield (Tons/Hectare)	10.3			3.2					
max (90%)	32.0			6.7					
min (10%)	2.2			0.7					
Counties (n)	1,523			2,303					

1/ Own elaboration using data from Sistema de Informacion Agroalimentaria y Pesquera (SIAP)

Table 1.1.b WII's Coverage by Crop, Year, Municipio, Extension, Production Value, Premium and Indemnity Payments

	Counties	Extension	Value	Premium	Indemnity
1.1 Maize Insurance					
2003	5	69,010	24,912,610	2,389,119	0
2004	39	189,742	142,306,500	17,803,054	0
2005	162	756,806	431,086,720	59,951,795	75,726,560
2006	552	1,069,670	625,505,760	68,524,501	11,596,080
2007	507	1,117,200	658,377,600	77,109,615	38,441,200
2008	633	1,532,239	1,197,676,908	192,455,049	73,061,820
1.2 Barley, Beans and Sorghum Insurance					
2003	5	38,611	13,938,571	1,336,709	0
2004	19	58,741	44,055,750	5,093,475	0
2005	126	409,515	234,898,560	41,368,288	29,357,360
2006	194	348,430	249,844,080	34,509,445	9,932,960
2007	181	401,538	249,367,200	38,361,415	1,985,200
2008	195	356,685	260,500,644	47,118,240	4,015,080
1.3 Total Insurance					
2003	5	107,621	38,851,181	3,725,828	0
2004	41	248,483	186,362,250	22,896,529	0
2005	213	1,166,321	665,985,280	101,320,083	105,083,920
2006	573	1,418,100	875,349,840	103,033,946	21,529,040
2007	527	1,518,738	907,744,800	115,471,030	40,426,400
2008	656	1,888,924	1,458,177,552	239,573,288	77,076,900

Data source: SAGARPA, own elaboration

Table 1.1.c PROCAMPO Beneficiaries that produce Maize under Rain-Fed Agriculture (2002-2008)

		Beneficiaries			Hectares used for production		
		Total	Large (>20 hs)	Private	Total	Large (>20 hs)	Private
2002	Total	1,687,743	17,604	36,977	5,630,904	653,717	182,761
	Mean	714	7.44	15.64	2,381	276.41	77.28
	Standard Dev.	1,114	28.94	69.08	4,134	1,093.94	358.54
	Min (10%)	34	0	0	66	0	0
	Max (90%)	1,782	17	17	6,244	571	88
2003	Total	1,672,421	17,163	37,049	5,525,560	626,282	187,132
	Mean	705	7.24	15.62	2,329	264.03	78.89
	Standard Dev.	1,106	29.00	68.37	4,060	1,070.44	367.19
	Min (10%)	33	0	0	67	0	0
	Max (90%)	1,753	16	21	6,121	538	96
2004	Total	1,602,172	17,520	35,446	5,302,351	649,102	186,008
	Mean	675	7.38	14.92	2,233	273.31	78.32
	Standard Dev.	1,066	31.40	65.65	3,902	1,183.48	364.78
	Min (10%)	32	0	0	60	0	0
	Max (90%)	1,644	15	18	5,805	521	94
2005	Total	1,424,022	14,942	33,142	4,608,866	549,668	165,984
	Mean	599	6.28	13.94	1,938	231.15	69.80
	Standard Dev.	956	24.31	62.80	3,239	941.80	318.05
	Min (10%)	27	0	0	56	0	0
	Max (90%)	1,480	14	18	5,104	460	90
2006	Total	1,400,508	13,659	32,763	4,434,112	492,459	161,292
	Mean	589	5.75	13.79	1,866	207.26	67.88
	Standard Dev.	946	21.17	62.49	3,068	811.19	310.18
	Min (10%)	26	0	0	56	0	0
	Max (90%)	1,429	12	18	4,950	422	88
2007	Total	1,394,590	14,554	31,991	4,485,397	531,032	161,821
	Mean	587	6.12	13.46	1,887	223.40	68.08
	Standard Dev.	942	24.31	60.75	3,147	967.67	313.22
	Min (10%)	25	0	0	54	0	0
	Max (90%)	1,450	13	18	5,059	431	89
2008	Total	1,664,619	17,399	36,325	5,474,625	621,664	187,240
	Mean	699	7.31	15.26	2,300	261.20	78.67
	Standard Dev.	1,120	29.22	67.14	4,044	1,081.29	363.22
	Min (10%)	27	0	0	59	0	0
	Max (90%)	1,734	16	21	5,886	531	97

Source: Own elaboration using data from the PROCAMPO beneficiaries' dataset.

Table 1.1.d Pre-Weather-Indexed Insurance County Characteristics (2000)

Variable	Treated	Not Treated	Difference	Standard Error
Mean Population	47,743.07	28,827.12	-18,915.9***	(4,401.72)
Mean % Illiteracy	15.30	18.18	2.89***	(0.47)
Mean % No Primary	37.03	41.79	4.76***	(0.59)
Mean % No Sewage	9.14	11.47	2.32***	(0.26)
Mean % No Electricity	3.97	6.51	2.54***	(0.35)
Mean % No Running Water	16.96	18.79	1.83***	(0.87)
Mean % Dirt Floor	21.23	28.08	6.85***	(0.96)
Mean % Rural	65.08	79.48	14.40***	(1.43)
Mean % Indigenous	11.95	21.45	9.50***	(1.20)
Mean % Men Labor Force	74.43	75.16	0.73***	(0.33)
Mean % Female Labor Force	25.57	24.84	-0.73***	(0.33)

	Treated	Not Treated	Total
Number of Counties	810	1,546	2,356

Table 1.1.e Pre-Weather-Insurance Insurance Household Level Characteristics (ENIGH 2002)

Variable	Treated	Not Treated	Difference	Standard Error
Log of Per Cap Income	7.03	7.02	0.017	(0.06)
Log of Per Cap Expenditure	7.01	6.92	0.086	(0.06)
Head's Years of Formal Education	7.68	7.01	0.668	(0.62)
Number of elderly	3.18	3.08	0.103	(0.08)
Real Oportunidades Support	20.10	24.25	-4.147**	(2.09)
Real PROCAMPO Support	22.86	27.59	-4.729	(5.09)

	Treated	Not Treated	Total
Number of households	1,379	4,689	6,068

Table 1.2.a WII's Insurance Effect on Log of Maize Yield at the County Level

VARIABLES	(1) Log Maize Yield	(2) Log Maize Yield	(3) Log Maize Yield	(4) Log Maize Yield	(5) Log Maize Yield	(6) Log Maize Yield	(7) Log Maize Yield	(8) Log Maize Yield
WII Presence (dummy)	0.0588*		0.0564*		0.0505*		0.0504*	
	(0.030)		(0.029)		(0.029)		(0.029)	
WII Coverage (% of land sowed)		0.0656*		0.0624*		0.0649*		0.0672*
		(0.037)		(0.036)		(0.034)		(0.034)
Rain Deviation			0.0878***	0.0878***	0.0717***	0.0716***	0.0683***	0.0681***
			(0.026)	(0.026)	(0.021)	(0.021)	(0.021)	(0.021)
Temperature Deviation			-0.491**	-0.495**	-0.404**	-0.405**	-0.401**	-0.401**
			(0.187)	(0.186)	(0.184)	(0.182)	(0.186)	(0.184)
% of PROCAMPO in Private land							1.588**	1.593**
							(0.598)	(0.600)
% of Maize Producers in <20 hectares							0.17	0.166
							(0.616)	(0.615)
% of Land covered by PROCAMPO (maize production)							-0.0895	-0.0935
							(0.058)	(0.058)
Constant	0.382***	0.384***	0.383***	0.386***	0.410***	0.412***	0.233	0.241
	(0.004)	(0.003)	(0.004)	(0.003)	(0.022)	(0.022)	(0.612)	(0.611)
Observations	14,791	14,791	14,791	14,791	14,791	14,791	14,791	14,791
R-squared	0.002	0.001	0.008	0.008	0.026	0.026	0.029	0.029
Number of Counties	2,316	2,316	2,316	2,316	2,316	2,316	2,316	2,316
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of maize yield" defined as total production (in tons) over number per county harvested hectares. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. The fourth to sixth right hand side variables come from the PROCAMPO beneficiaries dataset whereby the first one is the proportion of PROCAMPO beneficiaries that produce maize in private land, the second one is the proportion of beneficiaries that have land smaller than 20 hectares and the third one is the proportion of total land dedicated for maize production covered by PROCAMPO program. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level.

Table 1.2.b WII's Insurance Effect on Log of Maize Cultivated Hectares at the County Level

VARIABLES	(1) Log Maize Cultivated Hectares	(2) Log Maize Cultivated Hectares	(3) Log Maize Cultivated Hectares	(4) Log Maize Cultivated Hectares	(5) Log Maize Cultivated Hectares	(6) Log Maize Cultivated Hectares	(7) Log Maize Cultivated Hectares	(8) Log Maize Cultivated Hectares
WII Presence (dummy)	-0.0442**		-0.0443**		-0.0249		-0.0229	
	(0.021)		(0.021)		(0.026)		(0.018)	
WII Coverage (% of land sowed)		-0.124***		-0.124***		-0.102**		-0.0680**
		(0.032)		(0.032)		(0.040)		(0.027)
Rain Deviation			0.000477	0.00113	-0.00413	-0.00298	-0.00218	-0.00153
			(0.018)	(0.017)	(0.016)	(0.016)	(0.013)	(0.013)
Temperature Deviation			-0.035	-0.043	0.010	0.000	0.038	0.032
			(0.139)	(0.136)	(0.138)	(0.138)	(0.112)	(0.112)
% of PROCAMPO in Private land							-0.343	-0.341
							(0.467)	(0.473)
% of Maize Producers in <20 hectares							-4.457***	-4.468***
							(0.720)	(0.723)
% of Land covered by PROCAMPO (maize production)							-1.300***	-1.295***
							(0.122)	(0.123)
Constant	7.202***	7.206***	7.202***	7.206***	7.218***	7.223***	12.53***	12.54***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.011)	(0.012)	(0.705)	(0.708)
Observations	14,791	14,791	14,791	14,791	14,791	14,791	14,791	14,791
R-squared	0.002	0.007	0.002	0.007	0.009	0.013	0.288	0.290
Number of Counties	2,316	2,316	2,316	2,316	2,316	2,316	2,316	2,316
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of maize cultivated hectares" defined as the log of hectares of maize sowed in each county each year. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. The fourth to sixth right hand side variables come from the PROCAMPO beneficiaries dataset whereby the first one is the proportion of PROCAMPO beneficiaries that produce maize in private land, the second one is the proportion of beneficiaries that have land smaller than 20 hectares and the third one is the proportion of total land dedicated for maize production covered by PROCAMPO program. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level.

Table 1.3.a Relation between WII's Presence and Real Per Capita Household Expenditure from ENIGH 2002-2008

VARIABLES	(1) Log Per Cap Expenditure	(2) Log Per Cap Expenditure	(3) Log Per Cap Expenditure	(4) Log Per Cap Expenditure	(5) Log Per Cap Expenditure	(6) Log Per Cap Expenditure	(7) Log Per Cap Expenditure	(8) Log Per Cap Expenditure
WII Presence (dummy)	0.042		0.106**		0.0954**		0.0873**	
	(0.05)		(0.04)		(0.04)		(0.04)	
WII Coverage (% of land sowed)		0.0332		0.0882***		0.100**		0.0807**
		(0.03)		(0.03)		(0.04)		(0.03)
Rain deviation from 1990-2008 mean	0.121	0.12	0.0974	0.0939	0.1000**	0.0947*	0.0588	0.0578
	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Maximum Temperature deviation from 1990-2008 mean	-0.805*	-0.797*	-0.731**	-0.708**	-0.767**	-0.726*	-0.519	-0.486
	(0.41)	(0.41)	(0.35)	(0.35)	(0.37)	(0.37)	(0.32)	(0.33)
% of PROCAMPO beneficiaries in Private land			0.00512	-0.00671	-0.554	-0.683	-0.446	-0.507
			(0.36)	(0.37)	(2.36)	(2.24)	(2.30)	(2.23)
% of Maiz Producers who own < 20 hectares			-1.628**	-1.637***	-1.215*	-1.229*	-0.933	-0.922
			(0.61)	(0.61)	(0.65)	(0.64)	(0.62)	(0.60)
% of maize land covered by PROCAMPO			-0.0627	-0.0526	-0.0229	-0.016	-0.0884	-0.0763
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
PROCAMPO Real per Capita Transfers			0.00035***	0.00036***	0.00045***	0.00045***	0.00045***	0.00045***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OPORTUNIDADES Real per Capita Transfers			-0.0020***	-0.0021***	-0.00072***	-0.00074***	-0.00077***	-0.00078***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Years of formal education			0.0645***	0.0646***	0.0578***	0.0579***	0.0580***	0.0580***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	7.029***	7.027***	8.437***	8.434***	8.273***	8.316***	8.025***	8.021***
	(0.05)	(0.05)	(0.59)	(0.59)	(1.09)	(1.05)	(1.06)	(1.03)
County Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	NO	NO	YES	YES
Observations	36,190	36,190	36,190	36,190	36,190	36,190	36,190	36,190
R-squared	0.004	0.004	0.153	0.154	0.341	0.342	0.344	0.345

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1 Note: We use household level information from the National Household Income and Expenditure Survey (ENIGH) for 2002, 2004, 2005, 2006 and 2008. However, we only take into account households that live in rural settings. We use OLS to estimate the relationships. We include county fixed effects and year fixed effects, as well as a set of controls. The left hand side variable is the log of per adult equivalent real household expenditure. The first right hand side variable for the odd regressions (WII Presence) is a dummy variable that takes the value of 1 if WII has presence on the county where the household is located, and zero otherwise. The first right hand side variable for the even regressions (WII coverage) is the proportion of land destined for maize production covered by the WII program. The second and third variables are yearly rain deviation (in millimeters) from mean rainfall between 1990 and 2008 and maximum temperature deviation with respect to average 1990-2008 maximum temperature. The fourth one is a variable that takes the value between zero and 1 and is the proportion of PROCAMPO beneficiaries that produce in private land (as opposed to communal land or 'Ejidos'). The fifth one is the proportion of PROCAMPO beneficiaries that produce maize and have less than 20 hectares (proportion of small-scale producers), and the sixth is a variable that describes the proportion of land dedicated for maize production in each county covered by PROCAMPO. The seventh and eighth are PROCAMPO and OPORTUNIDADES real per capita transfers received by each beneficiary household and finally, years of formal education is the number of years that the head of household reported having received of formal education. Finally, we cluster at the State-Rural level.

Table 1.3.b Relation between WII's Coverage and Real Per Capita Household Income from ENIGH 2002-2008

VARIABLES	(1) Log Per Capita Income	(2) Log Per Capita Income	(3) Log Per Capita Income	(4) Log Per Capita Income	(5) Log Per Capita Income	(6) Log Per Capita Income	(7) Log Per Capita Income	(8) Log Per Capita Income
WII Presence (dummy)	0.075		0.145***		0.146***		0.0832*	
	(0.05)		(0.04)		(0.04)		(0.04)	
WII Coverage (% of land sowed)		0.0655*		0.128***		0.145***		0.0793**
		(0.03)		(0.03)		(0.05)		(0.04)
Rain deviation from 1990-2008 mean	0.0968	0.094	0.0734	0.0682	0.101*	0.0930*	0.0578	0.0569
	(0.08)	(0.08)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Maximum Temperature deviation from 1990-2008 mean	-0.805*	-0.791	-0.724*	-0.692	-0.509	-0.446	-0.46	-0.428
	(0.48)	(0.48)	(0.43)	(0.42)	(0.40)	(0.39)	(0.36)	(0.36)
% of PROCAMPO beneficiaries in Private land			-0.00614	-0.024	-0.756	-0.92	-0.578	-0.644
			(0.36)	(0.37)	(1.72)	(1.59)	(1.80)	(1.74)
% of Maiz Producers who own < 20 hectares			-2.093***	-2.101***	-1.213*	-1.222**	-1.239	-1.231*
			(0.55)	(0.55)	(0.62)	(0.61)	(0.74)	(0.72)
% of maize land covered by PROCAMPO			-0.0783	-0.064	-0.0648	-0.0537	-0.108	-0.0959
			(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
PROCAMPO Real Transfers			0.00062***	0.00062***	0.00073***	0.00073***	0.00074***	0.00074***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OPORTUNIDADES Real Transfers			-0.0024***	-0.0025***	-0.00097***	-0.00099***	-0.0011***	-0.0011***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Years of formal education			0.0682***	0.0684***	0.0578***	0.0579***	0.0575***	0.0576***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	7.058***	7.053***	8.925***	8.916***	8.478***	8.522***	8.505***	8.505***
	(0.05)	(0.06)	(0.53)	(0.53)	(0.89)	(0.86)	(0.96)	(0.94)
County Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	NO	NO	YES	YES
Observations	36,190	36,190	36,190	36,190	36,190	36,190	36,190	36,190
R-squared	0.003	0.004	0.165	0.167	0.353	0.355	0.357	0.357

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, we are cluster at the State and Rural levels Note: We use household level information from ENIGH for 2002-2008. However, we only use households that live in rural settings. We use OLS to estimate the relationships. We include county fixed effects and year fixed effects, as well as a set of controls. The left hand side variable is the log of per adult equivalent real household income. The first right hand side variable for the odd regressions (WII Presence) is a dummy variable that takes the value of 1 if WII has presence on the county where the household is located, and zero otherwise. The first hand side variable for the even regressions (WII coverage) is the proportion of land destined for maize production covered by the WII program. The second and third variables are yearly rain deviation (in millimeters) from mean rainfall between 1990 and 2008 and maximum temperature deviation with respect to average 1990-2008 maximum temperature. The fourth one is a variable that takes the value between zero and 1 and is the proportion of PROCAMPO beneficiaries that produce in private land (as opposed to communal land or 'Ejidos'). The fifth one is the proportion of PROCAMPO beneficiaries that produce maize and have less than 20 hectares (proportion of small-scale producers), and the sixth is a variable that describes the proportion of land dedicated for maize production in each county covered by PROCAMPO. The seventh and eighth are PROCAMPO and OPORTUNIDADES real per capita transfers received by each beneficiary household and finally, years of formal education is the number of years that the head of household reported having received of formal education. Finally, we cluster at the State-Rural level.

Table 1.4 WII's Insurance Effect on Log of Maize Yield at the County Level: Income Effect

VARIABLES	(1) Log Maize Yield	(2) Log Maize Yield	(3) Log Maize Yield	(4) Log Maize Yield	(5) Log Maize Yield	(6) Log Maize Yield	(7) Log Maize Yield	(8) Log Maize Yield
WII Presence (dummy)	0.0744***		0.0713***		0.0658***		0.0654***	
	(0.023)		(0.022)		(0.022)		(0.022)	
WII Coverage (% of land sowed)		0.0807**		0.0762**		0.0776**		0.0799**
		(0.035)		(0.034)		(0.032)		(0.031)
Rain Deviation			0.0883***	0.0882***	0.0746***	0.0744***	0.0711***	0.0708***
			(0.024)	(0.024)	(0.019)	(0.019)	(0.019)	(0.019)
Temperature Deviation			-0.444**	-0.451**	-0.361*	-0.364*	-0.358*	-0.360*
			(0.189)	(0.187)	(0.184)	(0.183)	(0.186)	(0.184)
% of PROCAMPO in Private land							1.587**	1.592**
							(0.594)	(0.598)
% of Maize Producers in <20 hectares							0.158	0.153
							(0.623)	(0.624)
% of Land covered by PROCAMPO (maize production)							-0.0961*	-0.101*
							(0.056)	(0.057)
Constant	0.376***	0.379***	0.378***	0.381***	0.402***	0.405***	0.24	0.252
	(0.003)	(0.003)	(0.003)	(0.003)	(0.022)	(0.022)	(0.620)	(0.620)
Observations	14,587	14,587	14,587	14,587	14,587	14,587	14,587	14,587
R-squared	0.003	0.002	0.009	0.008	0.027	0.026	0.029	0.029
Number of Counties	2,316	2,316	2,316	2,316	2,316	2,316	2,316	2,316
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of maize yield" defined as total production (in tons) over number per county harvested hectares. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. The fourth to sixth right hand side variables come from the PROCAMPO beneficiaries dataset whereby the first one is the proportion of PROCAMPO beneficiaries that produce maize in private land, the second one is the proportion of beneficiaries that have land smaller than 20 hectares and the third one is the proportion of total land dedicated for maize production covered by PROCAMPO program. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level. Note that as opposed to models corresponding to table 2.a., in this case we dropped county level observations after receiving indemnity payments with the objective of testing income versus insurance effects.

Table 1.5 Test of Exogeneity of the Weather Indexed Insurance rollout

	County level annual performance	
	Maize	Beans
Panel A: Yearly average yield growth		
Year WII was introduced	-0.032	-0.0131
	(0.027)	(0.019)
Observations	2,146	1,507
R-squared	0.084	0.029
Panel B: Yearly average yield		
Year prior to WII	0.041	0.009
	(0.063)	(0.052)
2 years prior to WII	-0.018	-0.013
	(0.082)	(0.052)
3 years prior to WII	-0.052	-0.049
	(0.091)	(0.063)
4 years prior to WII	-0.079	-0.016
	(0.088)	(0.059)
5 years prior to WII	-0.073	-
	(0.101)	-
Observations	3,061	2,297

Robust standard errors in parentheses
Significance *** p<0.01, ** p<0.05, * p<0.1
Panel A: County/year growth weighted regression with year fixed effects, for pre-treatment period 2002 2007. "Year WII was introduced" gives numerical year WII was introduced in each municipality.
Panel B: County/Year growth (level) regression with year fixed effects, for pre-treatment period, 2002 to WII's entry.

Table 1.6.a Matching using CONAPO's Marginalty Index at the County Level 2000: WII's Insurance Effect on Log of Maize Yield at the County Level

VARIABLES	(1) Log Maize Yield	(2) Log Maize Yield	(3) Log Maize Yield	(4) Log Maize Yield	(5) Log Maize Yield	(6) Log Maize Yield	(7) Log Maize Yield	(8) Log Maize Yield	(9) Log Maize Yield	(10) Log Maize Yield
WII Presence (dummy)	0.0504*		0.0298		0.0453		0.0686***		0.0638**	
	(0.029)		(0.063)		(0.057)		(0.020)		(0.029)	
WII Coverage (% of land sowed)		0.0672*		0.0746		0.0851		0.0832***		0.0481
		(0.034)		(0.062)		(0.069)		(0.025)		(0.047)
Rain Deviation	0.0683***	0.0681***	0.0820*	0.0801*	0.0257	0.0248	0.0848*	0.0851*	0.0970**	0.0967**
	(0.021)	(0.021)	(0.040)	(0.040)	(0.019)	(0.019)	(0.044)	(0.044)	(0.043)	(0.044)
Temperature Deviation	-0.401**	-0.401**	-0.460*	-0.440	-0.304	-0.308	-0.479*	-0.469*	-0.359	-0.367
	(0.186)	(0.184)	(0.260)	(0.253)	(0.240)	(0.235)	(0.258)	(0.254)	(0.433)	(0.432)
% of PROCAMPO in Private land	1.588**	1.593**	0.987***	0.979***	-0.231	-0.255	3.587**	3.595***	2.034**	2.056**
	(0.598)	(0.600)	(0.138)	(0.129)	(0.405)	(0.397)	(1.296)	(1.296)	(0.904)	(0.882)
% of Maize Producers in <20 hectares	0.17	0.166	0.757***	0.719***	-0.325	-0.353	1.263**	1.251**	-0.117	-0.144
	(0.616)	(0.615)	(0.193)	(0.178)	(2.284)	(2.277)	(0.592)	(0.582)	(1.004)	(1.014)
% Land covered by PROCAMPO (maize)	-0.0895	-0.0935	-0.000415	-0.00355	-0.201**	-0.203**	0.0928	0.0815	-0.0857	-0.0912
	(0.058)	(0.058)	(0.045)	(0.046)	(0.079)	(0.078)	(0.111)	(0.111)	(0.089)	(0.090)
Constant	0.233	0.241	-0.641***	-0.601***	0.655	0.685	-0.937	-0.914	0.905	0.942
	(0.612)	(0.611)	(0.189)	(0.174)	(2.290)	(2.282)	(0.641)	(0.631)	(0.973)	(0.983)
Observations	14,791	14,791	2,465	2,465	5,730	5,730	3,094	3,094	3,502	3,502
R-squared	0.029	0.029	0.044	0.045	0.035	0.036	0.045	0.044	0.028	0.027
Number of Counties	2,316	2,316	384	384	897	897	477	477	558	558
Matching Group	ALL	ALL	VERY POOR	VERY POOR	POOR	POOR	MEDIUM	MEDIUM	OTHER	OTHER

Marginality Index is presented by the National Population Council (CONAPO in Spanish). It is calculated for each county using the 2000 national population census using the method of principal components based on 10 indicators: population, % illiterate older than 15 years, % with no primary school older than 15, no sewage in the house, no electricity in the house, no running water in the house, overcrowding, dirt floor, % rural population in the county and % earning less than 2 minimum wages. The result is an index that takes continuous values from 3.4 (county with highest marginality) to -2.5 (county with lowest marginality). Similarly, CONAPO divides counties in groups depending on their marginality index. For example, the first group is the very poor or counties with "high marginality" (with indices that go from 3.4 to 1), poor counties or "marginal" ones (from 1 to -0.1), medium (from -0.1 to -0.69), low level of marginality (from -0.7 to -1.27) and very low level of marginality (from -1.28 to -2.44). In this table we present fixed effect models that uses the full set of counties (in columns (1) and (2)), and subsets, like only very poor counties (columns (3) and (4)), poor counties (columns (5) and (6)) and medium counties (columns (7) and (8)). Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 1.6.b WII's Insurance Effect on Log of Fruit Yield at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log Fruits Yield	Log Fruits Yield	Log Fruits Yield	Log Fruits Yield	Log Fruits Yield	Log Fruits Yield
WII Presence (dummy)	0.0136		0.0136		0.025	
	(0.024)		(0.024)		(0.023)	
WII Coverage (% of land sowed)		0.0258		0.0259		0.0385
		(0.027)		(0.028)		(0.026)
Rain Deviation			-0.00507	-0.00527	-0.00445	-0.00468
			(0.017)	(0.017)	(0.017)	(0.017)
Temperature Deviation			-0.027	-0.029	-0.009	-0.014
			(0.099)	(0.099)	(0.097)	(0.096)
Constant	1.787***	1.787***	1.787***	1.787***	1.782***	1.783***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.013)	(0.013)
Observations	8,153	8,153	8,153	8,153	8,153	8,153
R-squared	0.000	0.000	0.000	0.000	0.002	0.002
Number of Counties	1,390	1,390	1,390	1,390	1,390	1,390
County Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of fruit yield" defined as total production (in tons) over number per county harvested hectares. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level.

Table 1.6.c WII's Insurance Effect on Log of Vegetables Yield at the County Level						
VARIABLES	(1) Log of Vegetables Yield	(2) Log of Vegetables Yield	(3) Log of Vegetables Yield	(4) Log of Vegetables Yield	(5) Log of Vegetables Yield	(6) Log of Vegetables Yield
WII Presence (dummy)	0.101		0.0997		0.0813	
	(0.074)		(0.073)		(0.059)	
WII Coverage (% of land sowed)		0.126		0.124		0.103
		(0.083)		(0.083)		(0.066)
Rain Deviation			-0.0134	-0.0119	-0.025	-0.0238
			(0.044)	(0.044)	(0.044)	(0.044)
Temperature Deviation			0.355	0.336	0.240	0.216
			(0.474)	(0.475)	(0.540)	(0.541)
Constant	-0.175***	-0.171***	-0.173***	-0.169***	-0.154***	-0.152***
	(0.018)	(0.014)	(0.019)	(0.015)	(0.024)	(0.025)
Observations	1,008	1,008	1,008	1,008	1,008	1,008
R-squared	0.014	0.013	0.016	0.014	0.037	0.037
Number of Counties	264	264	264	264	264	264
County Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of vegetables yield" defined as total production (in tons) over number per county harvested hectares. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level.

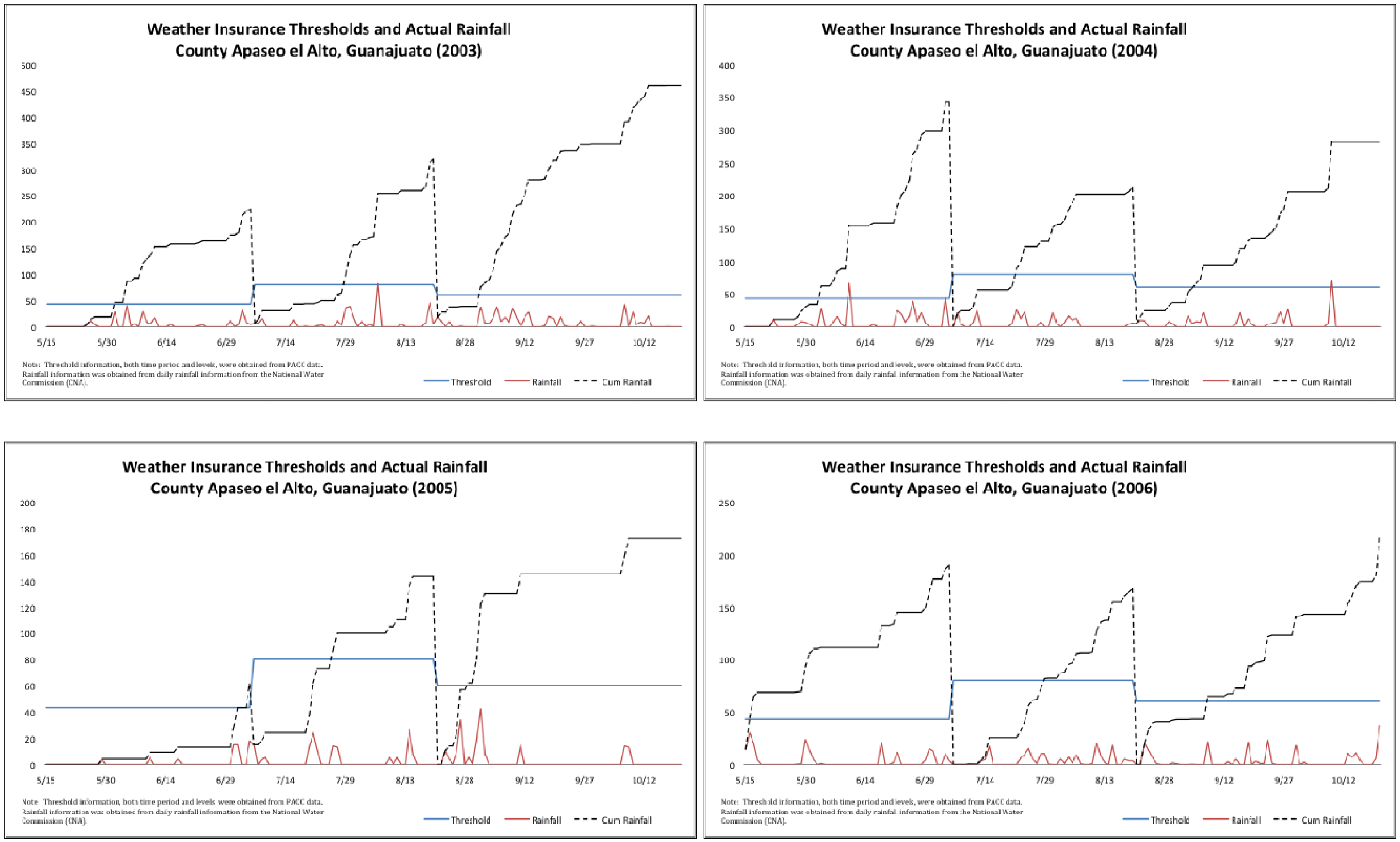
Table 1.6.d WII's Insurance Effect on Log of Pod Vegetables Yield at the County Level

VARIABLES	(1) Log of Pod Vegetables Yield	(2) Log of Pod Vegetables Yield	(3) Log of Pod Vegetables Yield	(4) Log of Pod Vegetables Yield	(5) Log of Pod Vegetables Yield	(6) Log of Pod Vegetables Yield
WII Presence (dummy)	0.0376*		0.0369		0.0457*	
	(0.019)		(0.024)		(0.024)	
WII Coverage (% of land sowed)		0.0402		0.0362		0.0459
		(0.038)		(0.041)		(0.042)
Rain Deviation			0.0912***	0.0904***	0.0925***	0.0919***
			(0.026)	(0.026)	(0.027)	(0.026)
Temperature Deviation			0.591	0.591	0.626	0.627
			(0.425)	(0.444)	(0.441)	(0.458)
Constant	0.0266***	0.0291***	0.0276***	0.0305***	0.0064	0.0114
	(0.004)	(0.005)	(0.005)	(0.005)	(0.025)	(0.025)
Observations	2,440	2,440	2,440	2,440	2,440	2,440
R-squared	0.002	0.001	0.015	0.014	0.022	0.021
Number of Counties	519	519	519	519	519	519
County Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES

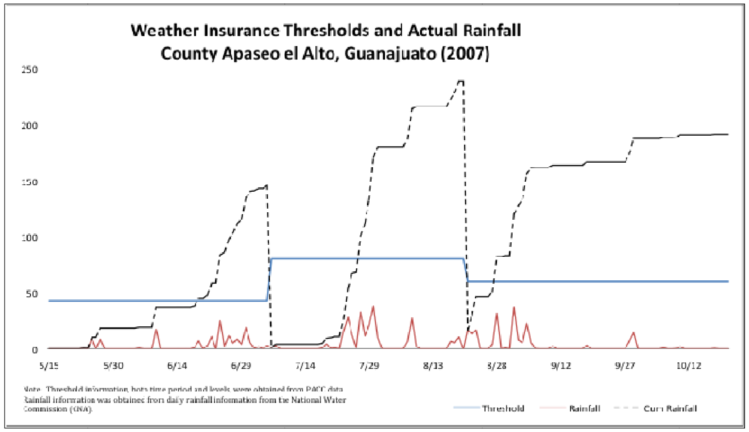
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the county or 'municipio'. The left hand side variable is "log of Pod vegetables yield" defined as total production (in tons) over number per county harvested hectares. The first right hand side variable for the odd number regressions is WII Presence at the county (a dummy variable), and for the even numbered regressions is the proportion of land devoted for maize production covered by WII in each county. The 'Rain Deviation' variable is rainfall deviation defined as the difference of the log of average rainfall (in millimeters) from 1990 to 2008 minus the log of average rainfall for each year. Temperature deviation is calculated in a similar way, but takes into account the maximum monthly average temperature. Moreover, in addition to controlling for county fixed effects, we include year fixed effects in the last two specifications. Finally, we cluster at the State level.

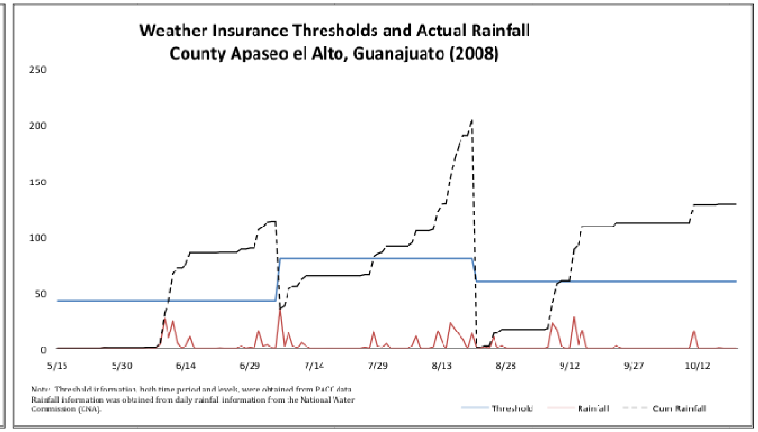
Figures

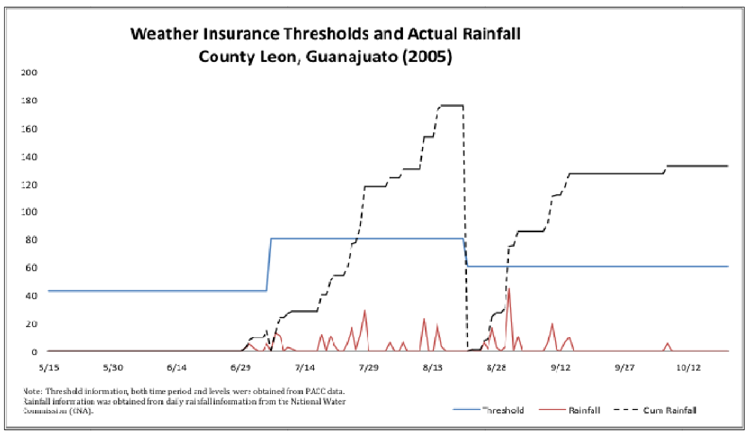
Figure 1.1.a, 1.1.b, 1.1.c and 1.1.d



Figures 1.1.e, 1.1.f, 1.1.g and 1.1.h







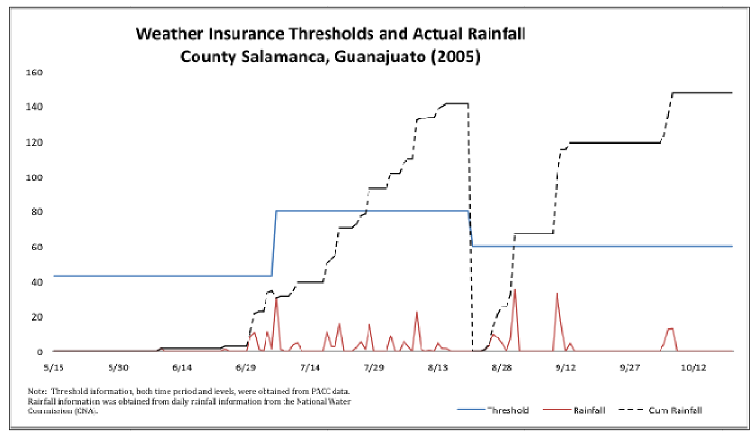


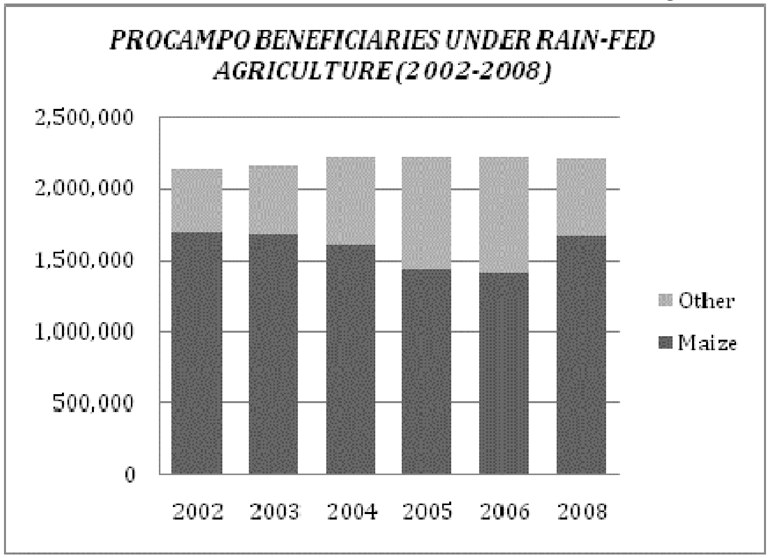
Figure 1.1.1

Figure 1.1.2

Figure 1.1.3

Figure 1.1.4

Figures 1.2.a and 1.2.b



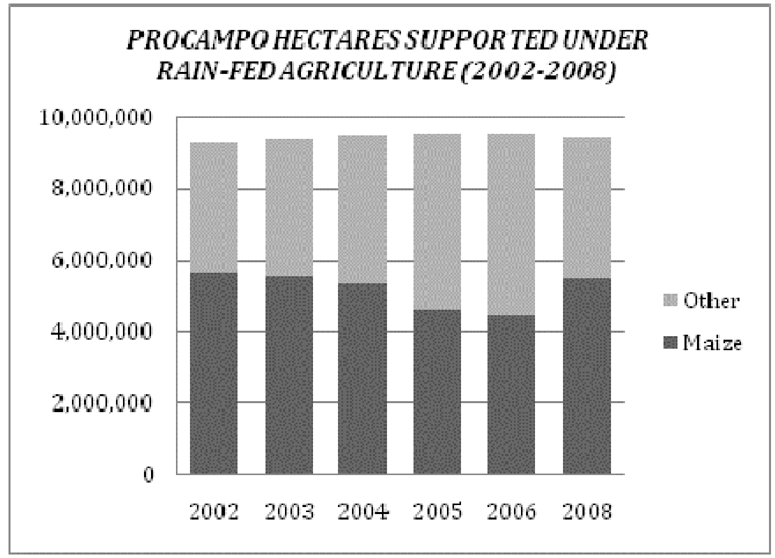


Figure 1.2.c

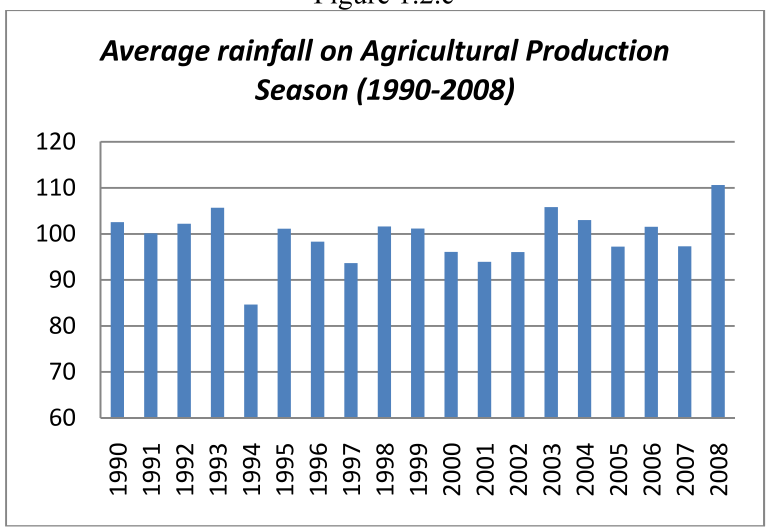


Figure 1.3.a Maize Productivity Yield Growth

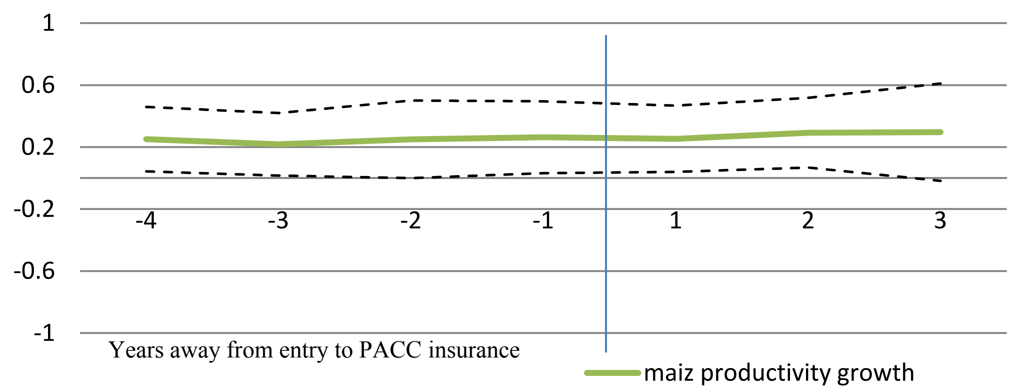
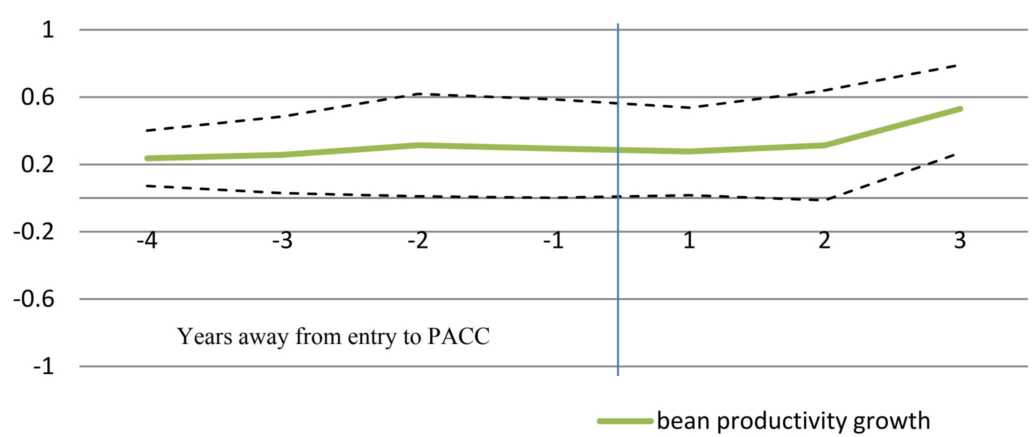


Figure 1.3.b Bean Productivity Yield Growth



Chapter 2

Voters Response to Natural Disasters Aid: Quasi-Experimental Evidence from Drought Relief Payment in Mexico

2.1 Introduction[24]

Are there electoral returns to government disaster aid? This is a central question in terms of political accountability in democratic societies and has recently attracted scholarly attention in political economy.

Identifying the effect of government transfer policies --such as disaster relief-- on individual political behavior is a challenging task. A set of growing literature provides empirical evidence of a positive electoral effect of government provision of economic benefits (Manacorda, Miguel and Vigorito 2010; Pop-Eleches and Pop-Eleches 2009; Litschig and Morrison 2009; Rodriguez-Chamussy 2009). However, assessing voter's response to compensation received after a natural contingency imposes additional difficulties. In effect, empirical studies trying to test voter responsiveness to disaster aid face at least three types of problems. First, the targeting of relief action and resources may not be exogenous as politicians might target public resources towards swing voters or channel resources to core supporters as a reward to their loyalty. Second, even when the natural shock producing adverse effects for the population may be exogenous, the extent of the damages and losses is potentially endogenous as vulnerability to natural catastrophes may differ among localities and populations. Finally, there are several confounding factors interacting with government disaster spending (media coverage, actions of NGOs and volunteer aid, etc) and some of these may cancel out estimates of a potential effect of relief transfers.

[24] This paper is co-authored with Lourdes Rodriguez-Chamussy. Permission was received from the coauthor to use it on this dissertation.

In this paper we use a quasi-experimental approach to provide evidence on the electoral effect of government economic transfers as compensation for the damage caused by a natural shock: severe drought on rain-fed agricultural regions. Exploiting the discontinuity in payment of a government funded climatic contingency aid program in Mexico, we show that voters reward the incumbent presidential party for delivering drought relief compensation. Our estimates suggest 7.6 additional percentage points for the presidential incumbent's share of votes in those electoral sections that received government transfers six to nine months before the election.

Our study builds on the empirical literature about electoral accountability and retrospective voting by providing at least two key contributions. First, we analyze a specific policy that provides indemnity payments to small-scale farmers if the amount of accumulated rainfall within a specific time period falls below an exogenous and pre-established threshold. This allows the use of a quasi-experimental approach --using regression discontinuity design-- to credibly identify causal effects of government transfers on electoral results. Moreover, studying the case of the Mexican Weather Indexed Insurance (WII) allows us to compare voter response in areas that have similar and comparable levels of vulnerability. Second, we collected, constructed and use electoral data at the lowest aggregation level: the electoral section. As already described, the multiple confounding factors that potentially make difficult to identify an effect of disaster spending even with the use of panel data are minimized in our setting as we use small units of analysis and compare electoral outcomes of a single election. To the best of our knowledge, this is the first study that exploits the key features of a weather-indexed insurance scheme using GIS methods to produce a complete dataset allowing the empirical test of voter's response to government disaster spending.

Evidence in the context of developing countries is very limited with the exception of India (Cole, Healy and Werker, 2009). Our findings complement the existing literature and are consistent with the results in previous studies for the US context (Healy and Malhotra 2009, Chen 2009, Chen 2008) and Germany (Bechel and Hainmueller, 2010).

Some have argued that voters are not collectively rational as they often respond to situations that are beyond politicians' control such as economic crises or natural disasters. For example, Achen and Bartels (2004) --using historical data from the US-- find that voters punish incumbent governments for shark attacks and droughts, as long as they can find some "psychologically appealing connection" linking disaster and government.[25] Similarly, Cole, Healy and Werker (2010) --using the quality of the monsoon rains as an exogenous shock to welfare-- examine voters' decisions in state elections in India and confirm that elected officials fare worse when natural disasters strike. They show that, on average, incumbent parties that run for reelection get punished for bad weather, loosing more than three percent of the vote for each standard deviation that district level rainfall

[25] They focus on American historical electoral politics in the early 20th century and use the particular case of President Wilson's reelection.

deviates from its optimum level. However, they also confirm that incumbents fare better when they respond to disasters with emergency relief: disaster relief increases lead to voters' rewards.

Bechtel and Haimuller (2010) explore the short and long-term electoral returns to disaster aid using the 2002 Elbe flooding in Germany as a natural experiment. Their findings extend previous results by Healy and Malhotra (2009) who show that voters reward incumbents for disaster relief but not for the more efficient disaster preparedness spending.

Our paper also relates to a different set of literature using quasi-experimental methods to show electoral response to government transfers. In general, these aim at providing empirical evidence in support of leading political economy theories that focus in trade-offs between consumption and political ideology. For example, Manacorda, Miguel and Vigorito (2009) estimate the causal effect of government transfers on political support for the incumbent party using data from Uruguay's conditional cash transfer program called PANES. Arguing that PANES' assignment near the threshold was as "good as randomly assigned", they find that beneficiaries were between 25 and 33 percentage points more likely than non-beneficiaries to favor current government. In addition, they find that the effect of government transfers on political support is significantly larger among poorer households, and among those near the center of the political spectrum as they are less attached to extreme political ideologies. In a similar study, Pop-Eleches and Pop-Eleches (2010) analyze the case of a Romanian program that awarded low income families with school age children vouchers for purchasing new personal computers and find that it had a significant impact on political attitudes and electoral behavior. In particular, voucher recipients were more likely to report vote intention in upcoming elections, and governing parties reaped most of the benefits of increased participation. They also find some evidence of vote switching from the main opposition party to the current incumbents and this effect was substantially stronger in towns where the governing parties controlled the local government.

This paper is structured as follows: Section 2 briefly describes the electoral context in Mexico and the Weather Index Insurance program. Section 3 presents the data. Section 4 discusses the statistical methodology and presents the main results. Finally, section 5 discusses the implications of the results found from the perspective of the study of political behavior and voter responsiveness to relief aid after a natural disaster.

2.2 The context

Weather shocks are one of the main causes of rural households' income fluctuations, which often destroy assets and translate into changes in consumption levels. In particular, drought periods can have significant environmental, agricultural, health, economic and social consequences. Additionally, these shocks tend to affect poor rural households in a much harsher way as they are not only closer to subsistence, but tend to live in more vulnerable locations and are particularly dependent on the weather as agriculture is their main source of income.

According to the Mexican Ministry of Agriculture, around 80 percent of catastrophic risks in Mexican agricultural settings are caused by droughts. Consequently, in 2003 the Mexican Federal Government, through the Ministry of Agriculture, introduced a Weather Index Insurance (WII) scheme. The insurance's objective is to support small-scale farmers (i.e. owning 20 hectares or less) that "suffer atypical climatic contingencies, particularly droughts, get reincorporated into their productive activities". Insurance coverage is exclusively provided by Agroasemex, a national insurance institution formed in 2001, and insures what the Ministry of Agriculture considers the country's main crops produced under rain-fed agriculture: maize, beans, sorghum and barley.

Agroasemex uses a series of equations that acknowledges the relation between soil quality, crop growth and accumulated rainfall to design WII's schemes, tailoring policies for specific crops and regions to maximize the correlation between drought-induced harvest failure and indemnity payments. WII's coverage universe consists of crops that use rain as the main humidity input, and indemnity payments are provided if rainfall at any stage of the season is below the pre-established threshold measured in millimeters through local weather stations. National and State governments provide resources from their annual budgets to purchase insurance premium. Individual farmers do not have to pay in order to get rainfall index insurance. They become automatically enrolled if they live within the insured regions.

Although WII was designed as individual producer insurance for small-scale farmers, it could be argued that Agroasemex in fact insures federal and state governments' budgets. In other words, Agroasemex's WII serves as a state governments' budget risk management tool since it allows annual budget planning to minimize the risk of catastrophic expenditure should severe droughts occur. Nevertheless, Agroasemex's WII affects the individual producer's behavior: even when farmers pay nothing to get insurance coverage (premiums are paid through a direct government subsidy), they become automatically insured and get informed about their coverage status through officials at the Program for Direct Assistance in Agriculture (PROCAMPO) regional offices (Rural Development Support Centers (CADER) or in the "Ventanillas Autorizadas" depending on plots location and county).

Evidence of farmer's program awareness was provided by the Ministry of Agriculture in 2009 through WII's program external evaluation written by a local based University. The document describes that a subset of randomly selected farmers were surveyed and asked about their awareness and knowledge of WII. Among those who were interviewed, 98% knew about WII's existence, and over 80% said they would be willing to pay in order to get insurance against droughts if the government did not provide it.

To be more explicit about the way in which weather index insurance works, we use two counties of the state of Guanajuato and for the case of maize production in Figures 2.1.a.

and 2.1.b. Agroasemex offers the following contract for insuring maize in the selected counties (Apaseo el Alto and Salamanca): the first period, also known as the sowing period, runs from May 15 to July 5; the second period goes from July 6 to August 20; and the third, or harvesting period, from August 21 to October 31. The minimum amount of accumulated rain above which Agroasemex does not provide indemnity payments --known as the trigger threshold-- equals 43, 80 and 60 millimeters for the first, second and third periods, respectively. There were no indemnity payments in Apaseo el Alto, since accumulated rainfall was higher than the minimum thresholds in every period of 2005. However, indemnity payments were provided in 2005 for maize production in the county of Salamanca as accumulated rainfall was lower than the sowing period's minimum threshold. To get this information, Agroasemex takes advantage of existing and publicly available rainfall information from weather stations of the National Water Commission. Although there are more than 5 thousand weather stations in the country, WII only uses a subset since only few attain international standards and have more than 25 years of daily information, necessary to predict rain patterns.

WII was first piloted in five counties of the Mexican state of Guanajuato in 2003. In the following years, it expanded to other counties and states reaching more than 15% of the country's rain-fed agricultural land in 24 states in 2008 (close to 1.9 million hectares). The first year in which Agroasemex made indemnity payments was 2005 when it reached 15 states.

In 2005, -the year previous to the elections for President- 478,000 farmers in 107 municipalities were covered by WII and 115 weather stations were used for rainfall measurement. A total of US $9,553,000 in claims was paid. WII operational guidelines state that the minimum payout is US $82 per hectare for up to 5 hectares of land per farmer, which implies a maximum payout of $410 per farmer.[26]

2.3 Data

The smallest unit of analysis for which information on drought relief payments and electoral data can be matched is the "electoral section". An electoral section is a geographical unit grouping poll stations with an average of a thousand voters registered. By using GIS techniques we are able to match electoral sections in municipalities covered by the WII program to rainfall based on the geographic location on the weather stations.

The data used for the analysis come from four main sources. First, we use administrative data from de Ministry of Agriculture regarding WII's coverage. These data include municipality level coverage information in terms of weather stations used, insured crops (maize, beans, sorghum and barley), number of hectares insured, value of insured production, value of the premium paid, and indemnity payments (in case a drought

[26] Hazell et al (2010)

occurred). It is worth clarifying that this information is available and used at the weather station/municipality levels. To be explicit, we have information regarding the number of hectares covered --as well as value of production and premiums paid-- by weather station for each crop in each municipality. There are cases in which there is more than one weather station in the municipality, and we have information at the weather station. Similarly, there are cases in which one weather station --located close to a municipality boarder-- provides information to insure crops in more than one municipality. In these cases, we have information of the number of hectares covered --as well as value of production and premiums paid-- by each weather station in each municipality. The second source of data is the National Water Commission; the data consist of daily rainfall measures in millimeters for every weather station in the country from January 2004 until December 2008. Third, we use the geographic location data of electoral sections obtained from the Department of Cartography of the Federal Electoral Institute. Finally, data on the outcomes of Presidential elections in 2000 and 2006 by electoral section are public from the Federal Electoral Institute (IFE) website. In addition to these, we use complementary information on socio-demographic characteristics of municipalities from the 2000 Population Census and the 2005 Short Census or *Conteo*, publicly available from the National Institute of Statistics (INEGI) website.

Combining these data, we construct a dataset with the electoral section as the unit of analysis. We first identify the municipalities covered by the WII program and the weather stations used for each municipality. Municipalities in Mexico largely vary in size and population. The available data on insurance coverage does not allow us to identify those electoral sections -within each municipality- that are covered by the insurance and those that are not; therefore we use the distance from the weather station as a criterion to select electoral sections in our dataset. Using a 2006 GIS map of electoral sections, we calculate the distance from the weather station to the nearest frontier of the geographic polygon of an electoral section. For those cases in which more than two weather stations serve a single municipality we use the distance from the electoral section to the nearest weather station. Finally, we construct our dataset including only those electoral sections that are within a defined maximum distance from the weather station. Using the map of the State of Guanajuato, Figures 2.2.a and 2.2.b illustrate with an example the process of constructing the dataset.

We need to limit our analysis to the electoral units in the vicinity of the weather stations based on two reasons: First, to ensure that we are studying units that in fact contained insurance beneficiaries and, second, to minimize measurement error given that as the distance from the electoral section to the weather station increases, the probability of difference between the rainfall measure and the real conditions in the field increases (spatial basis risk). To define the benchmark distance for selection we identify the distance at which two criteria are simultaneously met: a) There is no overlap of weather stations in order to avoid a case in which the same unit would be matched with rainfall data twice, thus duplicating one observation and, b) Each municipality covered by the WII program would have at least one electoral section included in our dataset.

Our dataset contains 1,198 electoral sections located at a maximum distance of the defined benchmark distance of 2,131 meters from the corresponding weather station. For approximately 10% of these observations we are not able to match the results of the 2000 Presidential elections since the map of electoral sections was modified between 2000 and 2006. We therefore use for the analysis 1038 units comparable for the two elections. Summary statistics are described in Table 2.1. We observe that 30% of the observations received monetary compensation for drought during the 2005 agricultural season.

The share of votes for the incumbent party is the key dependent variable; it is calculated as the number of votes obtained by the incumbent party relative to the total number of valid votes casted in each electoral section.

The measure of rainfall is normalized using the threshold established for insurance payments. Figure 2.3 shows each unit's rainfall deviation from the threshold and whether or not drought relief compensation was received in 2005. As we can observe, all electoral sections covered by the government program did receive the payment when accumulated rainfall fell below the established threshold. Conversely, those units that were covered by the program but had rainfall levels above the threshold did not receive any payment.

2.4 Empirical Strategy and Results

In 2005, the Mexican Federal Government, after receiving indemnity payments from Agroasemex, delivered more than 9 million US dollars in drought compensation payments. Provided that the Weather Index Insurance program was designed to allocate indemnity payments according to a strictly defined pre-established rainfall cutoff, we employ a regression discontinuity (RD) design to compare outcomes across electoral sections that were covered during 2005 by the insurance program and had similar levels of rainfall but differed in whether they experienced government aid in the form of a monetary transfer or not. This enables us to address the possibility of omitted variable bias between recipients of relief compensation and their counterparts who experienced a drought but did not qualify for compensation.

The basic regression model used through the analysis is given by equation (1):

$$Vote_i = \delta BelowCutoff_i + f(rainfall_i) + \beta X_i + \varepsilon_i \qquad (1)$$

where $Vote_i$ represents the electoral outcome of interest --the share of votes for the incumbent party-- in the electoral unit i. $BelowCutoff_i$ is an indicator variable equal to 1 if the accumulated rainfall during the sowing season is less than the minimum cutoff for the program, and 0 otherwise. The main coefficient of interest in the analysis is δ, which indicates the effect of being in an area that corresponds to receiving government aid after a drought on the relevant outcome. The term *f(rainfall$_i$)* denotes a smooth function of rainfall, which is the forcing variable in the context of this regression discontinuity design.

Finally, X_i includes a set of control variables such as a dummy for each state, municipality average per capita income, average temperature measured by weather station, distance from the electoral section to the weather station, distance to the nearest river and distance to the *cabecera*.[27] Although units on each side of the discontinuity experienced similar rainfall levels, it is important to include these control variables since they are not necessarily geographically located next to each other. Table 2.1 shows that units in which payments were disbursed are located in wealthier municipalities but all other characteristics do not appear to be statistically different for electoral sections below and above the cutoff. Particularly, the average share of votes for the Presidential incumbent in the previous election --year 2000-- is not statistically different for the two groups.

To get a sense of the way in which observations distribute on each side of the discontinuity we consider Figure 2.4, which plots the level of rainfall normalized to the defined threshold in each electoral section and the corresponding share of votes for the incumbent in the 2006 Presidential elections. The non-parametric regression line jumps down at the discontinuity suggesting an effect of the drought compensation payment on voting behavior. In order to explore the significance and magnitude of this apparent effect we first specify a linear model of *f(rainfall$_i$)* and we allow it to vary on either side of the discontinuity.

Table 2.2 shows the results of estimating Equation (1) using OLS. Column (1) presents the results when no controls are used in the estimation. The coefficient for *cutoff* remains positive and stable as we add controls. Column (2) shows the estimates when we include a set of dummy variables for each state. Column (3) presents the results when we include also controls at the electoral section level such as altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Finally, Column (4) presents the estimates when controls at the municipal level are introduced. These specifications indicate a statistically significant effect of government disaster spending on the share of votes for the Presidential incumbent party. The magnitude of the coefficient decreases slightly once we control for the state and the characteristics of the electoral units and municipalities. With the full set of controls, our estimate suggests that receiving drought compensation had an effect of approximately 7.6 percentage points increase in the share of votes for the incumbent party.

Potential concerns on the validity of the RD estimates

In this section we discuss potential concerns for the validity of our main results and perform a number of tests to check their robustness. As a first validity check, we estimate Equation (1) for the pre-treatment election outcomes of 2000. If unobservable

[27] "Cabecera" refers to the Municipal seat. It generally corresponds to the biggest town in the municipality and the better connected in terms of transportation and information.

characteristics of the units receiving drought compensation were explaining electoral support for the incumbent, we might observe a discontinuous variation in the pre-treatment variable at the cutoff. Table 2.3 shows that there is no evidence of a difference in the share of votes for the incumbent in the 2000 elections for President. The coefficient for the below-cutoff variable is not statistically significant in the specification with the full set of controls. Therefore, estimates in Table 2.3 support the causal interpretation of an electoral response to government disaster spending suggested by the coefficient of 7.69 in Table 2.2.

An important assumption underlying the RD design is that producers are not able to manipulate the forcing variable. In our particular case, potential manipulation would have to be on the measurement of rainfall at the local weather stations, which seems extremely unlikely. Location and operation of weather stations were set many years before the specific insurance program we are analyzing and are independent of it. In 2005 and 2006, a total of 3,363 weather stations operated in the Mexican territory from which, 1200 under the coordination and supervision of the National Water Commission (CONAGUA). Furthermore, before paying any indemnities, CONAGUA is required to certify the weather data, which are sent to the international reinsurers. The Weather Index Insurance scheme is based on the fact that there is little reason to believe that the individual producer has better information that the insurer about the underlying index, and therefore little potential for adverse selection. One of the advantages of using the Mexican WII to test voter response to disaster spending is precisely the fact that under this scheme information asymmetries are minimized, as the producer cannot influence the realization of the weather index.

Another crucial assumption under regression discontinuity analysis is that the function of rainfall --which is the variable determining the disbursement of a government drought assistance-- has been correctly specified. Our primary specification is a linear model in rainfall estimated using OLS. Alternative polynomial functions are also estimated for robustness as shown in Table 2.4. From visual examination of the relationship plotted in Figure 2.4 we are able to determine a discernable discontinuity at the cutoff. The non-parametric graph suggests a linear relationship in the vicinity of the cutoff. Nonetheless, given the number of inflexion points in the plot, we test for higher-order polynomial functions including quadratic, cubic and fourth power terms in our specification. Table 2.4 shows that the coefficient of interest remains stable and the interactions are not statistically significant in columns (1) to (3). Column (4) shows that a fourth power polynomial function results significant and in this case the magnitude of the effect jumps to 10.1 percentage points. Figure 2.4 suggests however that the slope of the relationship on either side of the threshold is the same for levels of rainfall in the vicinity of the cutoff.

In order to explore the relationship at the discontinuity we narrow the window of analysis to include only units that experienced almost the same rainfall levels and provide yet another robustness check for our main specification. Table 2.5 shows that estimation of Equation (1) using observations on a window of 30mm and 20mm of rainfall around the threshold results in statistically significant coefficient estimates of 6.5 and 6.9 respectively.

Figure 2.4 describes the relationship between rainfall and electoral outcomes for the incumbent party and it is consistent with previous findings in the literature. Consistent with Achen and Bartels (2002) the slope appears to be positive for electoral sections on the right hand side of the threshold suggesting that voters punish the incumbent for adverse conditions --i.e. in this case drought--. The slope of the regression line is near zero for higher levels of rainfall. The econometric results confirm the discontinuity observed at the threshold.

Overall our findings provide strong evidence of an electoral reward for the federal incumbent party in electoral sections where government disaster aid was supplied. The magnitudes of the effects are consistent with the existing literature and in terms of the WII program figures for 2005. For Germany, Bechtel and Hainmueller (2010) estimate an immediate electoral gain of about 7 percentage points for the incumbent party in areas affected by flooding and their estimates suggest that 25% of this effect is carried to elections 3 years later. Cole, Healy and Werker (2009) find evidence suggesting that voters only respond to government relief efforts during the year immediately preceding the election. According to their estimates, an average increase in disaster spending will gain about half percentage point of vote share for the incumbent party.

The actual number of registered voters in each electoral section is not available from the data. However, we know that on average, an electoral section has about 1000 voters registered. Therefore, our analysis implies that there was an average effect of approximately 76 additional votes for the incumbent party in an electoral section close to a weather station that actually registered rainfall below the pre-established threshold. Given the nature of the government transfer, it is plausible that more than one vote is gained by beneficiary household. Nonetheless, our estimates are consistent with the aggregate sum of indemnities paid even if only one individual per household change her vote.

Mechanisms

In principle, there is no theoretical reason to expect an effect of disaster spending on electoral turnout. In the Political Science literature, a consistent finding is that bad weather conditions at the time of an election significantly reduce participation. However, here we analyze weather conditions six to nine months before the day of the Presidential elections. The relationship between economic conditions and participation is more complex and evidence goes in both senses. For example, Pop Eleches and Pop Eleches (2009) show that individuals located just below the income cutoff (end thus eligible for the transfer program they analyze) were significantly more likely to declare an intention to vote in the next election than survey respondents just above the cutoff. Similarly, De la O (2008) finds that cash transfers in Mexico increased turnout among voters that benefited from the program for a long period, but finds no effect among beneficiaries enrolled six months before the election. Moreover, Chen (2009) finds that hurricane aid awards in the US increased turnout among the incumbent party's supporters but decreased turnout among the opposition party's voters.

In order to test for this, we estimate the basic regression model outlined in Equation (1) but this time using the total number of votes casted in the 2006 in electoral section *i* as the dependent variable. Table 2.6 shows no evidence of an effect for the units that are geographically close to weather stations that received the government monetary transfer. This analysis indicates that higher voter support for the incumbent party in those sections close to weather stations that received drought compensation cannot be explained statistically by recipients of disaster aid voting relatively more or by non-recipients voting relatively less. Even though the coefficient is not statistically significant, its magnitude is not small and provides additional information to help constructing boundary conditions for the interpretation of our main effect.

To complement the analysis we test for an effect on the share of votes of contender political parties. Table 2.7 describes the results of estimating Equation (1) using the share of votes for the two main contestant political parties -PAN and PRD- and other small parties. We find negative and statistically significant coefficients for all specifications. Taken together, the results in Tables 2.2, 2.6 and 2.7 suggest an electoral reward for the incumbent party in electoral sections below the cutoff and a punishment in electoral sections above the rainfall threshold.

Under the most conservative interpretation of our results, the positive and significant effect of disaster aid on the share of votes for the incumbent would be driven by abstention among supporters of the contender parties in electoral sections close to weather stations that received drought compensations. Under the interpretation at the other extreme, the main effect is driven by a combination of voters switching towards the incumbent party in electoral sections close to weather stations that received drought compensations and a higher participation toward contender parties in electoral sections close to stations that did not receive payments.

2.5. Discussion

Empirical evidence of voters' response to disaster relief expenditures and preparedness initiatives is remarkably scant, especially for developing countries. This paper contributes to the literature on retrospective voting providing evidence that voters evaluate government actions and respond to disaster spending.

To evaluate the causal effect of government disaster spending on the electoral outcomes for the incumbent party, we take advantage of two fundamental aspects. First, we use a quasi-experimental approach exploiting the discontinuity in payment of a government climatic contingency aid program in Mexico. Second, we use GIS techniques to match data on drought relief payments, rainfall and electoral outcomes at the most disaggregated unit of analysis –the electoral section-, reducing measurement error and potential confounding factors.

We find that living within a short distance to a weather station that received drought compensation increased the share of votes for the presidential incumbent party. The result is robust to including controls at the state, municipality and electoral section levels as well as fourth-order polynomial terms for the forcing variable and narrowing the window of analysis around the threshold. Consistent with previous findings for the case of Germany, our estimates indicate that receiving drought compensation within six to nine months prior to the election had an effect of approximately 7.6 additional percentage points in the share of votes for the incumbent party. Results of our analysis suggest that recipients of disaster aid reward the incumbent party and non-recipients punish it voting in higher proportion for contestant parties.

Analyzing the case of a WII scheme not only provides an exceptional framework for the econometric identification of the effect, but also reveals an important interpretation of our results: Voters reward the incumbent party for disaster relief transfers under an insurance design. We are not able to identify whether voters reward the incumbent for insurance enrollment itself however, the results in this paper imply that politicians may find attractive to implement insurance programs that are more efficient than relief spending funded from fiscal resources.

2.6 References

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Tables

Table 2.1 Descriptive Statistics, electoral sections with insurance coverage in 2005

	Units WITH compensation	Units WITHOUT compensation
Altitude (meters)	1442.75	1554.19
	(43.48)	(23.39)
Distance from weather station (meters)	1088.12	1042.5
	(30.66)	(23.11)
Distance to cabecera (meters)	1792.98	1771.4
	(96.73)	(123.10)
Distance to nearest river (meters)	526.2	582.88
	(35.68)	(27.05)
Municipal infant Mortality	21.97	25.33
	(0.12)	(0.13)
Municipal income per capita (pesos)	1821.82	1233.51
	(26.97)***	(12.7)***
Number of votes, 2006	617.84	677.99
	(23.06)	(11.75)
Share of votes for incumbent 2000	32.35	32.22
	(1.08)	(0.48)
Number of votes, 2000	619.05	651.2
	(19.69)	(9.08)
Observations	305	733

Standard errors for the t-test in parenthesis. Null hypothesis is average characteristic is equal for the two groups. *** Indicates the null is rejected at 1% confidence level.

Table 2.2 Effect of Drought Relief Compensation on Share of Votes for the Incumbent, Main Results

	Dependent variable: Share of votes for incumbent in 2006			
	(1)	(2)	(3)	(4)
Cutoff	10.395	8.211	8.332	7.69
	(1.421)***	(1.040)***	(1.219)***	(1.000)***
Devrain	-0.078	0.057	0.045	0.03
	(0.012)***	(0.015)***	(0.018)**	(0.018)*
Constant	45.188	14.38	-13.398	7.255
	(0.845)***	(3.574)***	(10.258)	(9.071)
Observations	1038	1038	1038	1038
R-squared	0.12	0.78	0.79	0.82
State controls	No	Yes	Yes	Yes
Controls at electoral section level	No	No	Yes	Yes
Controls at municipal level	No	No	No	Yes
Mean of dependent variable	45.37	45.37	45.37	45.37

Robust standard errors in parentheses

State controls are dummy variables for each state. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.3 Validity check using the pre-treatment elections of 2000

	Dependent variable: Share of votes for incumbent in 2000
	(1)
Cutoff	-1.525
	(1.236)
Devrain	-0.036
	(0.015)**
Constant	49.032
	(9.619)***
Observations	1038
R-squared	0.75
State controls	Yes
Controls at electoral section level	Yes
Controls at municipal level	Yes
Mean of dependent variable	32.25

Robust standard errors in parentheses

State controls are dummy variables for each state. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.4 Estimates using a polynomial function of rainfall

	Dependent variable: Share of votes for incumbent in 2006			
	(1)	(2)	(3)	(4)
Cutoff	7.69	7.434	7.674	10.136
	(1.000)***	(1.087)***	(1.443)***	(1.650)***
Devrain	0.03	0.015	0.028	0.143
	(0.018)*	(0.041)	(0.068)	(0.077)*
Devrain^2		0.000	0.000	-0.007
		(0.000)	(0.001)	(0.003)***
Devrain^3			0.000	0.000
			(0.000)	(0.000)***
Devrain^4				0.000
				(0.000)***
Constant	7.255	6.754	7.216	13.666
	(9.071)	(9.252)	(9.515)	(9.647)
Observations	1038	1038	1038	1038
R-squared	0.82	0.82	0.82	0.82
State controls	Yes	Yes	Yes	Yes
Controls at electoral section level	Yes	Yes	Yes	Yes
Controls at municipal level	Yes	Yes	Yes	Yes
Mean of dependent variable	45.37	45.37	45.37	45.37

Robust standard errors in parentheses

State controls are dummy variables for each state. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.5 Robustness check, varying the window around the discontinuity

	Dependent variable: Share of votes for incumbent in 2006	
	Window of 30mm	Window of 20mm
	(1)	(2)
Cutoff	6.516	6.874
	(2.57)*	(2.72)**
Devrain	0.116	0.142
	(0.75)	(0.93)
Constant	52.325	48.997
	(4.69)**	(4.46)**
Observations	810	766
R-squared	0.88	0.84
State controls	Yes	Yes
Controls at electoral section level	Yes	Yes
Controls at municipal level	Yes	Yes
Mean of dependent variable	49.21	53.28

Robust standard errors in parentheses

State controls are dummy variables for each state. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.6 The Effect of Drought Relief Compensation on Turnout 2006

	Dependent variable: Total number of votes casted, 2006
	(1)
Cutoff	-55.228
	(37.058)
Devrain	0.028
	(0.426)
Constant	399.184
	(328.255)
Observations	1038
R-squared	0.2251
State controls	Yes
Controls at electoral section level	Yes
Controls at municipal level	Yes
Mean of dependent variable	664.51

Robust standard errors in parentheses

State controls are dummy variables for each state. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera". Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.7 The Effect of Drought Relief Compensation on the Share of Votes for other Parties

	Dependent variable: Share of votes for PRI, 2006	Share of votes for PRD, 2006	Share of votes for Other Parties, 2006
	(1)	(2)	(3)
Cutoff	-2.884	-3.876	-2.041
	(1.196)**	(0.965)***	(0.610)***
Devrain	-0.08	0.047	-0.013
	(0.012)***	(0.018)***	(0.007)**
Constant	20.962	65.546	21.014
	(9.658)**	(7.626)***	(4.040)***
Observations	1038	1038	1038
R-squared	0.6561	0.6719	0.3918
State controls	Yes	Yes	Yes
Controls at electoral section level	Yes	Yes	Yes
Controls at municipal level	Yes	Yes	Yes
Mean of dependent variable	27.934	20.933	6.03

Robust standard errors in parentheses

State controls are dummy variables for each state.. Controls at the electoral sections include altitude, distance from the weather station, distance to the nearest river and distance to the "cabecera".
Controls at the municipal level include municipal income per capita for the year 2000.

* significant at 10%; ** significant at 5%; *** significant at 1%

Figures

Figure 2.1.a Example of a county where no payments where disbursed.

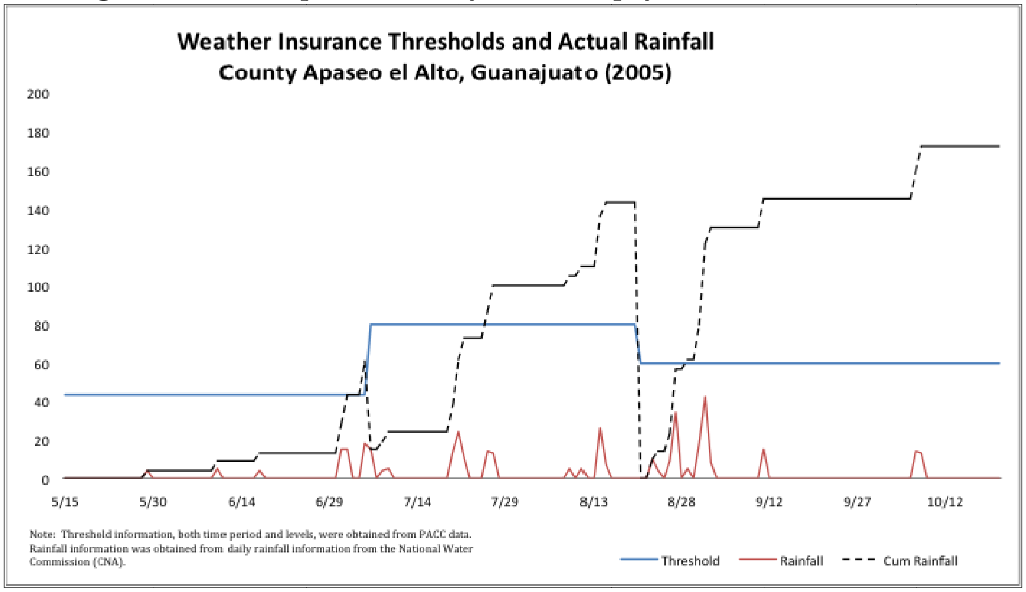


Figure 2.1.b Example of a county where payments were disbursed.

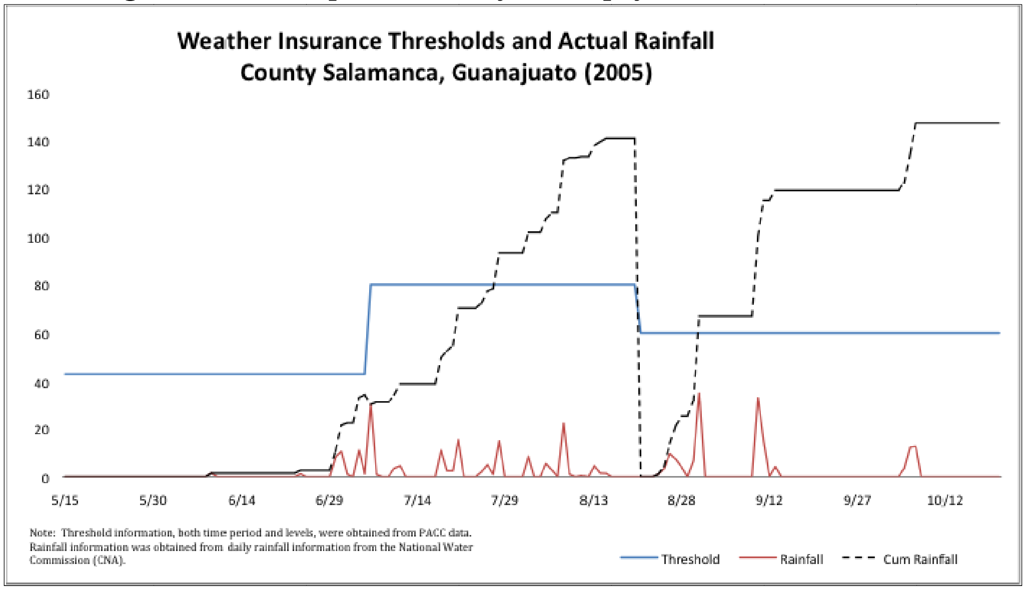


Figure 2.2a Map of municipalities covered by the WII and location of weather stations, example using the State of Guanajuato

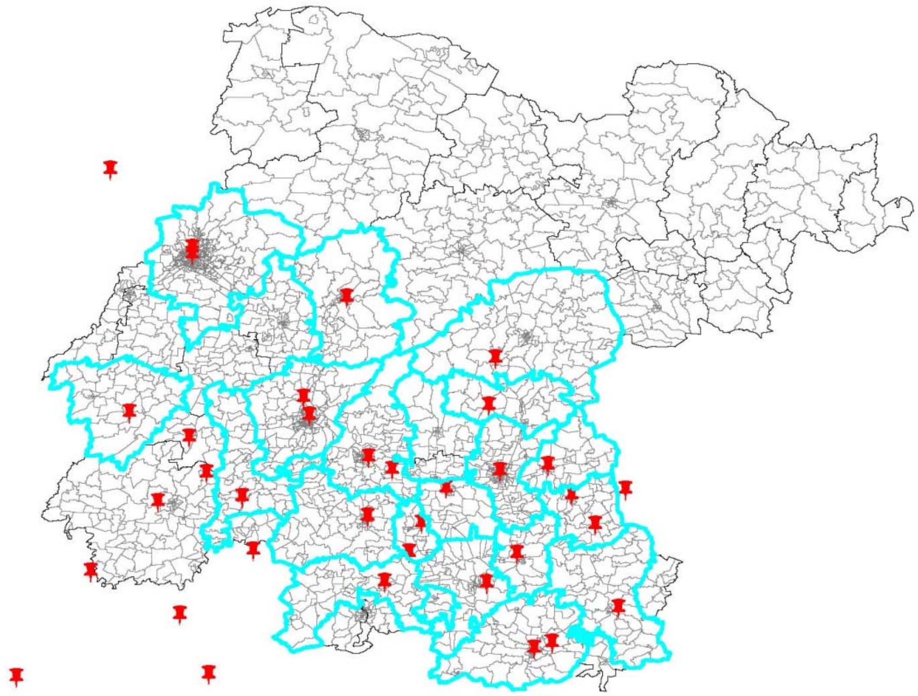


Figure 2.2b Map of electoral sections included for the analysis, State of Guanajuato

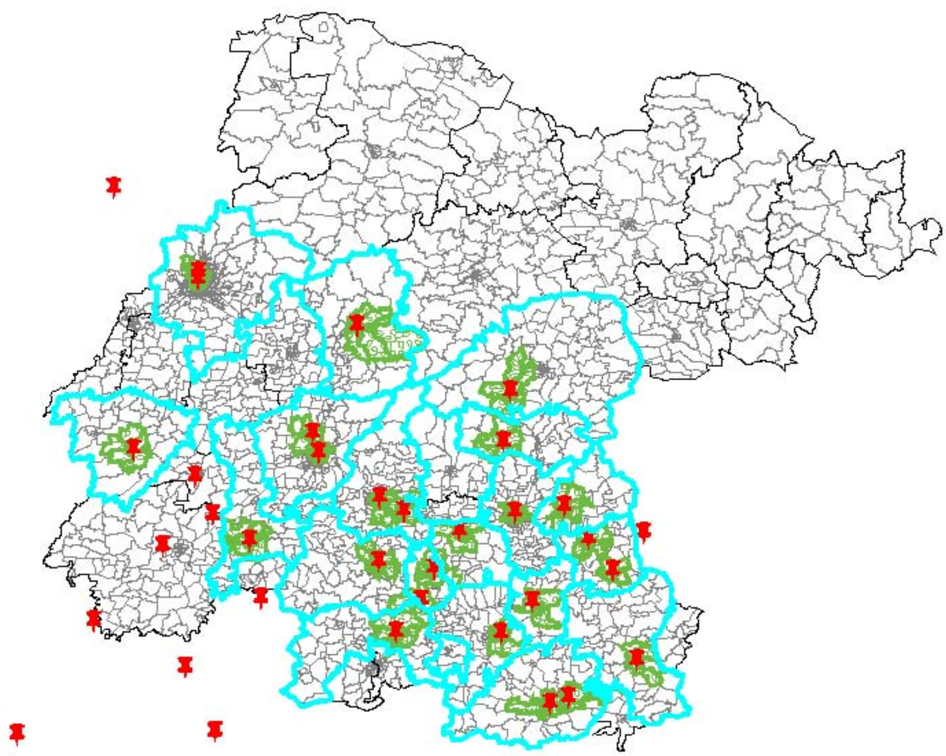


Figure 2.3 Electoral sections in municipalities with insurance coverage in 2005 and Drought Relief Compensation for corresponding weather stations.

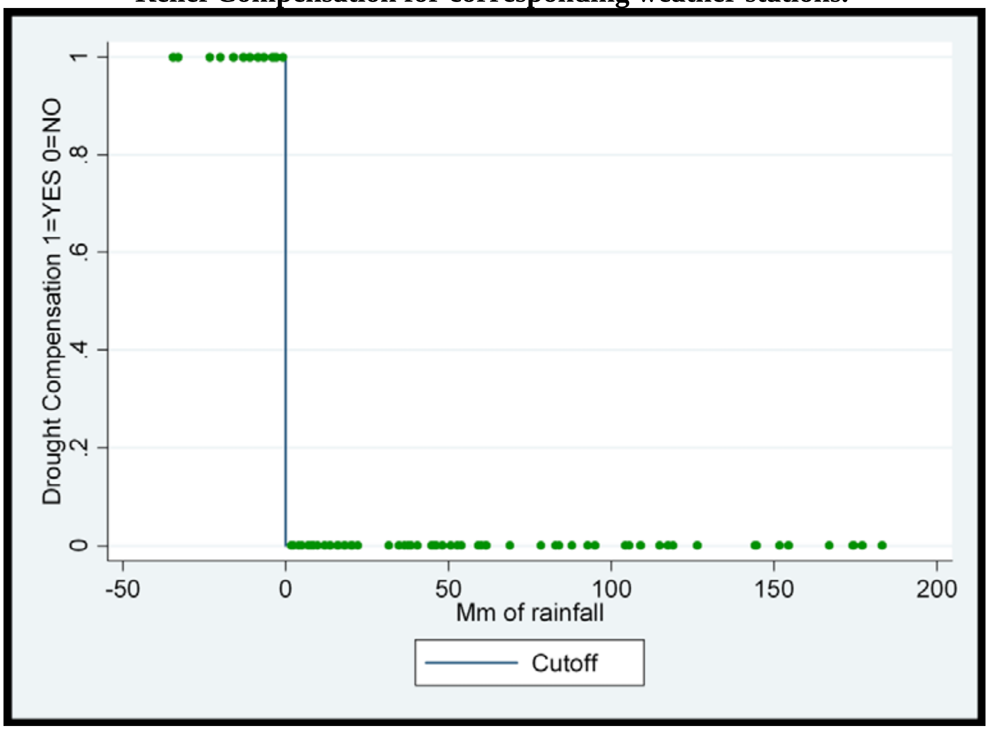


Figure 2.4 Non-parametric graphic analysis, share of votes for the incumbent in electoral sections with insurance coverage in 2005

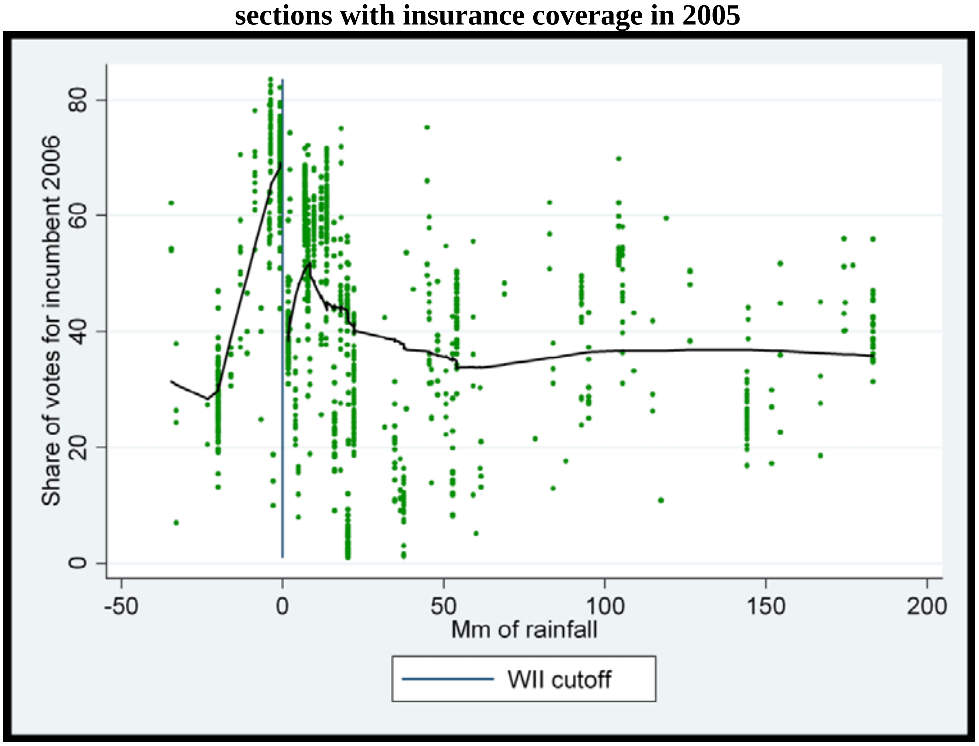
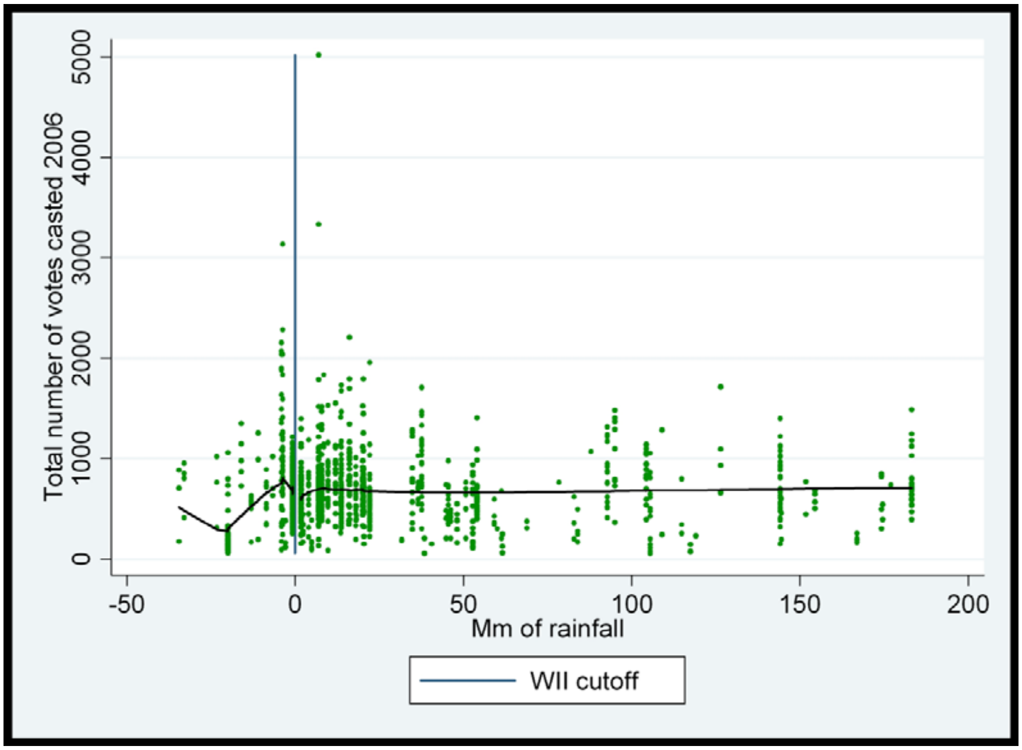


Figure 2.5 Non-parametric graphic analysis, total number of votes casted in electoral sections with insurance coverage in 2005



Chapter 3

Conditional Cash Transfers schemes and Households' Energy Response in Mexico

3.1 Introduction

Currently, nearly 2 billion people in the world live without electricity in their homes. This is likely to change over the next ten years as wide-scale anti-poverty programs, such as those under the Millennium Development Goals, lift the incomes of many of the world's poor. Increased energy consumption by families formerly living in poverty is likely to have broad implications for energy markets. This paper focuses on the role of household expenditures, particularly on energy-using durables, in the increase in energy demand. Specifically, we analyze the relationship between income and energy use in poor households in Mexico.

The analysis relies on a rich longitudinal data set from Mexico that was collected to evaluate Oportunidades (also known as Progresa), the country's largest poverty alleviation program. Oportunidades awards large cash transfers to poor households if they keep their children in school and acquire preventative medical care. The transfers have significant impacts on household incomes and cross-household variations in transfers are plausibly exogenous to other factors that could affect energy use. When Oportunidades started in 1997 it was targeted at rural households. However, it expanded to include urban households in 2002. We have data on Oportunidades beneficiary and control households for both the urban and the rural waves, including information on monthly energy expenditures and which of a set of appliances a household owns in a given year.

We use panel data from the Oportunidades urban wave to estimate short-run income elasticities for electricity demand and gas demand where -as usual in the literature- the short-run estimates hold households' appliance stock constant. Our estimates suggest that these are extremely small and statistically indistinguishable from zero. We show, however, that energy expenditures increase significantly when households acquire appliances, such as televisions, refrigerators and gas stoves. Because the panel data set from the urban data only follow households for two years in Oportunidades, we do not see significant appliance acquisitions as a function of transfers. Using the rural data set, which tracks households in the program from 1998 through 2007, we see that cumulative transfers have a significant effect on the likelihood that a household acquires a refrigerator and a stove. Combined, these estimates suggest that the long-run income elasticity is on the order of 13% for electricity and 8.9% for gas. Further, the results from the rural data suggest there is a nonlinear relationship between transfers and appliance acquisition, and that transfers need to exceed a certain threshold before they influence household decisions to acquire an appliance. Moreover, cross-sectional statistics also shed light on that pattern. For example, in Mexico in 2002, only 22% of urban households with monthly expenditures below $2,500 pesos per month owned refrigerators while 72% of urban households with expenditures just above $2,500 pesos owned refrigerators.

To correct for pre-treatment unbalances in the urban waves, we use a difference-in-differences matching estimator based on Behrman et al. (2005) as an additional check. The estimates of the difference-in-differences matching estimator suggest roughly similar results to those of the fixed effects models. For electricity we found a difference-in-differences estimate of 0.0853 and for gas was 0.1021. This can be interpreted as a significant increase in electricity expenditure by beneficiaries over non-beneficiaries on the two year period of 2.1%, and a significant increase of 2.5% on gas expenditure.

There is a rich literature examining household energy use and appliance acquisition in the developed world. A number of papers were written in the late 1970s and early 1980s in the midst of the last energy crisis (see, for example, Hausmann, 1981 and Dubin and McFadden, 1984). There is also a vast literature examining household expenditures in the developing world (Deaton and Case, 1987). To date, there has been very little work at the intersection, examining household energy use in developing countries. This paper sets out to fill that gap.

The document is organized as follows. Section 2 describes the theoretical background behind the empirical approach as well as the estimation strategy. Section 3 describes the data and provides a short description of the Oportunidades program. Section 4 describes the main results. Section 5 follows additional checks as well as the difference-in-differences Matching estimation, and finally section 6 concludes.

3.2 The Model and Empirical Strategy

We are interested in specifying the relationship between income and both energy use and appliance acquisition. This section outlines a theoretical framework for our estimation strategy and our approach to identification, focusing on the analysis with the Mexican Oportunidades data.

Theoretical Model

Households demand fuels and energy sources as means for attaining services such as light, refrigeration, entertainment and heating. However, to obtain a particular service, households need durable appliances (to produce the service) and an energy source (to power the appliance). There is an extensive literature that examines household choices over energy-using appliances, primarily using data from the developed world. This includes the seminal work of Dubin and McFadden (1984) on space- and water-heating and Baker, Blundell and Micklewright (1989) using microdata from the United Kingdom, who argue that household's demand for fuels can be viewed within a household production function where the underlying demands are for the services that these provide.

We begin by describing the typical setup of those papers, noting where our approach will depart from theirs. The main differences are driven by data availability. Those papers use cross-sectional data on households including detailed information on the available appliance choice sets such as prices and operating costs of the various appliances. In contrast, we do not have data on the types of appliances purchased nor available. However, with Oportunidades data we observe the same household over time subject to income shocks, noting how including household fixed-effects helps alleviates some concerns.

Consider first the household decision about purchasing a particular type of energy-using appliance. Assume households face a choice over m different appliances (e.g., over m different refrigerators or m different vehicles) $i = 1, \ldots, m$, each of which is associated with different periodic rental rates (r_i), usage prices (p_i) and attributes (s_i). For simplicity, we will consider the case where the appliance options are mutually exclusive. Some papers in the literature, especially those modeling large durable purchases such as vehicles, model the choice not to make a purchase (in other words they include an outside good), which we will include as we are focused on the binary choice of whether or not to get an appliance.

One insight of Dubin and McFadden (1984) was to note the interdependence between appliance choices and energy demand, suggesting the potential for bias if the two are not modeled jointly. They demonstrate how to specify the functional form for the indirect utility function --which is conditional on the appliance purchased-- and use Roy's identity to derive demand for energy, or define the parametric form of the energy demand equation and use it to derive the conditional indirect utility. For instance, one can begin with the following functional form for the conditional indirect utility function:

$$U_i = \left(\alpha_0^i + \frac{\alpha_1}{\beta} + \alpha_1 p_i + s_i^{'}\delta + w^{'}\gamma + \beta(y - r_i) + \eta\right) e^{-\beta p_i} + \varepsilon_i \qquad (1)$$

where w is a vector of observed household characteristics, y is household income, η and ε describe unobserved household and vehicle characteristics, respectively, and all of the other characters represent coefficients to be estimated.[28] This implies a usage demand of the following form:

$$x_i = \alpha_0^i + \alpha_1 p_i + s_i^{'}\delta + w^{'}\gamma + \beta(y - r_i) + \eta \qquad (2)$$

where x_i measures the usage demand (which can be translated into energy demand given the energy efficiency of appliance i) conditional on the purchase of appliance *i*. The endogeneity problem noted by Dubin and McFadden is apparent from the presence of several appliance-specific terms in the usage equation, such as p_i and s_i. As appliance choice based on the indirect utility in (1) reflects η, these terms will be correlated with the unobservable in equation (2). In practice, this could reflect, for example, a correlation between a household's high value for a particular fuel efficient vehicle and the likelihood that they will use it for long commutes.

To address the endogeneity of appliance choices, Dubin and McFadden propose either instrumenting for appliance choice, using as instruments the estimated probability of adopting appliance i from the discrete choice model, or including a conditional expectations correction term in the usage equation.

The model we propose to use in this study is based on the conditional expectation function that explains the relationship between household energy expenditure[29] conditional on household's time invariant unobservable characteristics and durable asset holdings.[30] The main equation is the following:

$$\begin{aligned} E\left(ln\left(C_{it}^{j}\right)\middle|X_{it}\right) &= E\left(ln\left(C_{it}^{j}\right)\middle|X_{it}, k_{it}^{j} > 0\right) * \left(Pr\left(k_{it}^{j} > 0\right)\right) + \\ &+ E\left(ln\left(C_{it}^{j}\right)\middle|X_{it}, k_{it}^{j} = 0\right) * \left(1 - Pr\left(k_{it}^{j} > 0\right)\right) \end{aligned} \qquad (3)$$

where C_{it}^{j} is the expenditure that household *i* destined for energy source *j* (*j=1* if gas and *j=2* if electricity) at time *t* (2002, 2003 or 2004). X_{it} is a vector of individual characteristics of household i in time t. k_{it}^{j} is a variable that represents durable asset possession for

[28] Given assumptions on the error terms in (1), one can derive specific functional forms for the choice probabilities implied by the indirect utility function.

[29] On an earlier version of the paper we used household per capita expenditure. However, as noted by Lanjouw and Ravallion (1995), adjusting household consumption on a per capita basis is probably incorrect because "even poor households face economies of size". Using data from Pakistan to test the empirical relationship between household size and consumption they find a fragile one particularly sensitive to differences in the assumed size elasticities. This relationship is even more evident when dealing with common consumption goods such as energy consumption. I thank Alain de Janvry and Elisabeth Sadoulet for bringing this point to my attention.

[30] We use this model because linear regression is a good tool for estimating this relationship. Moreover, it is the best linear predictor in terms of minimizing the mean squared error from the conditional expectation function.

household i that uses energy source j in time t (i.e. k_{it}^{j} is a gas stove if energy source $j=1$ for household i in year t, and a weighted index of refrigerator, television and washing machine if $j=2$). Consequently, when $j=1$ and $k_{it}^{j}=1$ then household i owns a gas stove in year t, and when $j=2$ and $k_{it}^{j}>0$, then household i owns either a refrigerator, a television or a washing machine in year t, or any combination of these.[31]

Empirical Specification

We are interested in estimating the effect of Oportunidades cash transfers on the change of beneficiary household energy expenditure. We observe only whether or not a household has purchased a particular type of appliance (e.g. a refrigerator or gas stove) and have no information on its purchase or usage price, nor on any of its characteristics. Our usage equation, therefore, equivalent to equation (2), is:

$$E\left(C_{it}^{j} \middle| X_{it}\right) = x_{it}^{j} = \beta_1 + \beta_2 \tau_{it} + \beta_3 k_{it}^{j} + \beta_4 k_{it}^{j} * \tau_{it} + \gamma_i + w_{rt} + \varepsilon_{it} \qquad (4)$$

where x_{it}^{j} is household $i's$ expenditure for energy source j (e.g., $j=1$ if gas and $j=2$ if electricity) at time t and τ_{it} is Oportunidades cash transfer for household i in time t, γ_i is the household level fixed effects, w_{rt} region-specific year fixed effects and ε_{it} the error term. The variable k_{it}^{j} is defined as above.

In contrast to equation (2), we use τ instead of y. As we are particularly interested in obtaining an unbiased estimate of the income elasticity, we are concerned about factors that could be correlated with both household income and energy consumption. For instance, if an adult in the household looses her job and consequently spends more time at home, this could lead to a negative correlation between household energy use and income. Alternatively, if the household begins some type of energy-using in-home production, this could lead to a positive correlation between energy use and income. We argue below that Oportunidades transfers are plausibly exogenous shocks to household income, and should be uncorrelated with other factors that could drive energy use.

As noted, unlike empirical papers based on equation (2), we do not have data on prices, although in some specifications, we estimate region-year fixed effects, which control for much of the cross-household variation in energy prices. In Mexico, electricity is provided by a single publicly owned firm (Comisión Federal de Electricidad (CFE) or Federal Electricity Commission in English). This company provides electricity regulated by region, season, purpose and intensity of use. Similarly, although in Mexico gas is supplied by private companies, they face regional maximum binding prices set by the Ministry of

[31] Notice that when $j=2$ and $k_{it}^{j}=1$, household i owns a refrigerator, a television and a washing machine in year t.

Commerce. Also, equation (2) stacks observations across consumers who have made different appliance decisions. We are constraining the year effects for these two types of households (those with the appliance and those without) to be the same, but all other variables are estimated freely for the two types of households.

Considering the endogeneity problem identified by Dubin and McFadden in our context, we might expect a correlation between a household's value for a gas stove of any type, and the intensity with which it uses it (e.g. based on family size or an individual household's utility from warmed meals). To the extent this correlation is driven by stable household characteristics, they will be captured by the fixed effect. In other words, our pre-transfer observation of the household will provide us with information on its tastes for energy-use. Nevertheless, if the unobservable household characteristics that are driving appliance use and acquisition decisions are changing over time, household fixed effects will not capture this. For example, a negative health shock within a household may increase their utility from a gas stove, and may also make them more likely to use it.

To aid interpretation of the coefficient on τ_{it} as elasticities, we take the natural log of both energy expenditures and transfers

$$E\left(ln\left(C_{it}^{j}\right)\middle|X_{it}\right) = \ln\left(x_{it}^{j}\right) = \beta_1 + \beta_2 ln(\tau_{it}) + \beta_3 k_{it}^{j} + \beta_4 k_{it}^{j} * ln(\tau_{it}) + \gamma_i + w_{rt} + \varepsilon_{it} \quad (5)$$

We do not use our energy-use equation to constrain the appliance acquisition model, and estimate models of the following form:

$$Pr\left(k_{it}^{j} > 0\right) = \alpha_1 + \alpha_2 ln(\tau_{it}) + \gamma_i + w_t + v_{it} \quad (6)$$

In equation (6) the parameter α_2 reflects the relative importance that Oportunidades cash transfers (τ_{it}) have on asset acquisition for household i in time t. γ_i respresents household level fixed effects, w_t year fixed effects and v_{it} the error term.

Given our empirical specifications, the income elasticities are defined as follows, where $\bar{\rho}$ is the average ratio of total income to Oportunidades transfers:

• Short run elasticity for households with ($k_{it}^{j} = 0$) is $\beta_2 * \bar{\rho}$,
• Short run elasticity for households with ($k_{it}^{j} > 0$) is $(\beta_2 + \beta_4) * \bar{\rho}$, and

• Long run elasticity[32] for households with $(k_{it}^{j}=0)$ is $\left(\beta_2+2\alpha_2\beta_4 ln\left(C_{it}^{j}\right)+\alpha_2\beta_3\right)*\bar{\rho}$
• We consider the long run elasticity for households with $(k_{it}^{j}>0)$ to be the same as the short run elasticity for these households since we do not observe the process of assets acquisitions.

Estimation Strategy: Household Fixed Effects

We rely on two sources of identification. First, there is considerable variation across beneficiary households in the amount of transfers they received. For example, beneficiary households without school-aged children received only the basic amount ($155 pesos in 2003), while the maximum amount a household could get was close to $2000 pesos. These variations were primarily driven by family structure, such as whether a family had school-aged children. We argue that transfer amounts are exogenous to energy demand and appliance acquisition decisions, particularly after we control for household fixed effects, which would capture the family structure variables that determine a household's transfer level.[33]

We test this identification assumption in several ways. Because the actual transfer amount a household receives in a given period is a function of household decisions, there is the potential for correlation between these decisions and energy use and appliance acquisition. For example, household heads could decide not to send some of their children to school and instead send them to work. This would lead to a lower Oportunidades payment, and if the decision to send the child to work is also correlated with energy use (e.g., with the child out of the house for work, the household prepares less food and uses less electricity for school homework), this could lead to a biased estimate of the impact of the transfers on energy use. Therefore, in some specifications, we will use potential transfers (the maximum amount a household could receive given household structure) as an instrument for actual transfers. We can see the relationship between actual and potential transfers in Figure 3.1.[34]

[32] We derive the long-run income elasticity for households that did not have a durable appliance at baseline as the sum of the short-run elasticity for that same group plus an application of the chain rule that considers the change in energy expenditure when asset possession changes multiplied by how asset possession changes when (log of) income changes:

$$\eta_{it,LR}^{j}=\eta_{it,SR}^{j}+\frac{\partial \ln\,(C_{it}^{j})}{\partial (k_{it}^{j})}\frac{\partial \ln\ k_{it}^{j}}{\partial C_{it}^{j}}$$

[33] It is unlikely that households modify their structure as a function of Oportunidades transfers since they would not get the benefit of having more children in the short run (the children have to be on Primary school age to qualify for the per/child transfer).

[34] To clarify this approach consider the fixed-effects model specified in (5), where we assumed that $E(\varepsilon_{it}|\tau_{it})=0$ (i.e. transfers are uncorrelated with the error term). However, this assumption need not be true: households could decide to send their children to school and receive the transfer or send them to work, potentially leading to a biased estimate of the impact of the transfers on energy expenditure.

The instrumental variable estimate of β_2 will be consistent if potential transfers are correlated with actual transfers and uncorrelated with the error term. Thus, potential transfers --denoted as z_{it}-- follow the assumptions that $Cov(z_{it},\varepsilon_{it})=0$ and $Cov(z_{it},\tau_{it})\neq 0$. Consequently, we use two stage least squares to estimate the instrumental variable specification. First stage:

$$\ln\left(\tau_{it}^{j}\right)=\delta_1+\delta_2 ln(z_{it})+\delta_3 k_{it}^{j}+\delta_4 k_{it}^{j}*ln(z_{it})+\gamma_i+w_{rt}+u_{it}$$

As a second source of identification, in some specifications, we include both Oportunidades beneficiaries and a set of control households that were surveyed as part of Oportunidades to aid with the program evaluation. As we describe more fully below, they were selected to have similar income levels and other household characteristics as the program beneficiaries, but there are still differences between the two groups, especially in the urban program. Because we are including household fixed-effects, our identification comes from comparing the change in energy expenditure for the program beneficiaries (transfer recipients) with the change in energy expenditure for those who are not participating in the program. This strategy rests on the assumption that Oportunidades' beneficiaries would have had the same growth in energy expenditure as the non beneficiaries with similar observable characteristics.

Our results may be biased if there is correlation between the error term ε_{it} and selection into the program, particularly if the correlation remains after we control for observable characteristics. For example, households where adults have good health may be less inclined to apply for the program and may also have less demand for energy-using appliances, independent of household income or transfers. If we include household fixed-effects, the source of bias is reduced since any fixed characteristics such as preference for cooking or lighting with a particular source of energy are absorbed by the fixed-effects.

There is another problem that might bias the fixed-effect estimator, particularly in the urban wave of Oportunidades, known as the 'Ashenfelter dip' which has been discussed in previous non-experimental evaluations of public programs. For example, Rouse (1998) describes this problem in the context of a public sector training program evaluation in which individuals who participate in training programs are observed to have unusually low earnings in the period in which they are selected for the program. If potential beneficiary households that actually applied for the program were having an unusually low income in the time that they were selected, then the fixed effects estimates might be biased. However, this is less likely to be the case in our context since Oportunidades participation is not only based on income levels (of the period prior to selection) but on several other household characteristics (such as household head's education level, house floor type, house roof type, among other things) that are unlikely to vary as much as income in the short run.

Finally, our fixed-effects estimator will be biased if the underlying trends in energy expenditures and appliance acquisition propensities vary as a function of beneficiary status or transfer levels. For example, if beneficiaries' energy expenditures had a faster growth trend than the non beneficiaries', then the fixed-effects estimates will be biased upward since part of this trend might be attributed to the effect of the program. Unfortunately, we do not have information of prior to baseline periods. Therefore, we will have to rely on the

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Second stage:

$$E[ln(C_{it}^{j})] = \beta_1 + \beta_2 \ln(\widehat{\tau_{it}}) + \beta_3 k_{it}^{j} + \beta_4 k_{it}^{j} * ln(\widehat{\tau_{it}}) + \gamma_i + w_{rt} + \varepsilon_{it}$$

'common trends' assumption reminding the reader to use caution when interpreting the results.

3.3 Oportunidades program and the data

Oportunidades Program

Oportunidades is the Mexican Federal Government's main poverty alleviation program. It is a cash transfer program targeted at poor households conditional on children's school attendance (children must attend a minimum of 85% of class days and cannot repeat a year), frequent medical checkups and attendance to community meetings where they are provided with information on personal health.

Table 3.1 describes the benefits that beneficiary households were entitled in 2003, which is roughly the midpoint of both our urban and rural data sets. While the benefit levels and the grades covered have changed over the program, its basic structure has not. In 2003, the basic transfer (called “Alimentary” or “Food” support) was $155 pesos per month.[35] Similarly, the per child scholarship in 2003 ranged between $105 pesos per month for children who attended more than 85% of the third degree of Primary School to $655 pesos for teenage girls who attend the third year of tertiary school. In 2008 these amounts range from $130 to $825. Finally, Oportunidades also provides a yearly stipend to buy school supplies for children who do not get them at school.

To become eligible, a household must qualify in terms of an official poverty index that includes consideration of household assets, education and materials of which the home is built. The program started as a pilot project in poor rural areas in 1997, and by 2007 it had over five million beneficiary households. Previous research has found the program increased school enrollment and attainment, reduced child labor and improved health outcomes (Behrman et al., 2005). This success spurred the program's extension through the 2000 presidential election and change in administration, its further expansion in rural areas, and ultimately, into urban areas in 2002.

Nevertheless, Oportunidades expansion into urban areas differed from its rural counterpart. This has important implications for its analysis and evaluation, as is well documented by the INSP (2002), Behrman et al. (2005) and Angelucci and Attanasio (2006). When the program was introduced and expanded in rural areas, due to budget constraints treatment was randomized at the rural village level. Within each village, a census survey identified eligible households and informed them of the program, minimizing selection bias.

Conversely, Oportunidades' expansion into urban areas was not random. Since doing a complete census of urban areas (defined for the program as those larger than 100,000

[35] The Alimentary support is the minimum support a beneficiary household is entitled for if they attend to medical check-ups and to the monthly orientation meetings. This is targeted at households that do not have eligible school age children.

people) was prohibitively costly, the enrollment strategy was different. Sign-up locations or registration offices were set up within areas where government officials had determined a high proportion of potential beneficiaries lived, and program advertisements were circulated in various forms.[36] To apply for the program, interested individuals had to go to the registration offices and answer a questionnaire related to their socioeconomic status. If a household appeared likely to be eligible for the program, officials made household visits to confirm that the information given was accurate and to determine official eligibility.

Similarly, since the program started in areas with high poverty concentration, treatment areas were potentially different from control areas. Consequently, urban blocks (manzanas) became the sample unit: blocks in treatment areas were matched to blocks with similar characteristics in control areas. Evaluation studies of the urban program usually have one treatment group and two controls. The treatment group is comprised of the potential eligible households that actually became beneficiaries. The control groups are (1) the potential beneficiaries that live in treatment areas but did not become part of the program and (2) potential beneficiaries that live in control areas or areas in which the program was expanded after 2004 (the third and last wave of the urban data set). Moreover, although the urban survey focused mainly on surveying poor households, it also collected information of ``almost poor'' and ``non poor'' households.

Data

The rural data used in this study comes from the Oportunidades Evaluation Survey (ENCEL), which is a panel data set that was gathered over six rounds. The first one was gathered a year after the program started, during the fall of 1998 and the second one in 1999. Similarly, during 2000 two different surveys were gathered, one in March 2000 and the other one in November 2000. The fifth one was gathered in 2003 and the last one was recently done in 2007.

The evaluation surveys gather information on an ample array of issues that the program may potentially affect, ranging from household and household members' characteristics, income and labor supply, expenditure, health and nutritional status, education, among other. Of particular importance for this study, the survey gathers information on energy powered household durable asset possession, such as refrigerators, gas stoves, televisions and vehicles. For 2007, a section for monthly expenditure on energy sources such as electricity and gas was also included. Consequently, we use information on household durable asset possession and its relation with the program's cash transfers.[37]

The urban data used in this study comes from the Urban Oportunidades Evaluation Survey (ENCELURB), a panel data-set that was gathered in three rounds. The first round corresponds to baseline data, gathered before beneficiary households received the program

[36] For example, a car with speakers drove around the neighborhoods announcing the program.
[37] For the analysis, we use a balanced panel of 10,753 observations per round.

benefits for the first time but after they had registered for the program. This was done in the fall of 2002. The following two rounds of data collection were done with a similar questionnaire and after beneficiary households had experienced one and two years in the program.[38] It has information of close to 16,000 households in 17 out of the 32 states of Mexico.

Like the rural data, the urban data also contains a wide range of household socioeconomic information. We focus on the information related to the household's expenditures, particularly on energy sources such as gas and electricity, and the household's assets ownership such as refrigerator, gas stove, television, and washing machine.

Tables 3.2a and 3.2b present summary statistics on the urban and rural data respectively. The top panels report summary statistics on household expenditures, the middle panels depict patterns in appliance ownership and the bottom panels summarize household structure characteristics. In each table, we compare summary statistics for non-beneficiaries to beneficiaries. Generally, reflecting the different approaches to randomization across the two waves of the program, the non-beneficiaries, depicted in the left-hand column, and the beneficiaries, depicted in the right-hand column, are more comparable in the rural program than in the urban program.

For the rural data, the balance between beneficiaries and non-beneficiaries was originally much more equal, but since the inception of the program and 2007, many of the original control households were enrolled in the program. The "never-beneficiaries" reflected on the left of Table 3.2b reflect households that remained out of the program. One might be concerned that subsequent enrollments were non-random, although the summary statistics in Table 3.2b suggest that beneficiaries and never beneficiaries are similar on observables (though this could reflect the small number of observations on the never beneficiaries).

For the urban program, non-beneficiaries generally appear slightly wealthier. Total monthly expenditure (measured in real November 2002 pesos) is higher for poor non-beneficiary households, and monthly expenditures on gas and electricity are also higher for non-beneficiaries. The pattern is also reflected (although much less dramatically) when we compare durable asset holdings. For example, 22.8% of the poor non-beneficiaries report having a refrigerator, while 21.1% of the poor beneficiaries do; 68.7% of the non-beneficiaries reported having a gas stove while 63.5% of the beneficiaries do. However, there are not large differences in household size and composition between both groups at baseline: the non-beneficiary average household size in 2002 was 5.17 members (2.97 adults and 2.2 children), while the beneficiary's average household size was 5.22 members (2.93 adults and 2.29 children).

[38] These were done in the fall of 2003 and 2004.

3.4 Results

Short-Run Income Elasticities: Electricity and Gas Expenditure

Table 3.3 presents the first set of results on the relationship of Oportunidades transfers and household energy expenditure using the urban dataset. As the surveys of the rural program did not ask about disaggregated energy expenditures (i.e., broken down by fuel type) until 2007, we will focus this analysis on the 2002-2004 panel data set from the urban data. Results from estimating equation (5) are presented in Table 3.3. For both electric and gas expenditures we report OLS and IV fixed-effects specifications over beneficiary households. All specifications regress the log of monthly energy expenditure on the log of monthly transfers, and household size, and the last two include an appliance dummy and the appliance dummy interacted with the log of monthly transfers. We also control for state specific time trends (e.g. to capture trends in local prices and other regional variation) with state by year dummies. In the instrumental variable specifications (Columns III and VI), actual transfers are instrumented for with potential transfers to the household.[39] There are no statistically significant differences between the OLS and IV specifications, so we discuss only the OLS specifications below.

For electricity, the specification includes the asset dummy for holdings of refrigerators, televisions and washing machines. The electric asset holding indicator is set to the sum of 0.75 if the household has a refrigerator, 0.15 if the household has a television, and 0.10 if the household has a washing machine.[40] Thus, if a household has none of those appliances, the variable is set to zero. If a household has all three, then the variable is equal to one. If a household has some, but not all of the durables then the variable is between zero and one. The regressions for electricity expenditure (Columns I, II and III) display small and insignificant relationships between electricity expenditures and both monthly transfers and monthly transfers interacted with the electric asset indicator. The coefficient of the electric asset dummy is positive and significant, suggesting increases in energy expenditures with increases in the appliance stock. Together, these results suggest no short term income elasticity of electricity expenditures. Importantly, this would suggest that increases in electricity use would be uneven as households acquire assets.

For LP gas (Columns IV, V and VI) the specifications are similar except that the appliance indicator is simply a dummy variable indicating whether the household owns a gas stove or not. The regressions display an insignificant relationship between cash transfers and LP gas expenditure for households with and without stoves. These are consistent with zero short-run income elasticities. We note that both specifications estimate positive and significant coefficients on the indicator variable for stove ownership. Unlike the electricity

[39] The relevant first stage coefficients on the log of potential per capita monthly transfers are statistically significantly higher than 0.79. Accordingly, the F statistic are large. Please refer to the Appendix for the first stage regression results.

[40] A study prepared by The Mexican Ministry for Social Development is the basis for these weights. This study uses information provided by the Mexican Federal Electricity Commission about average monthly time consumption of main household assets such as refrigerator, television, heating, air conditioning, iron, blenders, among other, as well as their average kilowatt hour consumption.

specification, this coefficient is being driven only by households that exhibit changes in their ownership of gas stoves, and not incremental changes in the electricity consuming durables. We consider this coefficient consistent with our priors, although the relative magnitude seems to be large.

Overall, these estimates suggest at most very small short term income elasticities. In addition, both the electricity and the gas specifications show a clear impact of durable good possession on energy consumption.

Long-Run Income Elasticities: Appliance Acquisitions

We next turn to an analysis of the relationship between Oportunidades transfers and appliance acquisitions. As shown in Table 3.4, Oportunidades transfers didn't have a large effect on gas stoves acquisition in urban areas, at least over the analyzed period. However, transfers had a significant effect on refrigerator acquisitions, although fairly small. A possible explanation for this phenomenon is based on the fact that the urban panel spans less than two years of the program. It is likely that households did not have time to save enough to acquire durable assets.

Consequently, we rely on the rural data set for this analysis, which spans roughly ten years. As documented in Table 3.5, over this period, a large fraction of both beneficiary and non-beneficiary households acquired refrigerators, and ownership rates rose from roughly 10 percent of the households to nearly 50 percent. This can also be seen in Figures 3.3 and 3.4 for refrigerators and gas stoves both in urban and rural settings. Simple difference-indifference calculations show no significant difference between beneficiaries and non-, although the small number of non-beneficiaries leaves us with little statistical power. We conjecture that the growth in ownership at the non-beneficiary households is driven by falling prices for energy and the refrigerators and generally rising incomes in Mexico, and these factors are also at play for the beneficiary households.

Focusing on only beneficiary households, Figure 3.2 plots the lowess smoothed mean appliance ownership fraction versus the log of cumulative transfers using a cross-section of households in 2007. We only include households that did not have a refrigerator at baseline. At low levels of cumulative transfers, there appears to be a weak relationship between the amount of transfers received and the likelihood that a household bought a refrigerator. After a certain threshold, however, there is an inflexion point in the relationship between transfers and refrigerator acquisition. Because the results presented in the graph are based on cross-sectional correlations, there is a distinct possibility that they reflect the spurious correlation between household characteristics and appliance acquisition, though we note that variations in transfers are driven by several factors, including the length of time the household has been on the program in addition to household characteristics.

Table 3.6 reports results from cross sectional analysis using log of energy expenditure on log of monthly transfers for the 2007 rural wave. Notice that we control for household characteristics such as the household head's gender, age and level of education (years of schooling), household structure (age and gender of children), spouse characteristics and whether the household is the owner of the house they are living in or not. The first two columns analyze the case for electricity expenditure whereas the second set of columns the gas expenditure case. For electricity expenditure the log of monthly transfer have a positive and significant effect, as well as the appliance ownership variable. However, the interaction between both seems to have a negative and significant effect. Conversely, gas expenditure only seems to be significantly affected by gas stove ownership.

Finally, Table 3.7 reports results from several linear probability models designed to explore the robustness of the positive relationship between transfers and appliance acquisition depicted in Figure 3a. In this case we use the full panel data set from 1998 to 2007 and include household fixed-effects to control for underlying differences in the propensity to acquire a refrigerator of stove which could be correlated with cumulative transfers.[41] While small, the coefficient on log of cumulative transfers is significantly different from zero, and the magnitudes suggest that with double the cumulative transfers, a household’s propensity to acquire a refrigerator goes up by about 1.5 percentage points. As these estimates try to fit a linear relationship to one that clearly has a nonlinear break, they understate the effect at the high end of the transfers. Estimates on just observations with more than the median cumulative transfer level yielded a coefficient nearly 5 times as big as those in Table 3.7. The last two columns report results for gas stove acquisition. The coefficient is positive and statistically significant at the 5% level, although very small in magnitude (ten times smaller that the coefficient corresponding to refrigerator). Moreover, while the IV coefficient is not significantly different from zero, the relative magnitudes suggest that instrumenting if anything increases the coefficient.

Combining the estimates of the short-run energy demand and appliance acquisitions, we can calculate the long-run income elasticity using the equation derived in section 3.2. In round numbers, the equation for electricity is $(0 + 2*(0.015)(0.2578)(\ln(62.16) + 0)*4$, suggesting that long-run income elasticities are around 0.1277, and for gas of 0.08931.

3.5 Robustness Checks: Matching difference-in-differences

Matching difference-in-differences Estimator

Following Behrman et al. (2005), we use a difference-in-differences (DID) matching strategy that allows for temporary invariant differences in outcomes between beneficiaries and non-beneficiaries. They use this technique on the same data (ENCELURB) and argue that this methodology could correct for pre-selection treatment differences between groups.

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[41] We calculate the transfers accumulated by the household since it started receiving transfers.

Conventional matching estimators assume that the mean outcomes are conditionally independent of program participation. However, it could be the case that there are systematic differences between participants and non participants after conditioning on observables, which could lead to a violation of the identification conditions required for matching. Matching difference-in-differences allows for imputing what would have been the outcome on the treated should they have not received the treatment. That is, given that we can observe what was the outcome of the treatment group when they received the treatment $E(Y_1|X, D = 1)$, we would be able to impute $E(Y_0|X, D = 1)$. Thus, we can use matching estimators if we believe that the outcome is independent of program participation conditional on a set of observable characteristics.[42]

By conditioning on observable characteristics we can get a consistent estimate of the average treatment effect (ATE) by comparing the difference in means between the change in the outcome of interest between the treatment and control groups. However, in practice it can be hard to implement matching methods when the set of conditioning variables (X_i) is large. Therefore, an important result or useful theorem under strongly ignorable treatment assignment --i.e. when both unconfoundedness and overlap assumptions are combined-- is that when matching on X is valid, it is sufficient to condition simply on $p(X_i) = E(D|X)$.

According to Behrman et al. (2005), the difference-in-differences propensity score matching estimator requires that $Y_{0t} - Y_{0t'}$ be orthogonal to $\left(D\middle|P(D = 1|X_i)\right)$, where t' is the pre-program time period and t is the post-program time period, as well as the common support assumption that must hold in both periods.

We differ from their definition of the local linear difference-in-differences estimator since we use an adjustment proposed by Hirano, Imbens and Ridder (2003). They propose weighting by the inverse of the propensity score as a method of adjusting for differences between treated and control units. We use the following estimator:

$$\hat{\alpha}_{DD} = \left(\sum_{i=1}^{N} \frac{(D_i)(Y_{1ti} - Y_{1t'i})}{\hat{p}(X_i)} \Bigg/ \sum_{i=1}^{N} \frac{(D_i)}{\hat{p}(X_i)} \right) - \left(\sum_{j=1}^{J} \frac{(1-D_i)(Y_{0ti} - Y_{0t'i})}{1-\hat{p}(X_i)} \Bigg/ \sum_{j=1}^{J} \frac{(1-D_i)}{1-\hat{p}(X_i)} \right) \quad (7)$$

[42] To use matching, we need to impose the following two assumptions: (a) Unconfoundedness: there is a set of observable conditioning variables for which the control group outcome (Y_0) is independent of treatment (D), $(Y_0, Y_1) orthogonal(D|X_i)$; and (b) Overlap or common support: for all observable characteristic, X_i, there is a positive probability of either participating on the program ($D=1$) or not ($D=0$), or $0 < P(D = 1|X_i) < 1$. When these two assumptions are combined we can say that treatment assignment is “strongly ignorable”.

where Y_{1ti} is the outcome of interest for a treated individual (household) after the treatment, $Y_{1t'i}$ is the outcome of interest for a treatment individual before the treatment and Y_{0ti} and $Y_{0t'i}$ are outcome of interest for control individuals before and after treatment. $\hat{p}(X_i)$ is the propensity score, D_i is an indicator that takes the value of 1 if the household receives treatment, N is the number of households that receive the treatment (beneficiaries) and J is the number of eligible households that do not receive treatment.

Propensity score, common support and estimation

Following Behrman et al (2005), we use propensity score matching methods to evaluate the impact of Oportunidades transfers on energy expenditure, where the matches are chosen on the basis of observable characteristics. Propensity score matching requires estimating the propensity score $\hat{p}(X_i)$ based on observable characteristics, and then using it to implement the matching estimator described by (7).[43]

The propensity score was estimated using logistic regression applied to data on households who are eligible to participate in Oportunidades program and actually applied, households that didn't apply and households that live in areas where the program had not been rolled out yet. We compare participant's outcomes with those of households that did not participate but could have done it if they would have attended the module, or lived in intervention areas.

Figures 3.5 and 3.6 show the propensity scores histograms for beneficiaries and non beneficiaries. There appears to be common support between both distributions meaning that for each participant household we can find good matches from the nonintervention group of households.

Table 3.8 presents difference-in-differences comparisons between the matched beneficiary and non-beneficiary households in terms of log of monthly expenditure in gas and in electricity in the upper and lower panels, respectively. The before period represents information of baseline (2002) before beneficiary households receive transfers, and the after period takes into account information from the 2004 wave (roughly after 2 years of exposition to the program). We notice that the difference-in-differences between beneficiaries and non- as well as before and after, are positive for both the log of gas monthly expenditure as well as for the log of electricity expenditure.

The matched difference-in-differences estimators, shown in Table 3.9, provide positive estimates. The estimates are $\hat{\alpha}_{DDgas} = 0.1021$ and $\hat{\alpha}_{DDelect} = 0.0853$, respectively, both

[43] Variables that are designed to capture key determinants of program participation decisions (such as the number of children in school age that will provide benefits to the household), household's poverty level (such as expenditure, education level, employment, health clinics availability) and variables that may affect family awareness of the program (such as geographic location, population living in the locality) are included. It is important to note that all variables are measured before the households know whether they will participate in the program or not. Thus, it is unlikely that the program had an impact on the latter set of variables.

significantly different than zero.[44] These were obtained by using the basic difference-in-differences specification:

$$ln\left(C_{it}^{j}\right) = \alpha_1 + \alpha_2(After) + \alpha_3(Beneficiary) + \alpha_4(After * Beneficiary) + \varepsilon_{it} \quad (8)$$

where *After* is a dummy variable that takes the value of one if the year is 2004, *Beneficiary* is a variable that takes the value of one if the household is an Oportunidades beneficiary, *After**Beneficiary* is the interaction between both, $ln\left(C_{it}^{j}\right)$ is as defined above and ε_{it} is the error term. The coefficient of interest is α_4, which provides the difference-in-difference estimates. This means that matched beneficiary households presented increases in monthly electricity and gas expenditures of 2.1% and 2.5%, respectively, over those of matched non-beneficiary households on the analyzed period.

Table 3.9 also provides results from similar specifications comparing beneficiary and non-beneficiary households but without the propensity score matching (columns 2 and 4). The coefficients are also positive and significant. Interestingly, the coefficient corresponding to the beneficiary variable is smaller in magnitude for the matched regressions than for the non-matched, indicating that the matching (at least partially) reduces between groups' differences.

3.6 Discussion

The previous sections seek to address the impact of anti-poverty programs on the growth in energy-use, focusing particularly on growth in energy-intensive durable ownership. From our analysis of the Oportunidades program in Mexico we show that the short-run income elasticities of poor households depend on their energy-intensive appliance stock. We also show that long-run elasticities are higher than short-run as households become first-time purchasers of energy intensive durables.

Our results have several implications for policy makers. To the extent that projections of growth in energy-use are based on historical growth, which has largely been driven by the moderate income households, this suggests that those maybe biased downwards in the context of widespread poverty alleviation programs, such as those under the Millennium Development Goals. Moreover, by learning how poor household change their energy use while increasing their income it is possible to project, prevent and account for future increases in energy demand.

Climate change and global poverty are two of the most pressing issues of our times. Though considerable attention, resources and academic work have been devoted to both

[44] The figures are exactly the same as those obtained by taking the differences. Refer to Table 8.

issues, comparatively little work examines their intersection. At a fundamental level, lifting millions of people out of extreme poverty is at odds with solving climate change, unless there are broad-based changes to the energy infrastructure. Similarly, changing household energy infrastructure may further induce poverty alleviation since it will help household overcome the poverty trap described by Duflo et al (2008): poverty leads to cheap low quality fuels use, indoor air pollution, poorer health, lower productivity and finally, to permanent poverty. More fine-tuned analyses of the issues, such as the one provided in our paper, can help us to think constructively about where these issues overlap.

3.7 References

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Tables

Table 3.1. Oportunidades Maximum Support Levels in 2003

BasicTransfer	$155		
PrimarySchool	Boys	Girls	School Utensiles[1/]
Third	$105	$105	$200
Fourth	$120	$120	$200
Fifth	$155	$155	$200
Sixth	$205	$205	$200
SecondarySchool	Boys	Girls	
First	$300	$315	$250
Second	$315	$350	$250
Third	$335	$385	$250
TertiarySchool	Boys	Girls	
First	$505	$580	$250
Second	$545	$620	$250
Third	$575	$655	$250

Max amount household can receive: $1,025 with children in Primary and $1,715 w/children in Secondary and/or Tertiary School

1/ These are only provided once per school year

Table 3.2a: Basic Descriptive Statistics (Urban)

	Poor Non-Beneficiaries		Poor Beneficiaries		Difference
Variable	N	Mean (SD)	N	Mean (SD)	(SE)[1/]
HouseholdExpenditures					
Total monthly Expenditures	4,899	2,174.98	4,958	1,822.43	352.55
(November 2002 pesos)		(1,114.5)		(1,217.6)	(48.78)**
Household Expenditure Electricity	3,420	81.27	3,607	62.16	19.11
(November 2002 pesos)		(80.3)		(72.0)	(2.61)**
Household Expenditure LP Gas	4,611	83.92	4,616	63.58	20.33
(November 2002 pesos)		(53.5)		(55.9)	(1.82)**
Energy as % of Total Expenditure		7.59%		6.90%	0.69%
		(0.09)		(0.07)	(.20%)**
Fraction Electricity		3.74%		3.41%	0.33%
		(0.07)		(0.06)	(0.077%)**
Fraction Gas		3.86%		3.49%	0.37%
		(0.05)		(0.04)	(0.098%)**
HouseholdAssets					
Refrigerator	4,899	22.78%	4,958	21.08%	1.70%
		(0.42)		(0.41)	(0.83%)**
Gas Stove	4,899	68.65%	4,958	63.51%	5.13%
		(0.46)		(0.48)	(0.95%)**
Television	4,899	80.96%	4,958	74.89%	6.07%
		-39.27%		-43.37%	(0.83%)**
Automobile	4,899	1.39%	4,958	0.63%	0.76%
		(0.12)		(0.08)	(0.20%)**
Motorcycle	4,899	0.96%	4,958	0.52%	0.43%
		(0.10)		(0.07)	-0.17%
HouseholdCharacteristics					
Family Size	4,899	5.17	4,958	5.22	-0.04
		(2.29)		(2.09)	(0.04)
Adult	4,899	2.97	4,958	2.93	0.04
		(1.56)		(1.45)	(0.03)
Children	4,899	2.2	4,958	2.29	-0.09
		(1.47)		(1.46)	(0.029)**

1/ Standard errors are in parenthesis in the column of differences. T-test of difference in means were followed. Difference * is significant at the 5% level, and ** is that the difference is significant at the 1% level. Information for this table was gathered from ENCELURB at baseline (2002). It only takes into account those households that are qualified as poor or below the poverty line dictated by the Mexican Ministry for Social Development (SEDESOL for its initials in Spanish).

Table 3.2b: Basic Descriptive Statistics (Rural)

	PoorNon-Beneficiaries		Poor Beneficiaries		Difference
Variable	N	Mean (SD)	N	Mean (SD)	(SE)[1/]
HouseholdExpenditures					
Total monthly Expenditures	42	1,736.94	8,152	2,102.85	-365.91
(November 2007 pesos)		(1,327.1)		(2,889.9)	(446.2)
Household Expenditure Electricity	41	126.49	8,058	115.89	10.6
(November 2007 pesos)		(161.9)		(134.3)	(21.1)
Household Expenditure LP Gas	41	57.8	8,107	64.62	-6.81
(November 2007 pesos)		(107.6)		(119.5)	(18.7)
Energy as % of Total Expenditure	40	13.63%	8088	10.37%	3.26%
		(0.19)		(0.12)	(0.019)
Fraction Electricity	40	9.83%	8019	7.34%	2.49%
		(0.17)		(0.10)	(0.016)
Fraction Gas	40	3.79%	8063	3.09%	0.69%
		(0.07)		(0.07)	(0.011)
HouseholdAssets					
Refrigerator	57	42.11%	10,709	40.33%	1.77%
		(0.50)		(0.49)	(0.07)
Gas Stove	57	36.84%	10,709	38.03%	1.19%
		(0.49)		(0.49)	(0.06)
Television	57	66.66%	10,709	70.85%	-4.18%
		-47.56%		-45.45%	(0.06)
Automobile	57	19.29%	10,709	11.44%	7.86%
		(0.40)		(0.32)	(0.04)
Motorcycle	57	0.00%	10,709	0.38%	-0.38%
		0.00		(0.06)	(0.01)
HouseholdCharacteristics					
Family Size	57	8.66	10,709	7.63	1.033
		(4.29)		(3.12)	(.4157)**
Adult	57	3.42	10,709	3.23	0.1834
		(1.69)		(1.32)	(0.18)
Children	57	5.25	10,709	4.399	0.85
		(2.60)		(1.80)	(0.239)**

1/ See Table 2.a

Information for this table was gathered from the last round of ENCEL (2007). It only takes into account those households qualified as poor or below the poverty line dictated by the Mexican Ministry for Social Development (SEDESOL for its initials in Spanish).

Table 3.3: Short-Run Income Elasticities for Energy Demand (ENCELURB)

Beneficiary Households	ln(Month Elect Expend)			ln(Month Gas Expend)		
	OLS	OLS	IV	OLS	OLS	IV
Ln(Monthly Transfer)	0.0057	0.0043	0.002	0.003	-0.002	-0.051
	(0.005)	(0.005)	(0.011)	(0.007)	(0.006)	(0.038)
Appliance Own Dummy		0.2578	0.3121		2.0618	2.0237
		(0.0657)**	(0.041)**		(0.0890)**	(0.148)**
Ln(Monthly Transfer)*Appl		0.0109	0.0161		0.053	0.0261
Own Dummy		(0.010)	(0.014)		(0.0123)**	(0.025)
Household Size	0.1499	0.1399	0.134	0.2912	0.1904	0.171
	(0.052)**	(0.051)**	(0.042)**	(0.073)**	(0.0484)**	(0.046)**
Observations	13,831	13,831	13,831	16,918	16,918	16,918
Households	5,734	5,734	5,734	6,594	6,594	6,594
R squared	0.047	0.163		0.0136	0.7036	
First Stage F-stat			1,536.14			1,585.72
Prob>F			0			0
Degrees of Freedom			(38, 8059)			(38, 10283)

Specifications include state*year fe and household fe. IV ln(Month Transf) with ln(Potenl Monthly Transfers).
Standard Errors clustered by household.
** is significant at the 1% level, * is significant at the 5%, and + is significant at the 10%

Table 3.4: Income Elasticities Gas Stove and Refrigerator Adoption (ENCELURB)

Dependent varible: Gas Stove & Refrigerator Ownership Dummy

Beneficiary Households	Refrigerator		Gas Stove	
	OLS	IV	OLS	IV
Ln(Monthly Transfer)	0.004	0.001	0.005	-0.0002
	(0.002)*	(0.002)	0.000	(0.004)
Household Size	0.028	0.023	0.024	0.042
	(0.019)	(0.019)	(0.030)	(0.030)
Observations	12,194	12,194	5,152	5,152
Households	4,386	4,386	1,843	1,843
R squared	0.19		0.28	
First Stage F-stat		1,254.75		568.3
Prob>F		0		0
Degrees of Freedom		(34, 7774)		(32, 3277)

Note: All specifications include state*year fixed effects and household fixed effects.
We IV for ln(Monthly Transfers) with ln(Potential Monthly Transfers).
Only households that didn't have assets at baseline are included.
Standard Errors clustered by household.
** is significant at the 1% level, * at the 5%, and + at the 10%

Table 3.5: Refrigerator Ownership Rates: Oportunidades Beneficiaries versus Non-Beneficiaries

Rural Oportunidades Evaluation Survey (ENCEL)

	Beneficiary Households		Non Beneficiary Households	
Wave	Households	% Owns Fridge	Households	% Owns Fridge
1998	9,242	7	49	12
1999	8,893	12	43	26
2000 March	9,056	16	41	32
2000 November	9,160	19	37	38
2003	10,622	29	57	35
2007	10,666	47	57	51

Table 3.6: Short-Run Income Elasticities for Energy Demand (ENCEL 2007 - Crossection)

Selection on Observables	ln(Monthly Electricity Expenditures)		ln(Monthly Gas Expenditures)	
	OLS	IV	OLS	IV
Ln(Monthly Transfer)	0.1193	0.1606	0.0059	0.0097
	(0.0257)**	(0.0474)**	(0.0090)	(0.0290)
Appliance Ownership Dummy	2.0719	2.4784	2.8084	2.8458
	(0.4319)**	(0.5839)**	(0.4205)**	(0.5000)**
Ln(Monthly Transfer)*Appliance	-0.1237	-0.1634	0.0114	0.0077
Ownership Dummy	(0.0415)**	(0.0565)**	(0.041)	(0.048)
Household Size	0.1031	0.0992	0.0211	0.0208
	(0.0126)**	(0.0131)**	(0.012)	(0.012)
Observations	5,712	5,712	5,742	5,742
R squared	0.07		0.38	
First Stage F-stat		859.87		808.08
Prob>F		0		0
Degrees of Freedom		(8, 5703)		(8, 5731)

Note: Standard errors clustered by locality. ** = significant at 1% level, * at 5% level, + at 10% level. Household characteristics include: Household size, head of household's gender, head of household's age,
head of household's education, spouse level of education, household's age structure and whether the household owns the house they live in.

Table 3.7: Income Elasticities Gas Stove and Refrigerator Adoption (ENCEL)

Dependent varible: Gas Stove & Refrigerator Ownership Dummy

Beneficiary Households	Refrigerator		Gas Stove	
	OLS	IV	OLS	IV
Ln(Cumulative Transfer)	0.015	0.02	0.0013	0.003
	(0.008)+	(0.003)**	(0.00)*	(0.003)
Observations	50,143	50,143	45,948	45,948
Households	8,606	8,606	7,658	7,658
R squared	0.15		0.098	
First Stage F-stat		13,580.89		11,961.85
Prob>F		0		0
Degrees of Freedom		(6, 41531)		(6, 36065)

All specifications include state*year fixed effects and household fixed effects.
We IV for ln(Monthly Transfers) with ln(Potential Monthly Transfers).
Only households that didn't have assets at baseline are included.
Standard Errors clustered by locality.
** is significant at the 1% level, * at the 5%, and + at the 10%

Table 3.8. Matched Diff-in-Diffs

Matched Ln(Gas expenditure)

	Before	After	
Beneficiary	3.1818	3.2998	0.1180
Non Beneficiary	3.8719	3.8878	0.0159
	-0.6901	-0.5880	**0.1021**

Matched Ln(Electricity expenditure)

	Before	After	
Beneficiary	3.7156	3.7123	-0.0033
Non Beneficiary	3.9982	3.9097	-0.0885
	-0.2827	-0.1974	**0.0853**

Table 3.9. Diff-in-Diffs and Matched Diff-in-Diffs

	Gas		Electricity	
	Matched	Not Matched	Matched	Not Matched
Beneficiary	-0.6901	-0.7068	-0.2827	-0.3393
	(0.0490)**	(0.0440)**	(0.0387)**	(0.0299)**
After	0.0159	0.0142	-0.0885	-0.0797
	(0.0306)	(0.0298)	(0.0285)**	(0.0269)**
Beneficiary*After	**0.1021**	0.1176	**0.0853**	0.0970
	(0.0437)*	(0.0424)**	(0.0374)*	(0.0352)**
Constant	3.8719	3.8789	3.9982	4.0332
	(0.0334)**	(0.0294)**	(0.0289)**	(0.0224)**
Observations	13,382	13,382	10,666	10,666
R squared	0.02	0.03	0.01	0.02

Robust standard errors in parenthesis, clustered at the household level.
** is significant at the 1% level, * at the 5%, and + at the 10%

Table A1. Household asset holding by Income[1/]

Variable	Non-Poor		Poor	
Household assets	N	Mean	N	Mean
Refrigerator	5,688	65.00%	9,857	21.92%
Gas Stove	5,688	96.26%	9,857	66.06%
Television	5,688	91.88%	9,857	77.90%
Automobile	5,688	6.91%	9,857	1.00%
Motorcycle	5,688	1.32%	9,857	0.74%

Source: ENCELURB 2002

1/ Poor have monthly income of < $2,500 pesos

Table A2 First Stage Regressions for IV estimations, ENCELURB

Poor Beneficiary Households	Ln(Monthly Transfer)	
Ln(Potential Monthly Transfer)	0.7977	0.80174
	(0.0057)**	(0.0053)**
Appliance Ownership Dummy	0.0904	0.0864
	(0.0255)**	(0.0188)**
Ln(Monthly Transfer)*Appliance	0.0939	0.046
Ownership Dummy	(0.0073)**	(0.0047)**
Household Size	-0.1115	-0.0608
	(0.0267)**	(0.0246)*
Observations	13,831	16,918
R squared	0.728	0.729
F-Statistic	1,585.72	1,536.14

Note: Standard errors clustered by household.

** = significant at 1% level, * at 5% level, + at 10% level.

Figures

Figure 3.1 Potential and Actual Oportunidades Transfers

ENCELURB 2003

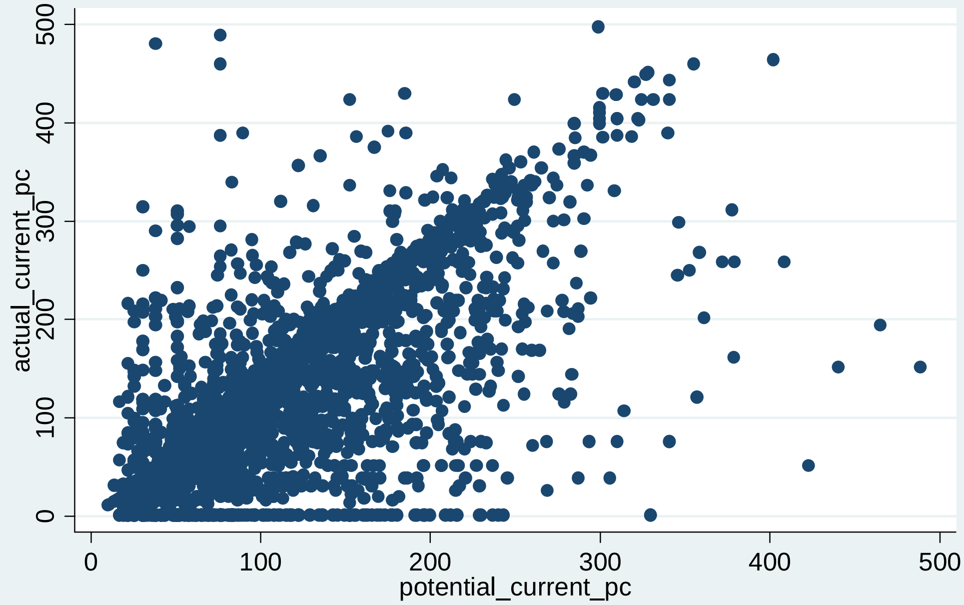
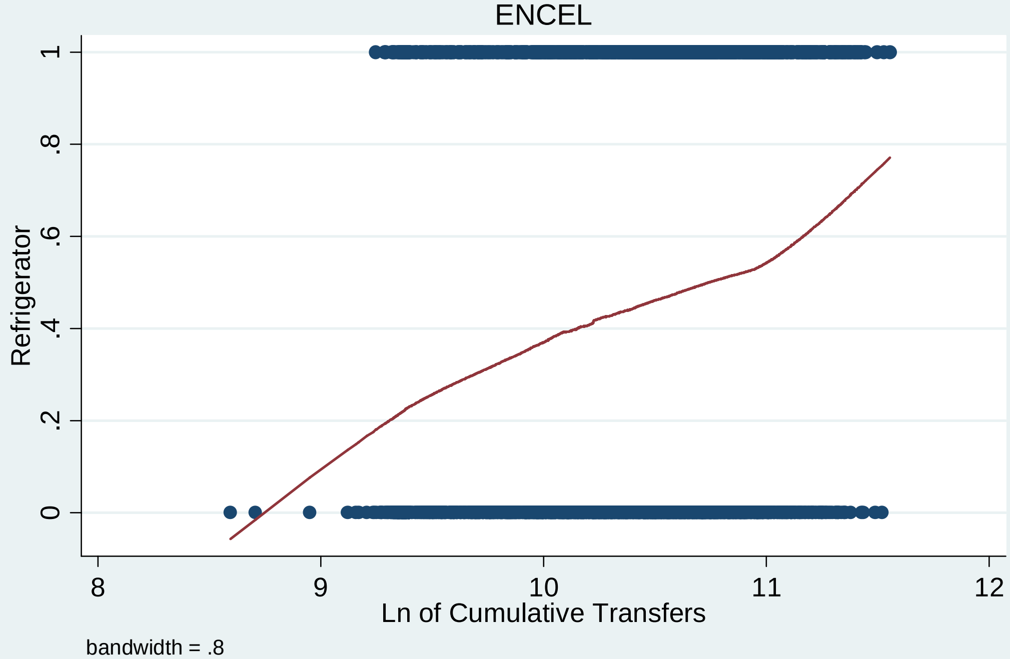


Figure 3.2 Lowess smoother Refrigerator Acquisition

ENCEL



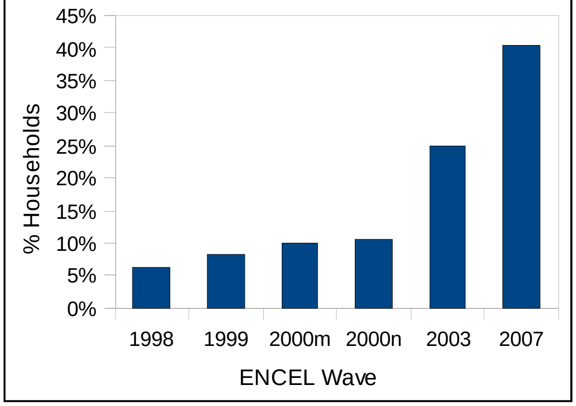


Figure 3.3a Percent of Households with Fridge (ENCEL)

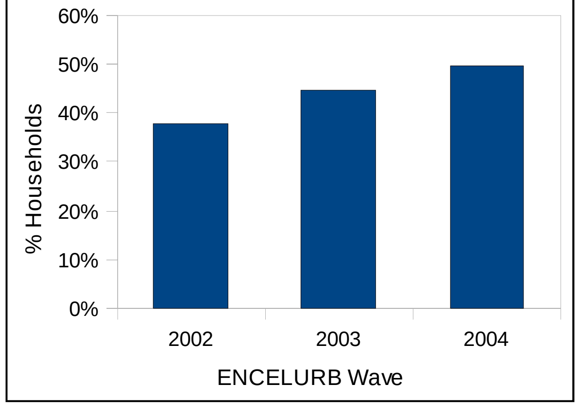


Figure 3.3b Percent of Households with Fridge (ENCELURB)

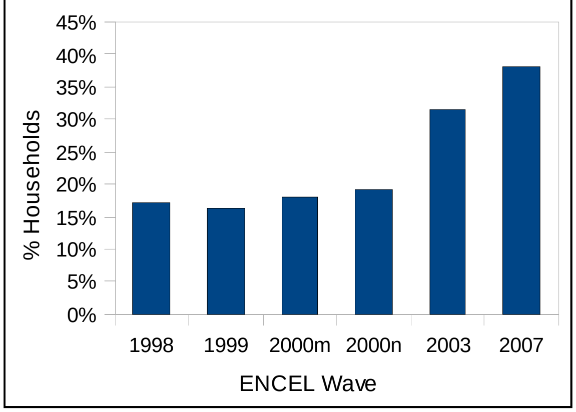


Figure 3.4a Percent of Households with Stove (ENCEL)

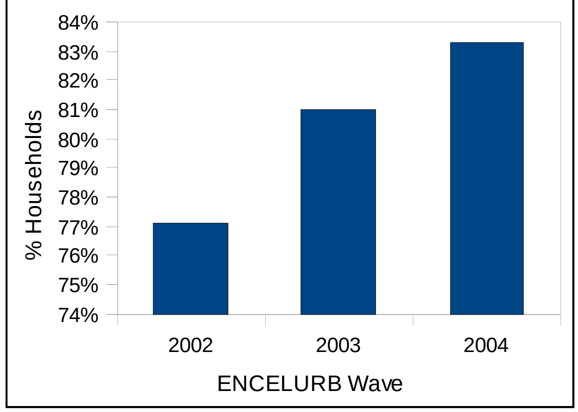


Figure 3.4b Percent of Households with Stove (ENCELURB)

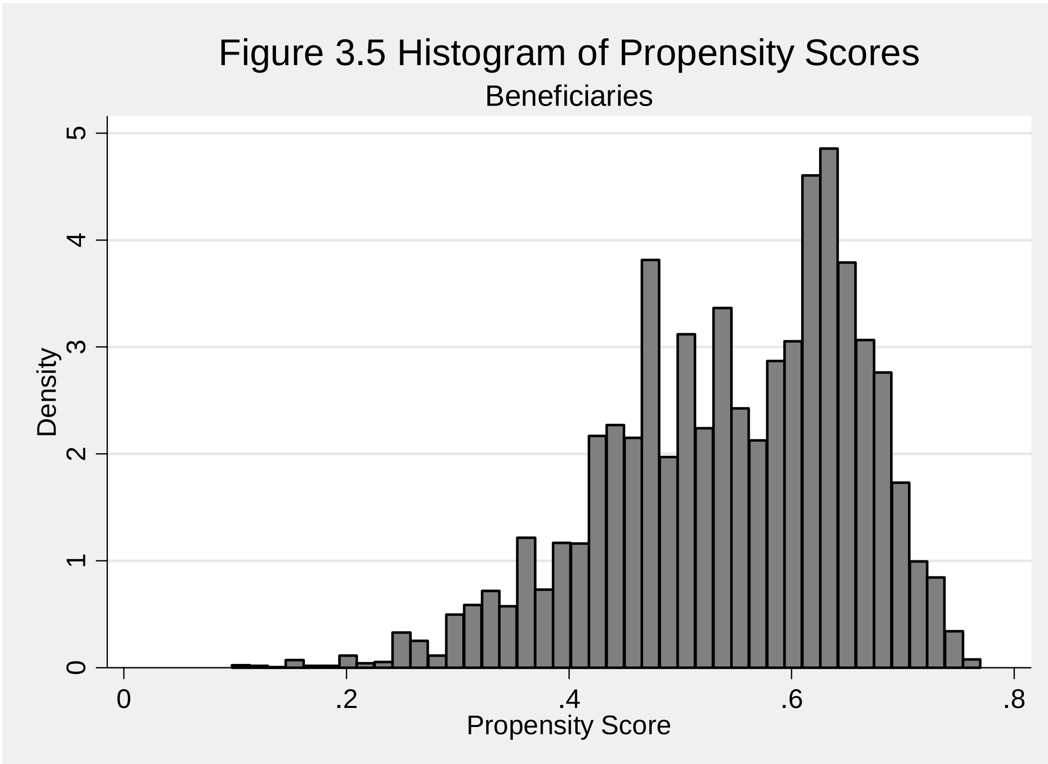


Figure 3.5 Histogram of Propensity Scores
Beneficiaries
Density
0
1
2
3
4
5
0
.2
.4
.6
.8
Propensity Score

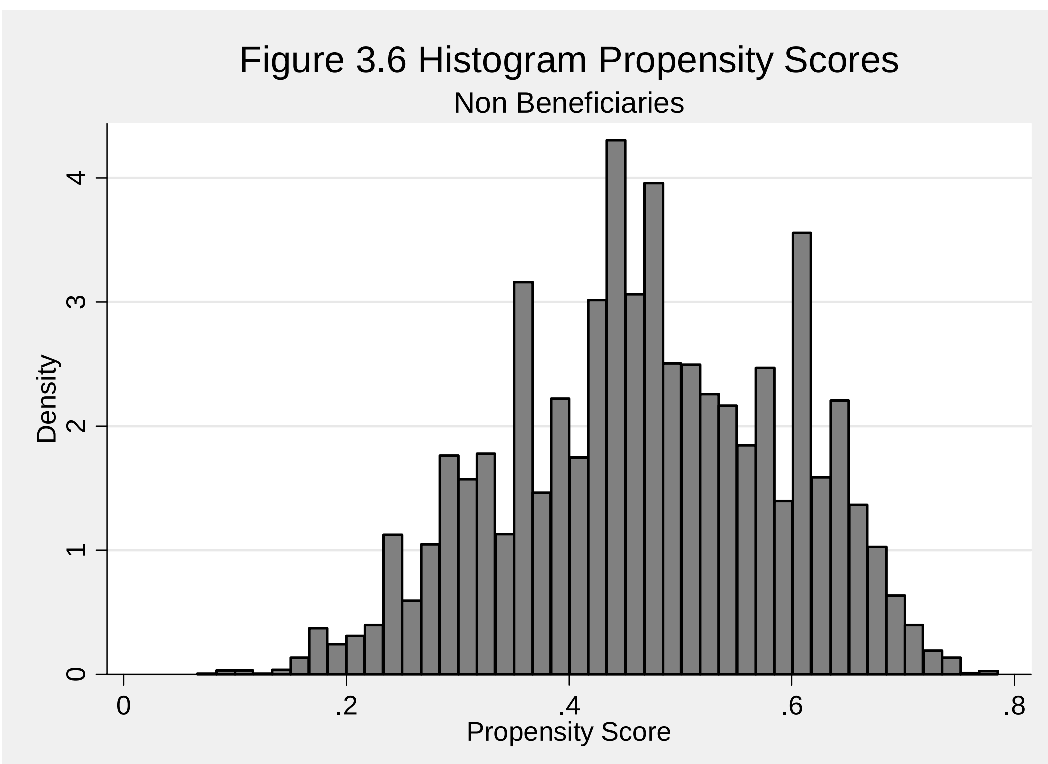


Figure 3.6 Histogram Propensity Scores
Non Beneficiaries
Density
0
1
2
3
4
0
.2
.4
.6
.8
Propensity Score