

Measuring Treatment Effects in Poverty Alleviation
Programs: Three Essays Using Data from Turkish
Household Surveys



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Chapter 1

Introduction

With over 1 billion people in the world living below the absolute poverty line as of 2008, poverty alleviation programs are at the forefront of development policies today. The first of the Millennium Development Goals (MDGs) set a target to reduce by half extreme poverty between 1990 and 2015. International donors and aid agencies have helped governments in many countries set up institutional mechanisms to track and monitor progress towards this goal. While one issue in poverty related research has been the pure "measurement" of poverty, another very important concern has been measuring the impact of specific poverty alleviation programs on beneficiary households.

Given the fiscal implications of implementing large-scale poverty alleviation programs, donors and government agencies have become interested in rigorously measuring impact and treatment effects of such programs. Monitoring and evaluation of programs have increasingly become streamlined into the development of projects, in order to create more accountability and see what works and under what circumstances. Establishing the counterfactual in the absence of the program in order to consistently measure treatment effects has been the main challenge in setting up these impact evaluations.

Social scientists, and a sub-group of development economists, have increasingly become interested in measuring impact through randomized controlled trials (RCTs), where, as a result of randomization, it becomes possible to get rid of "selection bias" in who gets enrolled in the program (Duflo et al., 2007). These randomized control trials have been called the "golden standard" of evaluations though there has also been a fair amount of criticism on their use (Ravallion, 2009; Deaton, 2009). One of the major concerns is that only a small fraction of development projects in the field can be evaluated using RCTs, and many important research questions from a policy and development perspective cannot be answered by the narrow scope of these randomized trials (Ravallion,

2009). The external validity of these experiments are often brought into question, as the underlying context and binding constraints in the field of experimentation determine to a large degree the success of each program. (Deaton, 2009). There may also be significant ethical issues that arise from intentionally withholding the benefits of the program from potential beneficiaries in the control group.

In the absence of randomized trials, quasi-experimental and experimental methods have been used to try and measure the treatment effects of poverty programs. This dissertation presents a series of three such papers that use quasi-experimental and experimental methods to measure treatment effects of various shocks (negative macro shocks) or of poverty alleviation programs on households. The three papers in the dissertation apply various techniques of impact evaluation, including an instrumental variables estimation, propensity score matching and a controlled experiment with a panel data set.

The first paper looks at how the macro shock from the 2008 financial crisis has translated into income and welfare shocks in the form of reduced earnings and expenditures at the household level in Turkey. This chapter uses a specialized welfare monitoring survey implemented in Turkey (Turkey Welfare Monitoring Survey TWMS) and implements an instrumental variables strategy to measure the treatment effect of the income shock on household expenditures and consumption.

The main questions the paper tries to find answers for are the following: (i) Who was most likely to get hurt by the crisis in terms of incomes? (ii) Which expenditure items in the household were likely to be adjusted in the face of the income shock at the household level? The paper first sets up a simple model of utility maximization for the household with a “*hierarchical preferences*” assumption, whereby each household has to first consume a minimum amount of food, before individuals can obtain utility from food and other goods. In this model, the household first consumes food up to the “*satiation point*” and then begins to consume any other goods (an extreme version of Engel’s Law). The model predicts different behavioural responses on the part of poor, middle income and high income households in the face of an income shock, whereby low income (poorer) households are more likely to reduce food expenditures and consumption.

In order to estimate results on who was most likely to get hurt by the crisis, the paper constructs a macro-shock proxy variable using as an indicator non-cash credit provided by the banks in the province. This province level macro shock variable enters into a regression (as an independent variable) where the paper tries to assess the relationship between the macro shock and the household level earnings shock controlling for household head and worker characteristics. In these “change in earnings” regressions, the analysis

reveals that workers employed informally and with lower levels of education (less than university degree) were more likely to report a reduction in their earnings following the macro shock. In the second set of results, a ML probit estimation is run to see the relationship between the household level income shock and changes in consumption patterns for various goods and services: these results show a clear association between reduction in earnings at the household level, and the probability of reducing expenditures related to food (the income shock is associated with a 16.2 percentage point increase in the probability of reduced expenditures on food), while other expenditures on education and health services are likely to remain stable. For poorer households, the likelihood of reducing food expenditures through the crisis period is higher (as predicted by the model). The findings in the paper suggest that food expenditures acted as the main adjustment mechanism in the face of the income shock, while education and health expenditures remained relatively stable. The probability of reducing food expenditures and consumption (as well as the amount of food provided to children) was highest among the poor that initially had low levels of household assets.

The paper recognizes that there may be significant issues related to “measurement error” in the collection of the survey (as it is a rapid monitoring survey that collects crude information on the change in earnings variable). There is also potentially a problem related to cognitive dissonance whereby respondents may have a tendency to report that they reduced expenditures on certain goods if they already reported reduction in earnings earlier in the survey. The paper attempts to mitigate these shortcomings by using an IV strategy and tries to estimate the changes in expenditures at the household level by instrumenting for the changes in earnings: the instruments used in the paper are a combination of the province level macro shock variable and household head characteristics (mainly the formal/informal employment status of the household head).

After running a series of tests of exclusion restrictions, I find that these two instruments are strongly correlated with the earnings shock at the household level and uncorrelated with the unobservable error; hence they make relevant and valid instruments for the estimation. The primary goal of the 2SLS estimation is to find consistent estimates for the impact of the earnings shock at the household level on household expenditures. The paper finds that as a result of attenuation bias due to measurement error the coefficients on the household level income shock were lower in the probit estimations, while the 2SLS estimation gives a higher coefficient on the household level income shock (33.3 percentage points increase in the probability of reducing food expenditures). For robustness checks, the same specifications are run using different outcome variables for changes in consumption behaviour (such as the changes in the amount of food provided

to children in the household, rather than changes in food expenditures) and these checks still reveal a strong link between the income shock and the household level changes in food consumption levels.

The second paper in the dissertation assesses the protective impact of a non-contributory health insurance program targeting poor households in Turkey (the Green Card program) through the same Crisis period. This paper makes use of the same welfare monitoring survey as was used in the first paper in the series. The paper essentially compares the changes in health care utilization behaviour of households that have access to health insurance through the Green Card and those that do not have access to any form of insurance through the Crisis.

The welfare monitoring survey asks retrospective questions to households on their health care utilization behaviour through the crisis period. These retrospective questions that ask the households about the “changes” in utilization over time are used in this paper as a quasi-panel data set that controls for household fixed effects. The paper uses three different estimation techniques, including a kernel non-parametric estimation, parametric LPM estimations and finally propensity score matching. In the parametric estimation, the paper uses a linear probability model where the dependent variables are two different binary variables for reducing health care utilization (preventive and curative care). The model looks at the probability of reducing health care utilization, given access to the green card, an income shock at the household level and an interaction term between the green card and the income shock.

The parametric results from the LPM regression suggest that having the Green Card was associated with a 12.5 percentage points lower probability of reducing visits to the doctor for preventive care (and 15.8 percentage points lower probability of reducing visits for curative care) through the crisis, compared to households with no health insurance. The analysis is then repeated using a propensity score matching technique, where the propensity of each household to receive Green Card is estimated and then households are matched using several different matching techniques. The average treatment effect of the card is estimated at somewhere between 12.7 - 20.9 percentage points reduction in the probability of reducing health care utilization in the propensity score matching results. The findings of the paper therefore suggest that the Green Card program was an effective and functional safety net, protecting the health care utilization of the poor through the Crisis.

The third paper in the series considers the impact of an agricultural extension program implemented in a post-conflict area in eastern Turkey. The paper builds on previous theoretical models of agricultural technology diffusion and tests some of the arguments

in these models looking at the heterogeneous impact of the program on adoption rates of “excluded” and “non-excluded” groups in the villages. The model explored in the paper predicts that in the earlier stages of a technology’s diffusion, the adoption “levels” of the “excluded” groups in society are likely to be lower, and their adoption “rates” (changes in adoption levels over time) are also likely to be lower than the non-excluded group. In the later stages of adoption, on the other hand, the “excluded” group may catch up with the rest with higher adoption rates. Two different technologies introduced by the implementing NGO at different initial baseline adoption levels are considered in the paper -inoculation of fruit trees (early stage adoption) and vaccination of livestock (later stage adoption)- to test these hypotheses. The impact of the program on use of publicly provided agricultural consulting services is also considered as an outcome variable.

The paper makes use of a uniquely designed panel survey collected in treatment and control villages before and after program implementation where the experimental nature of data collection allows for controlling for time-trends (and regional developments) outside of project villages. The location of the project is a post-conflict area in eastern Turkey where most beneficiaries are Kurdish speaking households from villages that had a history of being evacuated (and partially incinerated) by the Turkish military in mid 1990s. This post-conflict region is characterised with low economic growth rates, and high and chronic poverty rates: in such a region issues and concerns of exclusion at a political, economic and social level are significant. The paper then, all-be-it in a descriptive way, analyses the heterogeneous impact of this agricultural extension program, on those considered to be ”politically/economically” and ”socially” excluded in these villages.

The main results in the paper are consistent with the predictions of the model presented: for instance in the early stages of adoption, the existence of the agricultural extension program increased the adoption rates in the villages significantly for all households: treatment is associated with an increase in the rate of adoption of inoculation of fruit trees by 26.2-31.4 percentage points depending on the empirical specification. One can also test for the “inclusiveness” of the NGOs efforts by looking at the heterogeneous impact of the program on adoption rates of the excluded group and find that those in the excluded group (defined as political and economic exclusion) have an even higher likelihood of adoption for this technology. We also test for the adoption rates of the excluded group in the absence of the program, and find that –as predicted by the model- their adoption rates would have been lower than the non-excluded group in the early stages of adoption (tested in the model with inoculation of fruit trees), while their rate of adoption is higher for the later stage technology (vaccination of livestock) as they

catch up with the rest of the group.

An interesting descriptive finding in the paper that merits further study is the contrast in results for the politically/economically and socially excluded groups. The paper finds that while the politically and economically excluded groups, may be reached and can benefit from the inclusive policies in the villages, those in the “socially” excluded group and that do not have many social interactions with the rest of the village community remain excluded from the benefits of the program.¹ The fact that the NGOs efforts are able to reach the politically/economically excluded, while not reaching the socially excluded in the village may be explained by the fact that the socially excluded households are unable to hear about and gain access to program information through their community. This is an important finding that indicates that different types of underlying exclusion in communities may result in different outcomes in terms of the success of poverty alleviation programs in disseminating information and distributing benefits to the targeted population.

Three common themes connect these papers presented in my dissertation:

First, as described above, each of the papers uses an experimental or quasi-experimental method in the identification strategy in order to make causal arguments between the intervention/shock of interest and outcomes at the household level. The first paper uses an IV strategy for identifying the impact of the macro shock on household incomes and welfare; the second paper uses a parametric estimation using a quasi-panel data set as well as a propensity score matching technique to identify the differences between the counterfactual control group and the treatment group, and the final paper uses a panel data set and a controlled experimental set up to identify changes in household behaviour with the treatment.

Second, all three papers fully explore impact heterogeneity since it is expected that the shocks and interventions studied in these papers will have different impacts by participant characteristics. The papers are all concerned with how the shocks/interventions hurt or benefit those in the poorer sub-groups of the population, possibly with lower levels of education and other social vulnerabilities. In order to measure participant heterogeneity, these papers carefully include interaction effects in modelling impacts. All distributional analysis in the papers has been carried out using household asset indices that make use of principal components analyses. This was done primarily in order to

¹The definition of social exclusion here is that the household is not listed by any of the households in the village as being an acquaintance they have occasional interactions with, hence it is defined as a lack of “weak social links” with the community. Political/economic exclusion on the other hand is defined as being in the poorest quintile, not speaking Turkish or not having any formal education. The description of both exclusion variables are provided in detail in Section 4.3.2.

identify the “structurally poor” in the population (McKay, 2009) and reduce measurement error in the reporting of income and consumption in the surveys.

Third, there is a geographic thread that connects the papers: the data for all three papers come from two main household surveys collected in various parts of Turkey. I was personally involved in the survey design, data collection, data cleaning and entry for both of these survey projects. The survey used in the first and second papers (Turkey Welfare Monitoring Survey) was collected from 2402 households in 7 provinces in Turkey including: Ankara, Istanbul, Izmir, Adana, Kocaeli, Gaziantep and Erzurum. I was among the principal investigators for this survey and took a leading role in survey design and mobilizing data collection. For the third paper (Bitlis Özyeğin Rural Development Program Survey), the data was collected from 326 households (in 12 villages) in the Bitlis Province of Turkey. I was the main investigator for the study, where I applied for funding, prepared the survey questionnaires for both rounds of the survey, conducted the enumerator training in eastern Turkey and oversaw data entry and cleaning procedures.

This volume of papers makes original contributions to the welfare literature in general:

First of all, the use of an instrumental variable that directly links the macro shock of the Global Financial Crisis to the micro level household welfare has not been widely used before in the literature. The instrument used in the first paper that proxies for the macro shock (and is used to instrument for the household level income shock) - the change in rate of expansion of non-cash credit from Banks- provides a direct way to measure the province level severity of the Crisis in Turkey and may in the future be replicated in other country contexts as well. Second, papers that look at the impact of non-contributory health insurance programs have previously considered increases in health care utilization and changes in health outcomes as a result of the program, but none have so far looked at the “protective” impact of such a program through a Crisis. In this sense, the second paper in the series makes an original contribution to the literature by looking at an outcome variable that has not been explored before. Third, there are no studies in the literature that look at agricultural technology diffusion in a post-conflict setting and the third paper in the series contributes to this literature by means of the location of the survey data collected. The differentiation in this paper between the politically and socially excluded groups is also new and original and opens a new track of research ideas for exploring differences in access to benefits for these different types of excluded groups.

These papers also contribute to the policy debate on poverty related issues and come at an opportune time for the analysis of poverty and social policies in Turkey: Turkey in

the last decade has made very important strides in poverty reduction and development of social policies to address poverty and inequality. The period prior to the Crisis (2002-2008) has been characterized by pro-poor growth rates where the lower consumption deciles in the country, have experienced higher rates of growth in their welfare levels and this has led to reduced inequality (measured in terms of consumption) (Aran et al., 2010). The government has also expanded in this time period, social safety net programs such as the Green Card non-contributory health insurance program and the Conditional Cash Transfer program (to improve access of poor households to health and education services) (Hentschel et al., 2010). The papers in this volume have been presented to government officials in multiple occasions and have contributed to the policy debate in Turkey on measuring the impact of social policies and constitute part of an effort to build evidence-based social policies in the country.

Chapter 2

Welfare Impact of the Global Financial Crisis of 2008-2009 on Turkish Households

2.1 Introduction

2.1.1 Motivation

While the centre of the Global Financial Crisis of 2008-2009 was the developed world, many developing countries have also been impacted by the aftershock of the Crisis. At the macro level, the impact of the crisis can be measured in terms of increases in the unemployment numbers and reductions in GDP growth. But how has the macro shock translated into income shocks at the household level and then consequently to changes in welfare in terms of food, and non-food consumption as well as investments in human development such as education and health expenditures, in different parts of the developing world? This is a critical question to answer for economists in order to fully understand how households in the developing world have ultimately been impacted by this a large-scale aggregate shock.

Several papers have been written with data from previous crises focusing mainly on household coping mechanisms and consumption responses to income shocks. McKenzie (2003) uses Mexican household surveys to examine the micro-impact of the 1995 peso crisis. The paper examines how the impact of the crisis differed across households. The data comes from four different years of household surveys from 1992 through 1998, and the author makes non-parametric comparisons (Welch tests) on the equality of means

for mean weekly labor hours, household structure and fertility levels, as well as school attendance of children across the years. He finds that consumption fell dramatically in this time period, showing that households could not fully smooth the shocks to their income. In the mean time, household structure did not change dramatically over the crisis period and the coping strategy of adding more household members to the labor force was not widely used. The author links this to weak labor demand through the crisis period and also finds that the reduction in labor market opportunities also reduces the opportunity cost of schooling: he finds that school attendance rates actually *rose* among 15-18 year olds during the crisis period.

A number of other studies also look at the relationship between aggregate income shocks and investments in education and find that there is no negative impact of these shocks on educational enrolment for children. Escobal (2005) studies the effect of economic shocks on household human capital investments using a sample of 6-14 year old children from the Young Lives Survey in Peru. This study finds evidence that economic shocks have an impact on the quality rather than the quantity of education. They find that a negative income shock does not produce a change in the time spent on education, and find that it only reduces the effective accumulation of human capital through cuts in public spending on education. Schady (2002) analyzes the effects of the deep macroeconomic crisis in Peru in 1988-92 on the schooling and employment decisions made by urban school-age children. He finds that the crisis had no effect on the attendance rates of school-age children, while the share of children who were both employed *and* in school fell significantly during the crisis. He finds a positive effect of aggregate macroeconomic shocks on school expenditures and attainment. A low amount of crisis exposure (1-2 years) appears to have no effect on school attainment, while “high” crisis exposure 3-5 years, *increases* schooling by about 0.2 years.

On the other hand, one study by Duryea and Lam (2007) finds a negative impact of the crisis in Brazil on school attendance and enrolment: Brazilian youth adjust their school and labor force participation behavior in response to an unexpected transitory shock to the household by increasing their labor force activity. The authors compare households in which the male household head becomes unemployed during a four-month period with households in which the head is continuously employed. *Probit* regressions indicate that an unemployment shock significantly increases the probability that a child enters the labor force, drops out of school, or fails to advance in school. The results suggest that some households are not able to absorb short-run economic shocks, with negative consequences for children.

This paper looks at how the macro shock from the 2008-09 financial crisis has trans-

lated into income and welfare shocks in the form of reduced earnings and expenditures (particularly food, education and health consumption) at the household level in Turkey. Using a specialized household level survey in Turkey, and an instrumental variables technique, the paper estimates the causal impact of the income shock on household welfare and consumption. Instrumenting for the income shock at the household level, the paper establishes the link between the income shock and changes in expenditure patterns. It finds that while education and health expenditures and utilization were largely protected through the crisis in Turkey, most households have reduced their consumption on food products that also take up a large portion of the initial expenditure basket for Turkish households.

The main questions the paper attempts to answer are the following: (i) Who was more likely to get impacted by the macro shock? What types of workers and households were likely to report reductions in earnings? (ii) How did the macro shock impact income and expenditure of households? Which expenditure items were most likely to be reduced in the face of the income shock?

The outline of the paper is as follows: Section 2.1.2 continues with a description of the Financial crisis of 2008-2009 in Turkey. Section 2.2 provides the conceptual framework for how we envision the households were impacted in terms of their consumption, given an income shock. In this section, the empirical strategy for estimating the welfare impact of the income shock is also put forward. Section 2.3 provides information on the data sources used for this study and explains the construction of key variables in the analysis. Section 2.4 gives the empirical results for the *probit* and IV estimations and Section 2.5 concludes with main findings.

2.1.2 The Context of the Financial Crisis in Turkey

Turkey experienced a significant economic slow-down in 2009, following the Global Financial crisis. Turkish GDP contracted by 7 percent in the last quarter of 2008 compared to the 3rd quarter, and further declined in the first quarter of 2009 by 14.5 percent. Reductions in GDP level continued until the end of 2009 (See Figure 2.1). In 2009, the overall GDP level of Turkey declined by 4.7 percent (y0y). Unemployment levels, particularly among the young soared in the first quarter of 2009. After remaining stable at levels below 10% for several years, the unemployment rate in Turkey peaked at 16.1 percent in the first quarter of 2009 following the sharp contraction in GDP. Among the youth, ages 15-24, the unemployment level rose to an unprecedented 28.6 percent in the first quarter of 2009, with slower job creation through 2009 (See Figure 2.2). Part of

this unemployment increase was seasonal, and unemployment came down temporarily toward the end of 2009, however as of the first quarter of 2010 the unemployment level was at 14.5 percent, 2-3 percentage points higher than the earlier trend prior to the crisis.

There are three main channels through which a macro crisis could impact households: (i) through the reduction in labor income (which is discussed at great length in the paper), (ii) through changes in the price level and (iii) through a reduction in public expenditures which may adversely affect households. In Turkey, the price level through the 2008-2009 financial crisis remained relatively stable with year-on-year inflation at 5.3 percent between June-June 2008-2009. CPI stability is also demonstrated in Figure 2.1. Public expenditures in this time period were on the rise; hence households are not expected to be adversely impacted in this time period by reductions in public expenditures. The non-interest spending of the central government increased from 204 billion TL in 2007 to 227 billion TL in 2008 and 268 billion TL in 2009. The increases are 13.6 percent in 2008 and 21.9 percent in 2009, and in both years exceed the rate of inflation in Turkey, hence once can say there was a real increase in public spending through the period of the Crisis. Because of the reduction in GDP in the same time period, the share of government spending in GDP rose in this time period from 18.4 percent in 2007 to 22.6 percent in 2009. (Source data: Turkey Ministry of Finance Consolidated Budget Data). Given this macro background on the price level and fiscal spending, the main transmission mechanism through which the financial crisis impacted households was through reduced labor earnings.

Turkey had previously experienced a significant banking sector crisis which led to an economic slowdown in 2001. Back in 2001, the major transmission mechanism of the crisis to the household level was through changes in the overall price level (households had lower purchasing power that resulted from the change in the price level). In the first quarter of 2001, the consumer price index was up by 19.1 percent compared to the previous 3 month period, following the devaluation of the Turkish lira. In the same time period, GDP had declined by 10 percent. Compared to the 2001 Banking Crisis, there was a *sharper* reduction in GDP levels through the 2008-09 economic slowdown, though the price level stayed relatively stable, with a quarterly inflation level of less than 5 percent. Hence it is fair to say that the Global Financial Crisis of 2008-2009 has impacted households in Turkey mainly through changes in household income via reduced employment and earnings and the rest of the paper focuses primarily on this transmission mechanism in measuring changes to household welfare.

2.2 Conceptual Framework

2.2.1 The Model

In order to analyze changes in consumption behavior at the household level, this paper uses a conceptual model with “hierarchical preferences” in the household’s utility function. In this model, the utility function is defined whereby individuals require a minimum level of good (x) (in this case food) and they also consume other goods (y). Preferences are hierarchical such that, a minimum amount of food (x_0) needs to be purchased before individuals can obtain utility from food and other goods. The utility function is of the form:

$$U(x, y) = (x - x_0)^\alpha (y)^\beta \quad (2.1)$$

Subject to the food satiation constraint :

$$X \leq X_{max}$$

The part of the budget constraint that can be allocated by the household is expressed as the total income minus the amount of expenditure necessary to purchase x_0 :

$$I^* = I - p_x x_0 \quad (2.2)$$

In the face of an income shock, households with different initial income conditions respond to the shock in different ways because of the hierarchical preferences assumption. We consider here the hypothetical cases of a high-income, middle income and low income household operating under this utility function. Figure 2.3 provides the utility function and the changes in consumption of good x and good y in the face of an income shock for a high, middle and low income household. The red curve in the figure represents the budget constraint, which shifts back with the income shock experienced in the household. The Engel Curve outlined in yellow, starts on the x axis and continues along the x axis until the point consumption of x reaches x_0 , at that satiation point, the household begins to consume goods other than food. The simplified model with hierarchical preferences makes sure that a household consumes only food until they reach a satiation point of x_0 in their food consumption. The satiation point for food comes at some point and the Engel curve becomes vertical, with the household consuming only y with any extra income beyond this satiation point.

According to the permanent income hypothesis, consumption patterns are determined by a change in permanent income, rather than changes in transitory income.

Temporary changes in income should have little effect on the consumers spending behavior (Friedman and of Economic Research., 1957). If this hypothesis holds, and if households are able to smooth consumption, we should state that consumption changes occur because the household interprets a certain portion of the transitory shock to be permanent, or that the transitory shock is large enough to cause the permanent income of the household to come down. If however, households are not able to smooth consumption, we should see consumption coming down with the transitory income shock, even if the impact on permanent income is small. When looking at the ways in which households cope with the crisis, we find that households that are able to smooth consumption by accessing formal and informal safety nets, or through borrowing, were less likely to reduce consumption (for instance on food). In the absence of a mechanism to smooth consumption, the households respond to the transitory income shock by cutting back on consumption.

For the high income household described in Figure 2.3 Panel A the shift in the budget constraint, does not change the level of food consumption, since the household is already beyond satiation point and any reduction in income gets reflected on the reduction in the consumption of y , other goods. The middle-income household in Panel B, is initially below the food satiation point, hence a reduction in income reduces the consumption of both the food and non-food goods in the consumption basket. In Panel C, the situation of a low income household is depicted, whereby for this household $x < x_0$ in the initial conditions, and hence the income shock gets disproportionately reflected on household food consumption.

The model therefore predicts a greater probability in reduction of food consumption for poorer households. We can expect the pattern of changes in consumption to follow the model outlined here with poorer households having less fungible resources to allocate away from food expenditures, and hence having a higher likelihood of having to reduce food expenditures within the overall household budget.

Table 2.1 provides the levels of food and non-food expenditures in household budgets in Turkey as of 2008 (prior to the crisis), whereby Engel's Law can be observed for Turkish households, with households in the poorest decile allocating up to 43 percent of their total household expenditures to food. Housing constitutes the second largest expenditure item in the household consumption bundle for Turkish households in the poorest decile. Since housing expenditures, mostly in the form of rent, are discrete and more difficult to substitute away from, they are considered as *not* being part of "fungible" income in this model. A household would not be able to substitute away from or reduce rent expenditures in the very short-run, hence food expenditures are most likely to get

the brunt of consumption reduction in the face of an income shock for a poor household, as predicted in this model.

2.2.2 Empirical Strategy

The hypothesis put forward in the above model relates to the changes in the consumption patterns of households in the face of an income shock, namely that they reduce food consumption in the short-run particularly if they are in the poorer quintiles.

First, the paper looks at the probability of reporting reduction in earnings through the first 8 months of the global financial crisis: between October 2008 and May 2009 in order to establish what types of workers and households were most likely to be hurt in terms of their income in this time period. In the model, October 2008 and May 2009 are referred to as t_1 and t_2 respectively.

The predicted probability of lower earnings by the household head is estimated using a *probit* regression of the form:

$$\Pr(\Delta Y_i) = \alpha_1 \Delta X_p + \alpha_2 A_{i(t_1)} + u_i \quad (2.3)$$

$$\Pr(\Delta Y_i) = \alpha_1 \Delta X_p + \alpha_2 A_{i(t_1)} + \alpha_3 \Delta X_p A_{i(t_1)} + u_i \quad (2.4)$$

The dependent variable $\Pr(\Delta Y_i)$ in Equation (2.3) is the probability of reporting lower earnings in current job in time period 2 (t_2) compared to time period 1 (t_1). The workers who report being “employed” in t_1 and subsequently lose their job by t_2 are also recorded as having reduced earnings; hence the dummy variable for the dependent variable takes a value of one for those who actually receive lower earnings and for those who have lost a job. The explanatory variables in the first stage regressions include the province level macro shock variable (ΔX_p), which is defined as the rate of change in non-cash credit from banks in the province. In these regressions, ΔX_p can be interpreted as a proxy variable for the intensity of the “credit crunch” experienced at the province level (further details on the construction of this macro-shock proxy variable are provided in Section 2.3.2). $A_{i(t_1)}$ denotes the characteristics of the worker as of t_1 , and includes the labor status and the educational attainment of the household head. Each worker characteristic is provided as deviations from the mean in the regressions. In the second specification provided in Equation (2.4), the worker characteristics are interacted with the province level crisis proxy to see macro shock from the crisis had a heterogeneous impact on workers of different characteristics. The specification in Equations (2.3) and (2.4) are run for two different sub-samples: (i) all workers that held a job in t_1 and

(ii) workers who are also household heads and held a job in t_1 . In order to get robust standard errors for these regressions, the standard errors are clustered at the province level since at least one explanatory variable (namely ΔX_p) varies only at the province level and takes on only seven values.

Second, a *probit* estimation is run to establish the positive correlation between the income shocks experienced at the household level and whether this is associated with a reduction in welfare, in terms of the consumption of the household on food, education, health or other expenditures. The marginal effects of the following *probit* regressions are reported:

$$\Pr(\Delta C_j) = \beta_1 \Delta Y_j + \beta_2 A_{j(t_1)} + u_j \quad (2.5)$$

$$\Pr(\Delta C_j) = \beta_1 \Delta Y_j + \beta_2 A_{j(t_1)} + \beta_3 A_{j(t_1)} \Delta Y_j + H_j + u_j \quad (2.6)$$

where the dependent variable ΔC_j is the dummy variable for reporting lower expenditures or a change in behavior in consumption patterns between t_1 and t_2 . ΔY_j is the dummy variable for the household head reporting a reduction in earnings between t_1 and t_2 . Only for sample of household heads who were working in t_1 are included in these regressions. The characteristics denoted by A_j are provided at the household level; include urban/rural location, educational attainment of the household head and the household asset index and are demeaned in the regressions. The interaction term between household head initial characteristics and the dummy variable for reporting the earnings shock is added to the specification in Equation (2.6), H_j includes household composition variables (number of children and adults in the household) and u_j represents the error term in the equation.

The possible labor supply responses to the income shock are (i) the added worker effect (where household members who were not active in the labor market begin to look for jobs, or take jobs), and (ii) taking secondary jobs for those who are already employed. The variable in the regressions that defines the income shock is whether the household head has lost his main job in October 2008, and whether he/she reports a reduction in earnings from main job. If there is an additional job that the household head takes on, or if there is an added worker (with an extra individual in the household member entering the labor market), the actual income shock to the household would be smaller than described in the data. In this sense, the impact of the income shock (the coefficient on the income shock β_1 , in the consumption regressions in Equations 2.5 and 2.6, would be a lower bound underestimate of the actual impact of the labor income

shock on expenditures and consumption.

The specification in Equations (2.5) and (2.6) assumes the income shock at the household level as an exogenous variable and looks at its effect on consumption behavior. These *probit* regressions are run separately for food, education and health expenditures. The coefficient on β_1 gives the relationship between the earnings shock and changes in consumption, controlling for household head characteristics. In the specification with the interaction terms, the coefficient on β_3 gives the heterogeneous response of the households associated with an earnings shock.

The maximum likelihood *probit* model estimates on the coefficients of the earnings shock may be inconsistent and/or biased if (i) there is a correlation between the responses to the changes in income and the responses to the changes in expenditures and consumption questions (in which case the earnings shock variable would become endogenous in the model), and if (ii) there is a measurement error in the earnings shock variable, which would result in attenuation bias on the coefficient (β_1) of the earnings shock at the household level. We can suspect that both of these problems may exist in the survey data used in this paper:

Potential endogeneity of the earnings shock: the income shock and consumption changes are both subjectively reported in the rapid survey data and may be correlated with each other as a result of the respondent's desire to reduce "*dissonance*" in the responses. Cognitive dissonance can be defined as a discomfort caused by holding conflicting ideas simultaneously¹

1. Given that the data is based on "perceptions" of consumption, we may worry about people reporting lower levels of food consumption if they already reported lower levels of earnings in the data set. In that case, the income shock would not be exogenous to the probability of reporting a change in consumption. For instance, a household head that reports a reduction in his earnings may be more likely to also say that the household has reduced food consumption. This problem would result in an *overestimation* of the size of the β_1 coefficient in Equation (2.5).
2. Measurement error on the earnings shock: The data on earnings is based on recall data and is a categorical variable that asks the worker to assess whether their earnings in the current job (in t_2) are higher, lower or at the same level as their earnings at the onset of the crisis in t_1 . Any measurement error that results from recall data would generate an attenuation bias in the estimation of β_1 whereby the

¹The theory of cognitive dissonance proposes that people have a motivational drive to reduce dissonance and that they do this by changing their attitudes, beliefs, and actions (Festinger, 1957).

estimated plim ($\hat{\beta}_1$) is always closer to zero than β_1 . This measurement problem would result in an *underestimation* of the size of the β_1 coefficient in the maximum likelihood *probit* model in Equation (2.5).

In order to find consistent and unbiased estimates for the coefficient of the earnings shock in the model in Equation (2.5), the paper next implements an instrumental variables approach. The paper uses a 2SLS strategy to establish the causal link between the idiosyncratic income shock at the household level and the changes in different types of consumption.

The excluded instruments in the model have to satisfy the relevance and validity conditions. The instruments have to be strongly correlated with the earnings shock at the household level (X) and uncorrelated with the unobservable error, u . The instrumental variable matrix z , should have the property that changes in z are associated with changes in the earnings variable at the household level but do not lead to changes in expenditures/consumption (except indirectly through earnings). In this paper two variables are used to instrument for the earnings shock at the household level: the severity of the crisis at the province level (as proxied by the rate of change in non-cash credit available from banks in the province² and the formal/informal sector employment of the household head. The inspiration for the instrument in the 2SLS estimation comes from the earnings *probit* earlier provided in Equation (2.3) and later in Table 2.6. The paper has already established a strong linkage in these results between the province level macro shock and the probability of an earnings shock at the household level. The formal/informal sector employment of the household head was also strongly associated with the probability of receiving a shock to the earnings of the household head. In this section, the paper instruments for the potentially endogenous earnings shock variable using the province level macro shock variable and the (formal/informal) sector of employment of the household head. Both of these instruments are strongly correlated with the probability of the household head receiving an earnings shock in the crisis period (as will later be shown in first-stage regressions of the 2SLS estimation), and we expect them to be *uncorrelated* with consumption decisions at the household level.

In order to instrument for the household level earnings shock variable, which may potentially be endogenous or mismeasured, the paper uses two instruments that are closely linked to the predicted probability of receiving an income shock at the household level: (i) the intensity of the macro shock in the province where the household is located, and (ii) the formal/informal labor status of the household head prior to the onset of the

²The definition of the crisis proxy variable is described in detail in Section 2.3.2.

crisis in t_1 .

The 2SLS specification can be formally stated as follows:

$$\Pr(\Delta C_j) = \varphi_1 \Delta \hat{Y}_j + \varphi_2 (A_{j(t_1)}) + u_j \quad (2.7)$$

Where $\Delta \hat{Y}_j$ (the predicted level of the probability of receiving the income shock) is used to instrument for ΔY_j the probability of experiencing an earnings shock at the household, which is potentially endogenous to the reported change in consumption. A_j represent household head characteristics and, once again, in these regressions the variables are defined as deviations from the mean. The primary goal of the 2SLS estimation in Equation (2.7) is to find *consistent estimates* for the impact of the earnings shock at the household level on household expenditures and consumption. The heterogeneous impact of the income shock on different types of households becomes more difficult to measure using 2SLS methodology since the interaction terms each in turn need to also be instrumented for in order to get consistent results of this estimation. Hence, the *probit* specification in Equation (2.6) with the interaction terms is not repeated using the 2SLS estimation.

2.3 Data

2.3.1 Data Sources

The main data set used for this paper is the Turkey Welfare Monitoring Survey (TWMS) baseline survey. This is a household level survey that we designed as a rapid monitoring tool that would give immediate feedback to policy makers on the changes in the income and welfare level of households through the Global Financial Crisis in Turkey. The survey was fielded twice in the same households: in May 2009 (baseline) and in December 2009 (panel). The funding for the survey was provided by the World Bank and UNICEF and data collection was carried out by BAREM a local research institute. We have designed this survey with specialized modules that relate to coping strategies and access and utilization of safety nets. In this paper, only the baseline data from this survey is utilized. However, the baseline survey already had *retrospective* questions that asked households to compare their status of income, earnings, labor status, consumption and utilization of education and health services in May 2009 (t_2), with these levels in October 2008 (t_1). In the survey questionnaire, October 2008 was selected as the reference period for most of these comparison questions since it can be considered as the beginning/onset of the crisis in Turkey in terms of the macro figures.

The sample in TWMS included a total of 2,402 households in 7 provinces in Turkey. Figure 2.4 provides a map of the provinces where data was collected. For 5 provinces in the sample that represent urban city centres (Istanbul, Kocaeli, Izmir, Ankara, Adana), a sample of 2,102 households was selected using stratified sampling such that 100 PSUs were selected at the 5 city centre level (pooled) with oversampling of poor neighborhoods, and with random sampling of households within each PSU. The data sampling process was carried out in collaboration with the Turkish Statistical Institute (TURKSTAT) and the weighted estimates of population averages in the urban sample, such as average education attainment rates, labor force participation rates, employment composition by sector, compare closely with estimates provided by TURKSTAT in the official Labor Force (LFS) and the Household Budget (HBS) Surveys for Turkey. The two eastern rural provinces of Erzurum and Gaziantep in the sample include 300 households. This rural sample was not meant to be representative of a specific area. For the purposes of this paper, the data from rural and urban samples were pooled and weighting was not used in the regressions, although weights are used for urban observation when representing averages in summary statistics.

The second source of data, used in the paper, is financial administrative data on “non-cash credit available from banks” in Turkey by province, collected and compiled by the Turkey Banking Sector Regulatory Agency (BDDK) and made available publicly on their web site (www.bddk.org.tr). Financial administrative data provided by BDDK is used to construct the province level “crisis proxy” variable in the earnings equations as well as the instrument in the 2SLS regressions. Further information on the construction of the crisis proxy variable is available in the next section.

2.3.2 Description of Variables

The variables used in the Turkey Welfare Monitoring Survey are described in this section: The variable indicating the income shock at the household level comes from the labor module of the baseline survey (collected in May 2009), and asks the person to compare their earnings in the current job with Oct 2008. (“*Are your earnings in current job higher, lower or the same as earnings from job in May 2009?*”) The dummy variable for the earnings shock takes the value of “1” if (i) the person who was working back in Oct 2008 answers this question saying their earnings are lower in the current job or (ii) if they report that they were employed as of Oct 2008 and become unemployed as of May 2009.

The previous labor status of the worker takes only two values in the survey: formal

or informal sector employment. Formal sector employment is defined by social security coverage in the previous job (Question L11 in survey “*Did the person have social security coverage in previous job?*”). The educational attainment variables are defined in 4 categories of educational attainment (and are defined using Questions T12 in the survey “*What is the last diploma the person attained?*”). The four categories of attainment are defined as (i) illiterate or no diploma, (ii) primary school diploma, (iii) junior or secondary school diploma and (iv) higher education.

The change in consumption (welfare) variables is constructed using the expenditure and coping strategies modules of the survey. The expenditures module asks whether the household’s “expenditure” on each category of spending (including food, education and health) has increased, remained the same or decreased in the first 5 months of 2009, compared to the same time period in 2008. The coping mechanisms module includes questions on the household’s adaptation in behavior. The responses in this module are binary responses to questions such as “*Since October 2008, did you have to reduce the amount of food consumption at the household?*”, “*Did you have to reduce the amount of food provided to children?*”, “*Did you reduce the utilization of health services?*”, “*Did you have to withdraw a child from school or postpone enrolment?*” All of these coping questions are asked with the same time frame for the period between October 2008 and May 2009 and they provide binary information on whether the household resorted to this kind of an adaptation in consumption behavior through the crisis period. These questions are used in the analysis as robustness checks on the main expenditures dependent variables for food, education and health expenditures.

The asset index variable is constructed using household characteristics and assets in the housing module of the survey. The index is constructed using the Filmer-Pritchett methodology, whereby a principal-components analysis (PCA) is used to differentiate households according to the assets they own (Filmer and Pritchett, 2001). Each of the variables used in the asset index are checked first to see if they correlate positively with the income variable of the household. (Only variables that are positively correlated with income should be included in the estimation of the asset index). Factor analysis is run on these household assets and housing characteristics as listed in Table 2.2 and households are finally split into 5 equal sized groups to create the quintiles separated by the asset index.

The TWMS is a useful and unique data set for quickly measuring the responses of Turkish households to the aggregate macro shock during the period of the Global Financial crisis. The main limitation of the data set is that since this the survey was designed as a rapid-response monitoring survey, both the income and consumption questions in

the survey are based on perceptions of the respondent rather than on detailed income or consumption modules. These questions do not provide an indication on the “levels” of increase or decrease on income and consumption and merely provide dummy variables to be constructed for the shock. One would expect a larger income shock to have a different impact on consumption than a small income shock, though this kind of binary data allows us only to work with probabilities (discrete changes) and not continuous variables on income and consumption levels.

The second main data source used in this paper is the financial sector data at the province level. The main financial sector variable used in the construction of the instrument that predicts the severity of the financial crisis experienced at the household level, is the rate of change in the amount of non-cash credit available from all banks in the province. Non-cash credit from banks represent (i) letters of credit and (ii) letters of guarantee, particularly relevant for exporting companies to continue their business. This variable was chosen for the construction of the instrument as it is a viable province level predictor of the probability of receiving an earnings shock at the household level, while not being related to changes in consumption at the household level except through its impact on local companies in the province and the labor income/earnings of workers in the province. Since non-cash credit is provided only to companies and not to households, and does not translate into an increased monetary “liquidity” in the province, this variable is not *related* directly to the changes in consumption for households. The crisis proxy variable (X_p) in Equation (2.6) which feeds into the definition of predicted probability of receiving the earnings shock is constructed as a “*deceleration*” in the availability of non-cash credit (NCC) from Banks, in the following way:

Where NCC_p indicates non-cash credit available from banks in the province, and t_0 stands for the 9 month period Dec 2007-Sep 2008 and t_1 stands for the 9 month period Sep 2008-June 2009. It is important to understand the reason for using “rate of change” in non-cash credit (a *deceleration* variable) rather than a “percentage change” or “level” variable for this indicator: the seven provinces in the data set are different from each other in terms of economic development and financial penetration in the initial conditions, hence *levels* of non-cash credit cannot be used as a comparison variable for the change in economic conditions. The “percentage change” in non-cash credit available in these two time periods can also not be used as an indicator variable, since three out of seven of these provinces still display a positive increase in non-cash credit from banks even in the period Sep 2008 to June 2009, although the expansion of non-cash credit has slowed down as a result of the crisis. Using the positive percentage change indicator does not sufficiently describe the deceleration in growth taking place in these provinces.

Hence, it was essential to *de-trend* the growth trajectory in this variable and look at the *rate of change* in non-cash credit, comparing the growth in this variable in t_1 with growth in t_0 . A data summary of the changes in non-cash credit from banks variable and the calculation of the crisis proxy variable by province have been provided in Table 2.3.

2.4 Empirical Results

2.4.1 Summary Statistics

A large percentage of households in the Turkey Welfare Monitoring Survey sample report reduction in household income in the first 8 months of the crisis. In the total sample of 2,402 households, 16.6 percent of households report that the head of household had lower earnings in the main job (or had lost a job) during October 2008 - May 2009. Among households where the household head is employed informally, the percentage that report at least one person with lower earnings is much higher at 42.1 percent. Table 2.4 provides summary statistics on reduced reported earnings at the household level by the sector of employment (as of Oct 2008) of the household head.

Turkish households in the rapid monitoring survey sample most frequently report reductions in food expenditures and consumption, while expenditures on education and health services in the face of the crisis remain more stable (or increase). In the expenditures module of the survey households are asked if they had to reduce expenditures on certain items: 43.5 percent of households in the sample report having reduced expenditures on food items during October 2008-May 2009. In comparison, only 8.9 percent of household report reducing expenditures on education and 14.4 percent of households report reducing expenditures on health (See Table 2.5).

In the coping strategies module of the survey, households are then questioned about whether they had to change certain forms of behavior since the onset of the crisis and again we see significant adjustments in food consumption behavior: 70.9 percent of households mention they “substituted into cheaper food items”, 56.8 percent say they “reduced the amount of food consumed” and a worrying 24 percent of households in the sample mention they had to “reduce the amount of food provided to children” in the household. Health care utilization falls for about one-fifth of the sample of households: 20.5 percent of households report reducing utilization of health care services and 18.7 percent of households mention utilizing preventive care services less since the onset of the crisis. Educational enrolments are for the most part protected through this time period:

less than 3 percent of households report “withdrawing children from school/postponing admission to school”, or “transferring children to a cheaper public or private school” (See summary statistics in Table 2.5).

The reduction in food consumption and expenditures are more likely for the poorest households in the sample as predicted by the model presented in the conceptual framework. The overall changes in food, education and health expenditures are depicted in non-parametric form in Figure 2.5. In these figures, the y-axis varies between -1 and 1 and the dependent variable takes three values: 1 if expenditures in this category have increased, 0 if they have remained the same and -1 if they have decreased in the first months of 2009 when compared to the first 5 months of 2008. As reported in the top left hand panel of Figure 2.5, most households in the sample report reductions in food expenditures in this time period, and the likelihood of reporting these reductions in food expenditure increases with lower levels of the asset index . In other words, as predicted by the model, poorer households are more likely to report reductions on food expenditures. Changes in expenditures on education, health care and household durables are also provided in the other panels of this figure. For the lowest values of the constructed asset index, the mean of the categorical variable indicating changes in food expenditures is about -0.8 (on a range of -1 to 1). In contrast, in the same time period education expenditures were likely to *increase* for the poorest as well as richest households in the sample. The mean of the categorical variable on change in expenditures is around 0.2 for education expenditures. The change in health expenditures is also on average *positive* for the poorest asset households and we observe little change in expenditures on household durables, where the mean level of change hovers around zero for all wealth levels.

Most enrolments in Turkey in the basic and secondary schooling level are in public schools, where tuition is mainly free. ³ Since tuition is free in public schools, we could expect that in the short term through a transitory shock to incomes, enrolments may remain stable, while households may or may not report increases in education expenditures (depending on costs associated with non-tuition costs). This is in fact what we observe in the Turkey Welfare monitoring Survey: the data is collected in May 2009 and asks questions about changes in enrolment (whether children had to be taken out of school etc.) going back to October 2008. Especially since the baseline for the data question is in the same academic year, we do not observe a large percentage of

³In the 2007/2008 academic year, which just preceded the Crisis and the collection of this survey data, only 1.53 percent of enrolments in basic education level (grades 1-8) and 4.7 percent of enrolments at the secondary school level (grades 9-12) were in private schools (Education, 2008).

households reporting a change in enrolments⁴.

The insights we gain in Figure 2.5 are confirmed also by responses to other consumption related questions in the coping strategies module of the survey that relate to food consumption and utilization of education and health services through the crisis period. In the coping strategies module of the TWMS, the respondents are asked whether they had to change or adapt their behavior in certain respects in the period October 2008-May 2009. Their responses are coded as dummy variables and plotted against the asset index in Figure 2.6. The y-axis in this figure varies between 0 and 1 and provides the predicted probability of adopting a certain change in behavior through the crisis period, by levels of the asset index. In the top panels of the figure, we observe that the probability of reducing food consumption is highest for the poorest asset holders in the sample, with the predicted probability varying around 60-80 percent for the lowest levels of the asset index. The probability of reducing the amount of food provided to children is also around 40-50 percent for the poorest in the sample. In fact, only the very top levels of the asset index report no changes in food consumption and not having to reduce the amount of food provided to children where the predicted probability of reducing food consumption hits zero (see Figure 2.6 top two panels).

2.4.2 Main Results

Changes in household level earnings given the macro shock

The probability of reporting reduced earnings for all workers (and for workers that are also household heads) is linked closely to the macro level shock at the province level. The results of the earnings regressions that show the heterogeneous impact of the macro shock on workers by sector of employment and educational attainment – as stated in Equation (2.3) and (2.4) - are provided in Table 2.6. In the specification in Equation (2.3), where only the level effects of worker characteristics are considered, a 100 % increase in the macro-shock variable at the province level is associated with a 29.4 percentage point increase in the probability of reporting reduced earnings for workers who are employed formally and have a higher education degree (p value <0.01) (Table 2.6 Column 1). For the sub-sample of workers who are also household heads, the association between the macro shock and probability of reduction in earnings is even stronger with a coefficient of 37.7 percentage points (p value <0.05) (Table 2.6 Column 3) for formally

⁴In fact, the households that are more likely to have reported a change in school are those households where the household head has a higher education degree this is likely to be a function of the fact that children in private schools are children of parents with higher levels of education, and their enrolment in school may be more impacted by the Crisis than those children enrolled in public schools.

employed workers with degrees in higher education. Workers employed in the informal sector as of October 2008 and those with lower levels of education are more likely to have received a shock to their earnings. Being an informal worker is associated with an *increase* in the probability of reduction in earnings by 12.6 percentage points. Having no formal education is associated with an increase in the probability of reduced earnings by 14.1 percentage points in the sample of all workers (and 13.8 percentage points in the sample of household head workers) when compared to those with higher education degrees, and those with only primary school diplomas are 16.6 percentage points (18.6 percentage points in the sample of household heads) more likely to report reductions in earnings in this time period. So a worker who has a primary school degree and is informally employed as of October 2008 in the sample, is 29.2 percentage points more likely to report reductions in income in this time period in comparison to someone who is formally employed and holds a higher education degree.

The interaction terms in the specification (Table 2.6 Columns 2 and 4) show the heterogeneous impact of the crisis on different types of workers: workers employed informally are 32.1 percentage points more likely to reduce lower earnings with a 100% increase in the crisis proxy at the province level (rate of reduction in non-cash credit available from banks). Hence, it is possible to observe the heterogeneous impact of the crisis: for workers who were informally employed there is a level effect as well as a slope-effect associated with the crisis whereby the province level macro shock was associated with a higher probability of reduced earnings for such workers (See Table 2.6 column 2). In the sample of workers who are also household heads, having a secondary school diploma in the presence of the macro shock (or with increased intensity of the macro shock) is associated with lower earnings as well, when compared to university graduates, though the coefficient here is only significant at the 90 percent confidence level (See Table 2.6 column 4).

In the change in earnings regressions in Table 2.6, we observe that for the sample of all workers in the sample the Crisis has more of an impact on informal workers. The interaction term between the Crisis macro shock proxy variable and the dummy variable for being an informal worker takes on a positive and significant value. This is likely to be because for workers that have formal sector jobs, the severance pay is high and there is no mechanism for the renegotiation of salaries. (Note that Turkey has one of the most generous severance pay mechanisms in the world, as ranked by Holzmann et al. (2011). Through the Crisis, therefore, informal workers are more likely to both lose jobs and to get lower pay for the same amount of work, as they are less protected in their jobs. ⁵

⁵Also note that informality is more common among women in Turkey: only 9 percent of women

Changes in household expenditures given the earnings shock at the household level

The probability of reducing household food expenditures can in turn be linked closely to the earnings shock at the household level. This is demonstrated in the results first in the form of a maximum likelihood *probit* regression.

Probit results

The results of the empirical specification provided in Equation (2.5) and (2.6) are given in Table 2.7 for the four categories of expenditures (i) food, (ii) education, and (iii) health expenditures. The dependent variables in these *Probit* regressions are the dummy variables for reducing expenditures on these items in the first 5 months of 2009 compared to the first 5 months of 2008⁶. The first two columns of the table provide findings for the dependent variable on reducing food expenditures. In these regressions, the coefficient on the dummy variable for the reduction in earnings for the household head, denoted by β_1 in Equation (2.5) takes the value of 0.152 ($p < 0.01$) when controlling for the urban/rural location of the household, household head educational status and household asset index. In other words, a household where the household head experiences an earnings shock (between October 2008 and May 2009) is 15.2 percentage points more likely to reduce their expenditures on food in the first 5 months of 2009 compared to the same period a year earlier, and in comparison to households with similar characteristics but where the household head does not get an earnings shock. As the level of the asset index increases (and the household becomes wealthier) the probability of reducing expenditures on food declines (Column 1). Households where the household head only holds a primary school degree or secondary school degree are more likely to report reductions in food expenditures in this time period, compared to household heads with a higher education degree.

In the second column of results in Table 2.7, the same specification is run including the interaction terms between household characteristics and the earnings shock, thus including slope effects following Equation (2.6) in the specification. The coefficient β_1 is

employed were formally employed in 2010, while about 37 percent of men were in formal employment (Source: Turkey Labor Force Survey 2010, for workers ages 15+). When we limit the sample to household heads who are workers, rather than all workers, we get more of the male workers in the sample, as household heads are predominantly men. Hence it becomes more difficult to observe in the data the heterogeneous impact of the Crisis on informal workers when we look at household head workers only.

⁶Turkey experienced positive inflation through the time period analyzed. Hence, the households that reported no change in expenditures on a certain item, should actually be experiencing a reduction in consumption (in terms of the quantity of the good consumed). In this sense, the estimates reported are an underestimate of the impact of the macro shock on changes in consumption.

0.143 when controlling for interaction terms^{7, 8}.

The household composition variables -number of adults and children in the household- are also positively associated with the probability of reduced food expenditures at the household level. The coefficients on interaction terms would indicate the heterogeneous way in which households respond to an income shock at the household level. The coefficients on these variables (β_3) are generally not significant although the level effects associated with the asset index and low levels of education remain significant. This suggests that the poor are more likely to reduce their food consumption overall in this time period, however the existence of the income shock at the household level does not necessarily bring about different probabilities of reducing food expenditures for different types of households. On the other hand, the earnings shock is not associated in these *probit* regressions, with reduced levels of expenditures on health and education (represented in Table 2.7 columns 3-6). In households where the household head only holds a primary or secondary school degree, compared to higher education (university) degree, there is a higher likelihood of reducing education expenditures through this time period. However, in the face of an income shock these groups are less likely to reduce education expenditures in comparison to households where the household head holds a university degree.

2SLS and IVprobit estimation results

Next, the paper implements a 2SLS instrumental variables estimation (as described in Equation (2.7) of the empirical specification) in order to get more consistent results on the coefficient for the earnings shock impact on changes in food expenditures and other expenditures. As described in the empirical strategy section, one may suspect two types of problems leading to inconsistency in the results: in the *probit* results that the responses to the reduction in expenditures questions and the income/earnings questions

⁷The model here may contain a number of equations and the error terms across the equations may be correlated since spending decisions are jointly decided. As a robustness check, a seemingly unrelated regression (SUR) system with food, education, health and durables expenditures is set up whereby decisions on these expenditures are made concurrently. The results are robust to this estimation: the coefficient on the earnings shock changes from 14.3 (p-value<0.01) to 13.7 (p-value<0.01).

⁸The definition of the earnings shock at the household level included both lower earnings in the current job, as well as a shock to earnings as a result of a job loss. In order to see how a job loss may be differently associated with the changes in food expenditures, separate regressions with different earnings shock variables were also run. When the earnings shock is defined only in terms of a job loss this impacts only 2.4 percent of household head workers in the sample, while a reduction in earnings in the current job impacts 32.7 percent of household head workers. The sample for which we observe a job loss is very small and this variable does not take on a significant coefficient in the regressions. On the other hand, the coefficient on the earnings shock resulting from lower earnings in current job (14.1 with p-value<.01) is very similar to the original coefficient on the earnings shock variable (which was 14.3 with p-value<0.01 in Table 2.7).

in the survey may be correlated as a result of people’s *aversion to cognitive dissonance* and their desire to be consistent in their responses through the survey. Second, given that changes in earnings are not objectively measured and that they are subjective recall questions asking the household to evaluate changes to their expenditures, there may be significant measurement error in the measurement of the earnings shock, leading to “attenuation bias” in the coefficient β_1 in Equation (2.5).

The 2SLS specification given in Equation (2.7) is provided in Table 2.8. The coefficient on the predicted probability of having reduced earnings at the household level (φ_1) is significant in the regressions, where only intercept effects are controlled for (as in Equation (2.7)). The 2SLS results where the dependent variable is the dummy variable for reducing food expenditures, are reported in column 1 of Table 2.8 with robust standard errors. The coefficient on the predicted probability of lower earnings in the household is 0.333 (p value <0.1), hence an earnings shock in the household increases the probability of reducing food expenditures by 33.3 percentage points. In column 2 of Table 2.8, the same specification is run using an *IVprobit* estimator, which is a more suitable functional form given that the dependent variable in the regressions (reduction in various expenditures categories) are defined as binary variables. The marginal effects coefficient for (φ_1) in the *IVprobit* estimation is 0.330 (p value <0.1) with robust standard errors.

The asset index in these instrumental variables estimations again takes on a large and highly significant coefficient indicating that the initial wealth level of the household is important in determining the probability of reduction in food expenditures. The size of the coefficient for the earnings shock at the household level using the 2SLS and *IVprobit* estimations (φ_1) is higher than the size of the coefficient in the *probit* estimations (β_1). This suggests that the attenuation bias resulting from measurement error dominated the direction of the bias in the maximum likelihood *probit* results presented in Table 2.7. The same specification as in Equation (2.7) is run for education and health expenditures in Columns (4-9) of Table 2.8 and 2SLS and *IVprobit* results are presented with the first stage regressions. None of the earnings shock variables are significant in these regressions, once again establishing that the income shock did not lead to reduced education or health care expenditure for the households.

Tests of exclusion restrictions

Several tests are reported here documenting the performance of the instrumental variables used in the analysis:

Testing for the relevance of the instruments: In order to test the relevance of instruments, we need to establish that the instrumental variables matrix is correlated with

the earnings shock at the household level, formally $E(Z'Y) \neq 0$. The first stage results (reported in Table 2.7 Columns 3) suggest that both of the instruments are highly correlated with the earnings shock variable at the household level. The partial correlation coefficient of the crisis proxy is 0.298 (with p-value < 0.01) and the partial correlation coefficient on the informal labor status of the household head is 0.156 (with p-value < 0.01) in the first stage regressions (with robust standard errors). The F test of excluded instruments has the value 16.14 in the 2SLS regression, which is above the rule-of-thumb value of 10 and allows us to reject the hypothesis of weak instruments.

Testing for the validity of the instruments: In order to establish the validity of the instruments, we need to show that the instrumental variables matrix is uncorrelated with the error term, $E(Z'u) = 0$. In other words, the only way the instruments influence the outcome variable (changes in expenditures) is through their impact on change in earnings. The exclusion restriction can be tested since there are more excluded instruments than endogenous regressors in this overidentified model. The Sargan statistic (implemented under the assumption of i.i.d. errors) fails to reject that the excluded instruments are valid: Sargan statistic has a value of 0.396 and has a Chi2 (1) distribution with a p-value of 0.5292 in the 2SLS results⁹. Alternatively, to drop the i.i.d. assumption, we run the Hansen's test (following a GMM estimation of the same model)¹⁰ and the Hansen's J test statistic here is $\chi^2(1) = .387839$ (p-value = 0.5334) once again *failing to reject* the null hypothesis that the instruments are valid. The rejection of the null hypothesis in the Hansen-Sargan test could be interpreted as at least one of the instruments being not valid.

Testing for endogeneity: Next, we implement a test of endogeneity of the earnings shock variable in the *probit* regressions of Equation (2.5). Under the null hypothesis that the earnings shock variable is exogenous, the robust Durbin-Wu-Hausman test¹¹ is implemented and gives a p value of 0.307. The test fails to reject the null hypothesis that the earnings shock variable in the regular OLS regressions is exogenous. While the endogeneity of the earnings shock in the model is now less of a concern, there is still

⁹The Sargan test statistic is computed using the `estat overid` command after the 2SLS estimation using `ivregress` in STATA. The test of overidentifying restrictions regresses the residuals from the 2SLS regression on all instruments in Z. Under the null hypothesis that all instruments are uncorrelated with u, the test has a large-sample Chi2(r) distribution where r is the number of overidentifying restrictions, in this case 1.

¹⁰Hansen's test is implemented with the post estimation `estat overid` command following the `ivregress gmm` command for an overidentified model

¹¹Durbin-Wu-Hausman test is implemented using the postestimation command `estat endogenous` following the 2SLS estimation using `ivregress`. Durbin-Wu-Hausman $F(1,1155) = 1.04429$ (p = 0.3070)

a strong concern related to the measurement error on the earnings shock explanatory variable in Equation (2.5), hence using the 2SLS estimation to get consistent estimates of the coefficient on the earnings shock is still a suitable strategy.

Testing for underidentification. This test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the Anderson canon. corr. LM statistic has value 31.6. Under the null, the statistic is distributed as Chi2(2) and we can reject the null hypothesis indicating that the model is identified with p-value equal to zero. The rejection of the null indicates that the matrix is full column rank, and that the model is identified.

2.4.3 Robustness Checks

The results on changes in food expenditure patterns are also robust to different dependent variables that describe food consumption behavior. Robustness checks for the same empirical specification as in (7) are run using four different dependent variables in this section of the analysis, still revealing a strong link between the income shock at the household level and the changes in food consumption levels¹².

The results of the 2SLS and IVprobit regressions with food consumption dependent variables are provided in Table 2.9. The results (following specification in Equation (2.7)) show that households that face an earnings shock in this time period, also have a higher likelihood of “reducing food consumption”, “substituting into cheaper food items”, and “reducing the amount of food provided to children”. A shock to the earnings of the household head is associated with a 79.8 percentage point (p value < 0.01) increase in the probability of “reducing food consumption” and 45.2 percentage point (p value < 0.05) increase in the probability of “reducing the food amount provided to children” in the 2SLS estimation when controlling for household characteristics such as urban/rural location, educational attainment of the household head and the asset index. Urban households and households with lower asset index have a higher likelihood of changing food consumption behavior in these regressions. These households also report substituting into cheaper food items with a 55.1 percentage point higher probability (p value < 0.01). The asset index takes on a highly significant and large partial correlation coefficient in these 2SLS regressions, with a one unit increase in the asset index being associated with an 14.2 percentage point increase in the likelihood of reducing food consumption and a 14.9 percentage point increase in the likelihood of reducing the amount of food provided to

¹²The dependent variables in this section of the analysis are based on the coping mechanisms module of the survey, where households are asked if they had to change certain behavioral patterns between Oct 2008 and May 2009 to cope with the crisis.

children (both with $p\text{-value} < 0.01$)¹³. The IVprobit marginal effects results are provided on the same table for comparison with 2SLS results. The first stage results for the 2SLS estimation are also provided for each dependent variable in Table 2.9.

Finally, the 2SLS and IVprobit estimations using (7) are provided for these education and health utilization variables in Table 2.10. The 2SLS results show no apparent link between the earnings shock and changes in education enrolments, while there is a strong association between the earnings shock and reduced health care utilization for curative care at the household level.¹⁴

These regressions show that an earnings shock at the household level, was associated with a no change in educational enrolments and or use of preventive health care services (though there was some reduction in the utilization of curative health care services in the face of an income shock). In general, though, in the face of an income shock, households were less likely to change their consumption of education and preventive health care services, than they were to adjust their consumption of food. The reduction in demand for these mostly publicly provided services (that already made up a small share of the household budgets in the baseline (Table 2.1)) was smaller than the reduction in demand for food through this time period.

Further robustness checks were run using different definitions for the income shock variable, using the (i) the proportion of breadwinners in the household as the income shock variable at the household level (ii) a dummy variable that takes the value of 1 if anyone in the household has received an earnings shock (rather than just the household head). The findings with regards to changes in food consumption are robust to these different specifications of the income shock variable. When the earnings shock is defined as at least one individual in the household experienced lower earnings since October 2008, this variable is associated with an 8.9 percentage point increase in the likelihood of reduction of food expenditures. When the variable is defined as the proportion of breadwinners in household reporting lower incomes, then a 100 percent increase in this variable is associated with a 10.6 percentage point increase in the probability of reducing food expenditures. Both of these coefficients are statistically significant (with $p\text{-values} < 0.01$) however the size of the coefficients under these definitions is lower than when the earnings shock is defined as the household head worker receiving a shock to

¹³Note that the asset index takes on values between 1 and 7.73 in the sample, hence between the poorest and richest households in terms of assets there is a 6.73 unit difference in the measurement of the asset index.

¹⁴The results are robust to an IVProbit estimation using Neweys minimum chi-squared estimator with the two step option. In fact, the income shock gets an even higher coefficient (0.878 with $p\text{-value} < .10$) in the two-step IVProbit regression (not reporting marginal effects) compared to 0.861 (with $p\text{-value} < .10$) in the regular IV Probit estimation.

earnings.

2.5 Conclusion

Food expenditures which make up 44 percent of the household budget, as of 2008, for the poorest expenditure decile, acted the main adjustment mechanism in the face of the income shock in Turkey, while education and health expenditures remained relatively stable. Households managed to reduce expenditures on food either by substituting into cheaper food products, or directly by reducing their consumption of food. About 71 percent of the households in the sample reported substituting consumption into cheaper food items, and 57 percent reported directly decreasing the amount of food consumption at the household. 24 percent of the households reported reducing the amount of food provided to children in the survey period. The income shock at the household level was associated with a decline in food consumption and expenditures, while education and health care utilization were more protected even in the face of income shocks.

In the maximum likelihood *probit* regressions: the dummy for the income shock to household earnings is associated with a 16.2 percentage point increase in the probability of reporting reduced expenditures on food between Oct 2008 and May 2009. Due to measurement error on the earnings shock explanatory variable in these regressions, though, there is likely to be attenuation bias in the maximum likelihood *probit* results. This bias is corrected using a 2SLS and IV*probit* strategy, which consistently estimates the probability of reduction in food consumption. In the face of an income shock, the probability of reducing food expenditures increases by 33.3 percentage points, and the probability of reducing food consumption increases by 79.8 percentage points in the 2SLS model. The probability of “reducing the amount of food provided to children” is increased by 45.2 percentage points with a shock to the earnings of the household head. Through the period analyzed in the survey, the probability of reducing food consumption is highest among the poor that initially had low levels of household assets. While food expenditures and consumption provide the main buffer for households in the face of the crisis, there is little or no change in the education and health expenditures of households, and educational enrolment of children or the utilization of preventive health care services in the face of an income shock at the household level remain stable.

Figure 2.1: Severity of the Macro Shock: Changes in GDP and CPI (% change in 3 month period)

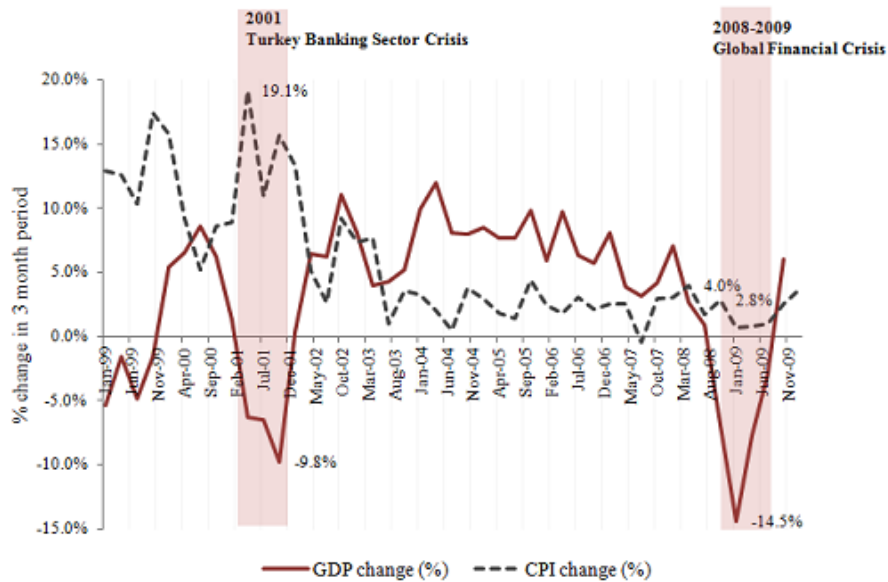


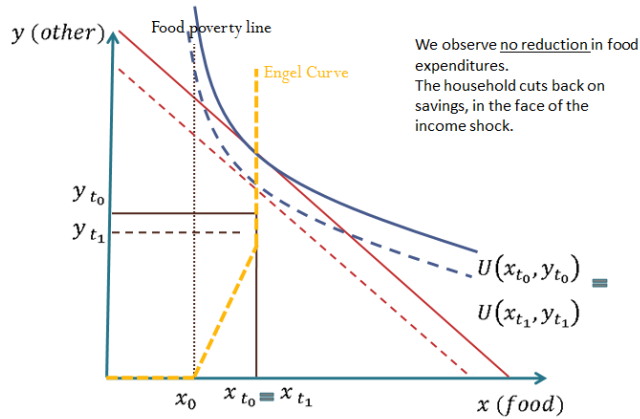
Figure 2.2: Unemployment and Youth Unemployment Rates in Turkey (%Jan 2005 - Jan 2010)



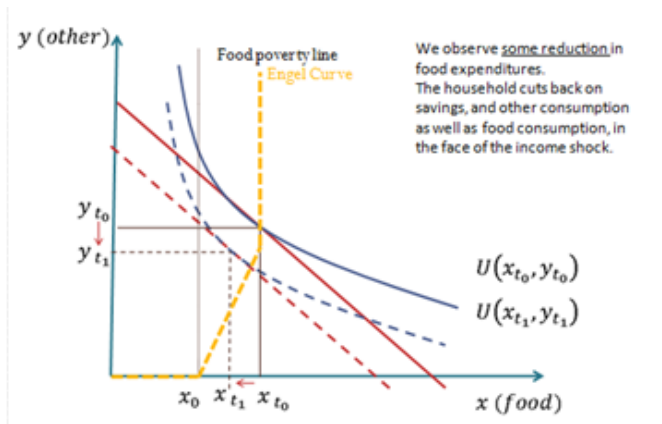
Source data: TURKSTAT

Figure 2.3: Conceptual Model for the Income Shock and Changes in Consumption

(a) Panel A: Income shock experienced by a high-income household



(b) Panel B: Income shock experienced by a middle-income household



(c) Panel C: Income shock experienced by low income household

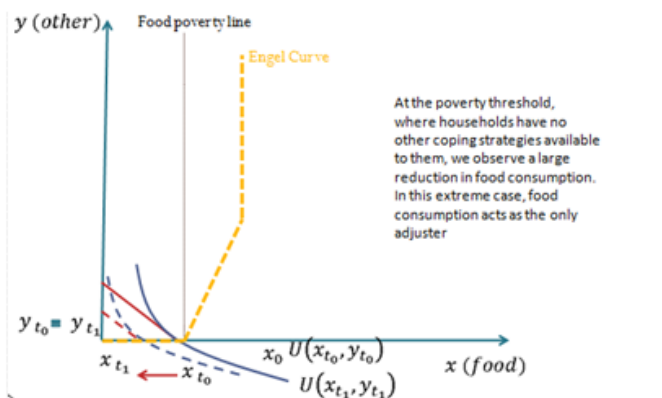
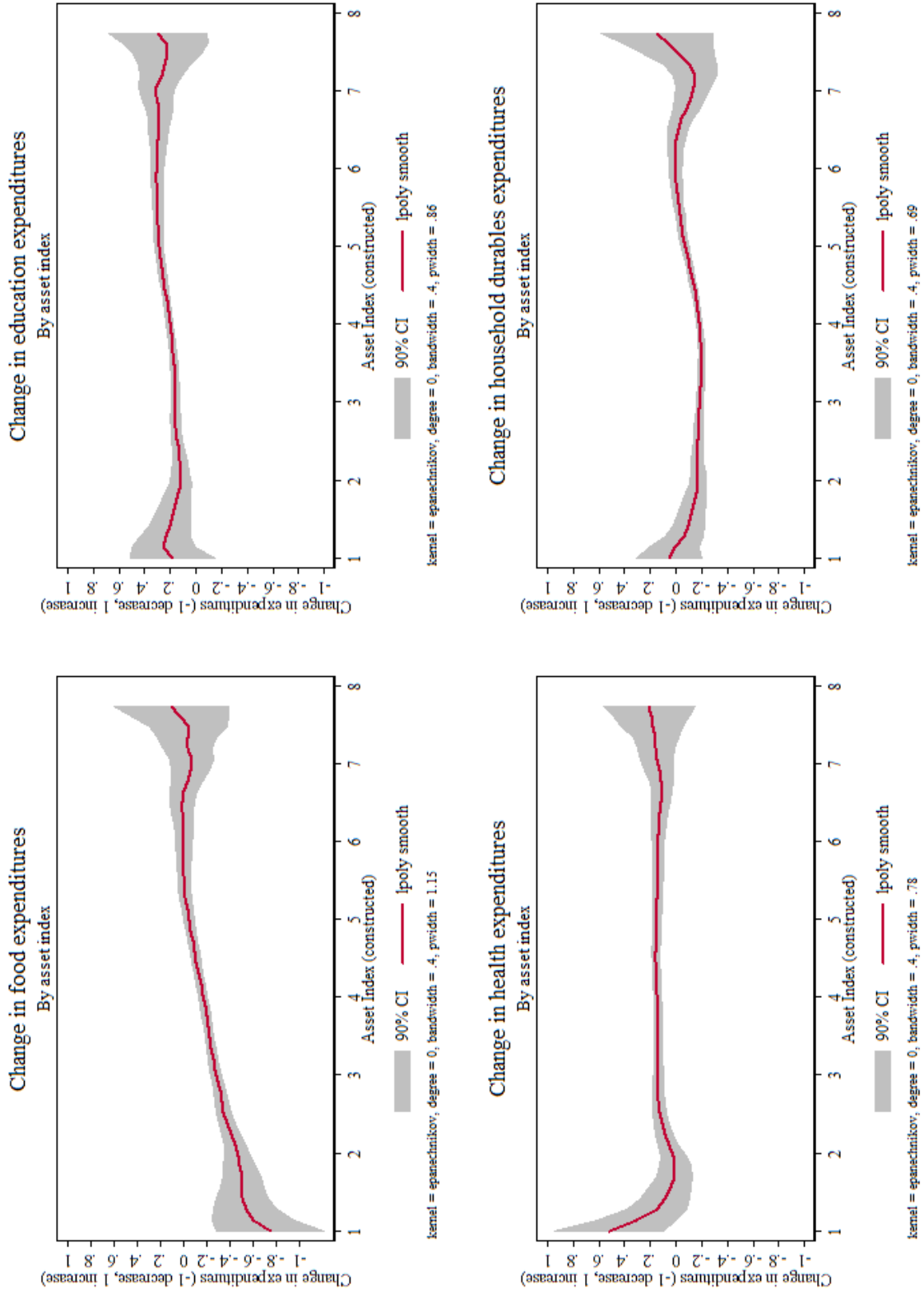


Figure 2.4: Map of Provinces Included in the Sample of the Turkey Welfare Monitoring Survey (TWMS)

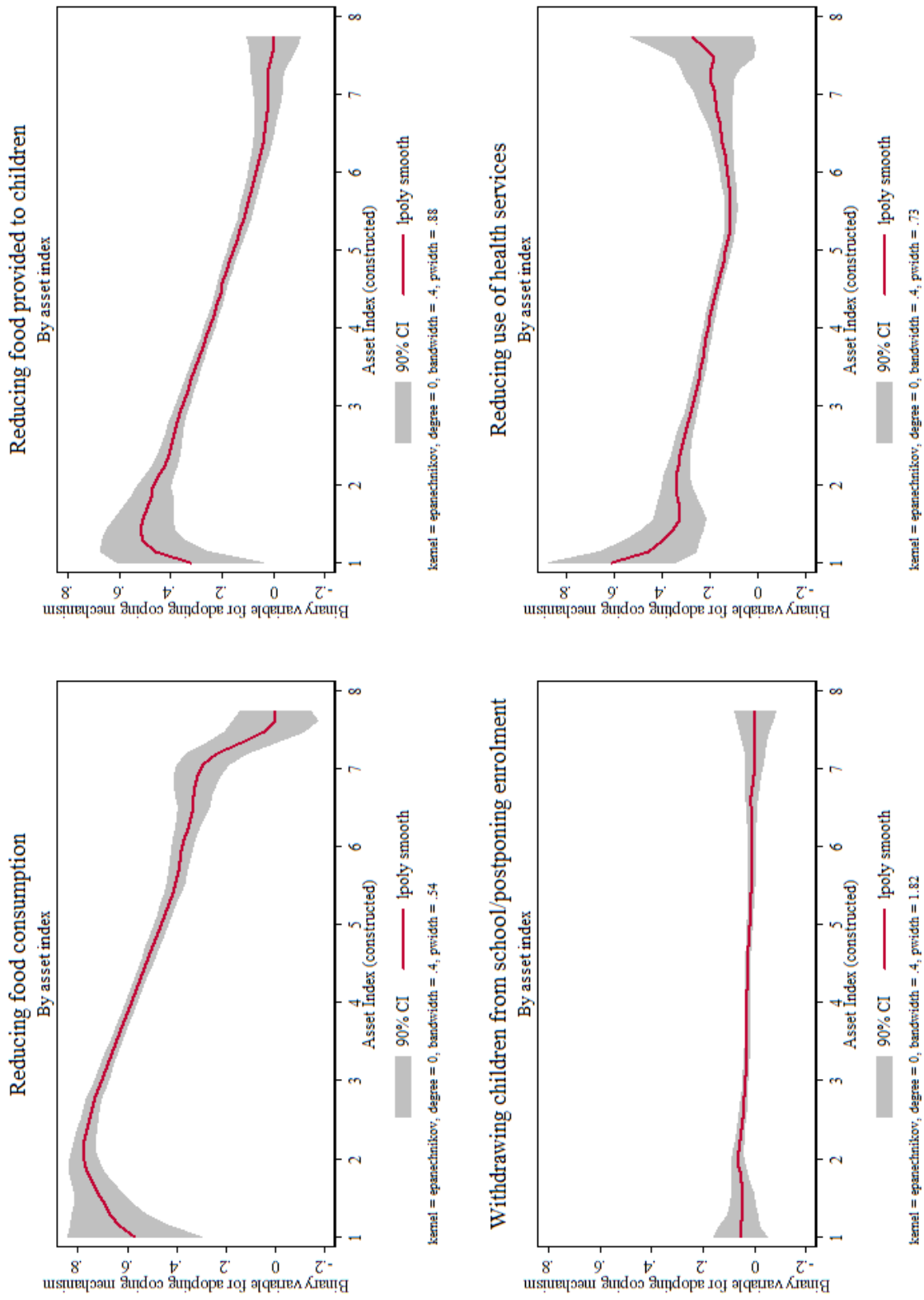


Figure 2.5: Changes in Expenditures, by Category



Note: The y-axis indicates a decrease in expenditures (-1), no change in expenditures (0), or an increase in expenditures (+1) as a categorical variable. The time frame for the changes in expenditures is January-May 2009 expenditure levels on these items compared to January-May 2008. Source data:: Turkey Welfare Monitoring Survey (May 2009)

Figure 2.6: Probability of Adopting Certain Changes in Consumption Behavior, by Household Asset Index



Source data:: Turkey Welfare Monitoring Survey (May 2009)

Table 2.1: Household Expenditures by Per Capita Expenditure Deciles (as % of total spending)

	Total	Food	Alcohol	Clothing	Housing	Furniture	Health	Transport	Communic.	Enterta.	Education
Poorest	100.0	43.5	9.8	7.5	25.2	5.5	3.1	8.1	5.7	1.7	4.7
2	100.0	37.1	10.0	7.2	28.0	5.7	2.7	8.6	5.0	2.4	4.7
3	100.0	32.7	9.4	6.6	29.9	5.2	2.8	9.0	4.9	2.0	5.0
4	100.0	29.8	8.7	6.4	30.6	5.7	3.0	9.7	4.9	2.8	4.6
5	100.0	27.6	7.5	6.7	31.9	6.1	2.7	10.0	4.7	3.1	4.8
6	100.0	26.5	7.6	7.0	30.4	6.2	2.6	10.6	5.3	3.2	4.5
7	100.0	24.7	7.2	7.3	31.7	6.0	2.5	11.4	5.0	3.1	5.1
8	100.0	23.8	6.8	6.9	30.3	6.4	3.5	12.7	5.2	3.0	5.5
9	100.0	21.8	6.0	6.8	29.2	6.4	3.3	14.8	5.1	3.4	5.9
Richest	100.0	15.1	3.7	6.9	23.4	6.7	3.7	26.2	3.8	4.4	9.4
Total	100.0	23.5	6.4	7.2	28.2	6.3	3.3	16.5	4.9	3.7	7.0

Source data: Household Budget Survey 2008

Table 2.2: Variables Used in the Construction of the Asset Index

Housing Characteristics:	Household Assets:	
Type of Housing	Fridge	Cable TV
Number of Rooms	Electric oven	Camera
Size of Housing	Microwave	CD Player
Source of Water	Dishwasher	Telephone
Type of Toilet	Blender	Cell Phone
Type of Floor	DVD Player	PC
	Washing machine	Internet
	Video Camera	Private Car
	Air conditioner	Taxi Minibus
	Satellite cable	Tractor
	Vacuum cleaner	Motorcycle
	TV	Bicycle
	Video	Number of TVs
	Number of Private Cars	Number of Cell Phones

Table 2.3: Administrative Data On Non-Cash Credit From Banks, By Province In Turkey

	December-07	September-08	June-09	A (% change in non-cash credit from banks between Sep 2008 and June 2009)	B (% change in non-cash credit from banks in province Dec 2007- Sep 2008.)	A - B Xp = Rate of reduction in non-cash credit available from banks
Adana	1,468,413	1,883,069	1,719,041	28.24%	-8.71%	36.95%
Ankara	19,481,350	24,677,791	31,753,881	26.67%	28.67%	-2.00%
Erzurum	165,603	195,135	183,117	17.83%	-6.16%	23.99%
Gaziantep	1,450,283	1,845,386	2,055,470	27.24%	11.38%	15.86%
İstanbul	50,478,581	62,978,770	66,351,274	24.76%	5.35%	19.41%
İzmir	4,317,569	5,522,260	5,128,869	27.90%	-7.12%	35.03%
Kocaeli	2,356,751	2,696,476	2,252,427	14.41%	-16.47%	30.88%
TURKEY	94,469,968	117,128,527	126,756,979	23.98%	8.22%	15.76%

Note: X_p = (% change in non-cash credit from banks between Sep 2008 and June 2009) - (% change in noncash credit from banks in province Dec

Source data: Turkey Banking Sector Regulation Agency (BDDK)

Table 2.4: Summary Statistics for Changes in Earnings of Household Head (Oct 2008–May 2009)

Probability of lower earnings reported by the household head

	Urban/Rural Location					
	Urban		Rural		Total	
	Mean (%)	SE	Mean (%)	SE	Mean (%)	SE
Educational Attainment of HH Head						
Illiterate or no schooling (n=223)	3.31	(1.25)	4.21	(2.51)	3.42	(1.14)
Primary School (n=1,130)	15.31	(1.52)	19.37	(2.30)	15.56	(1.41)
Junior or Senior Secondary School (n=784)	15.98	(1.90)	0.00	(0.00)	15.84	(1.89)
Higher education (n=265)	14.81	(3.08)	21.13	(14.80)	14.82	(3.07)
Total (n=2,402)	14.48	(1.08)	13.30	(2.20)	14.43	(1.04)
Labor Status of HH Head in October 2008						
Employed: Formal (n=963)	26.47	(2.27)	33.17	(7.07)	26.54	(2.24)
Employed: Informal (n=323)	33.74	(5.41)	54.92	(9.42)	35.00	(5.21)
Not working (n=1,116)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Total (n=2,402)	14.48	(1.08)	13.30	(2.20)	14.43	(1.04)
Asset index quintile						
1 (n=481)	17.38	(3.01)	20.44	(3.28)	18.11	(2.40)
2 (n=480)	20.55	(2.23)	13.42	(4.92)	20.09	(2.12)
3 (n=481)	17.19	(2.29)	8.01	(3.41)	16.91	(2.21)
4 (n=480)	13.46	(2.52)	0.00	(0.00)	13.20	(2.49)
5 (n=480)	11.85	(1.71)	0.00	(0.00)	11.76	(1.70)
Total (n=2,402)	14.48	(1.08)	13.30	(2.20)	14.43	(1.04)

Source: Turkey Welfare Monitoring Survey (TWMS) May 2009

Table 2.5: Summary Statistics for Changes in Expenditures and Consumption (Oct 2008-May 2009)

<i>Probability of reporting changes in consumption behavior</i>			
Variable	Mean	(Std. Dev.)	N
Reduced food expenditures	43.51	(49.59)	2402
Reduced education expenditures	8.91	(28.49)	2402
Reduced health expenditures	14.45	(35.16)	2402
Reduced expenditures on durables	22.11	(41.51)	2402
Reduced food consumption	56.79	(49.55)	2402
Substituted into cheaper food items	70.90	(45.43)	2402
Was short of money and had to stretch the food at home	51.04	(50)	2402
Had to reduce amount of food given to children	24.02	(42.73)	2402
Had to withdraw of postpone the admission of children to school	2.66	(16.11)	2402
Had to transfer children to cheaper public or private school	1.04	(10.15)	2402
Had to cancel health insurance	2.08	(14.28)	2402
Had to reduce the use of curative health services	20.48	(40.37)	2402
Had to reduce visits to the doctor for preventive care	18.65	(38.96)	2402

Source data: Turkey Welfare Monitoring Survey (May 2009)

[htbp]

Table 2.6: Link between the Macro Shock and Household Level Income Shock: the probability of getting shock to earnings given province level macro shock and worker characteristics
Reporting marginal effects results of the probit estimation

	(1) All workers	(2) All workers	(3) HH Head Workers	(4) HH Head Workers
Crisis proxy at province level	0.294*** (0.0937)	0.303*** (0.106)	0.377** (0.150)	0.381** (0.161)
Educ: Illiterate or no schooling	0.141** (0.0649)	0.271** (0.125)	0.138** (0.0657)	0.380 (0.248)
Educ:Primary School	0.166*** (0.0366)	0.170*** (0.0620)	0.186*** (0.0415)	0.154** (0.0648)
Educ:Junior or Senior Secondary School	0.0649* (0.0341)	0.0305 (0.0353)	0.0937* (0.0492)	0.0352 (0.0494)
Labor status of worker: Informal	0.126*** (0.0210)	0.0581* (0.0301)	0.160*** (0.0396)	0.0847 (0.0843)
Crisis proxy X Illiterate or no schooling		-0.588 (0.424)		-0.936 (0.878)
Crisis proxy X Primary School		-0.0133 (0.246)		0.168 (0.243)
Crisis proxy X Junior or Senior Secondary School		0.163 (0.128)		0.292* (0.159)
Crisis proxy X Informal Status		0.321** (0.143)		0.357 (0.321)
Observations	1889	1889	1163	1163

Marginal effects; Standard errors in parentheses

Source data: Turkey Welfare Monitoring Survey (May 2009).

(d) for discrete change of dummy variable from 0 to 1

* p<0.10, ** p<0.05, *** p<0.01

Table 2.7: Changes in Food, Education, Health and Durable Expenditures - Reporting marginal effects from Probit Regressions

(Refer to Equation (2.5) and (2.6) in Empirical Specification)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reduced Food Expenditures		Reduced Education Expenditures		Reduced Health Expenditures		Reduced Durables Expenditures	
The person has lower earnings now than in Oct 2008	0.152*** (0.034)	0.143*** (0.034)	0.009 (0.019)	0.016 (0.018)	0.028 (0.028)	0.025 (0.028)	-0.011 (0.030)	-0.012 (0.029)
Urban location	-0.081* (0.046)	-0.011 (0.079)	0.021 (0.030)	0.041 (0.052)	0.041 (0.033)	0.019 (0.041)	0.154*** (0.069)	0.237*** (0.114)
Educ: Illiterate or no schooling	-0.062 (0.111)	-0.215 (0.135)	0.054 (0.052)	0.071 (0.072)	-0.001 (0.062)	-0.001 (0.082)	-0.145 (0.094)	-0.209 (0.131)
Educ: Primary School	0.124** (0.052)	0.035 (0.059)	0.066** (0.031)	0.098*** (0.035)	0.047 (0.033)	0.052 (0.040)	0.014 (0.043)	-0.020 (0.046)
Educ: Junior or Senior Secondary School	0.091* (0.052)	0.040 (0.056)	0.042 (0.029)	0.049 (0.034)	0.046 (0.031)	0.037 (0.037)	0.069** (0.035)	0.041 (0.040)
Asset Index	-0.061*** (0.020)	-0.095*** (0.024)	-0.010 (0.011)	-0.006 (0.013)	-0.026* (0.014)	-0.018 (0.019)	-0.044** (0.019)	-0.061*** (0.023)
Earnings shock X Urban		-0.031 (0.106)		-0.006 (0.073)		0.059 (0.075)		-0.122 (0.091)
Earnings shock X Illiterate or no schooling		0.165 (0.190)		-0.150 (0.107)		-0.028 (0.128)		0.094 (0.193)
Earnings shock X Primary School		0.114 (0.124)		-0.161*** (0.057)		-0.019 (0.072)		0.048 (0.088)
Earnings shock X Junior or Senior Second. School		0.069 (0.119)		-0.054 (0.057)		0.034 (0.075)		0.055 (0.088)
Earnings shock X Assets index		0.059 (0.036)		-0.025 (0.019)		-0.031 (0.027)		0.042 (0.034)
Number of children in HH younger than age 15 (age <=14)		0.031* (0.016)		0.009 (0.008)		0.004 (0.010)		0.013 (0.013)
Number of adults in HH (age > 14) (non-children)		0.046*** (0.014)		0.021*** (0.007)		0.008 (0.011)		0.013 (0.013)
Observations	1,163	1,163	1,163	1,163	1,163	1,163	1,163	1,163

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source data: Turkey Welfare Monitoring Survey (May 2009)

Table 2.8: Changes in Food, Education and Health Expenditures (IV Regressions - Marginal Effects)

(Refer to Equation (2.7) in the empirical specification.)

	Reduced food expenditures			Reduced education expenditures			Reduced health expenditures		
	(1) 2SLS	(2) IV Probit mfx	(3) First stage results	(4) 2SLS	(5) IV Probit mfx	(6) First stage results	(7) 2SLS	(8) IV Probit mfx	(9) First stage results
Lower earnings	0.333* (0.193)	0.330* (0.170)		0.005 (0.114)	-0.001 (0.136)		-0.071 (0.124)	-0.070 (0.114)	
Urban location	-0.032 (0.081)	-0.028 (0.081)	-0.232*** (0.058)	0.021 (0.046)	0.018 (0.050)	-0.233*** (0.058)	0.015 (0.050)	0.012 (0.051)	-0.234*** (0.058)
Educ: Illiterate or no schooling	-0.120 (0.103)	-0.113 (0.105)	0.175* (0.095)	0.044 (0.064)	0.057 (0.066)	0.175* (0.095)	0.017 (0.066)	0.029 (0.075)	0.175* (0.095)
Educ: Primary School	0.068 (0.065)	0.076 (0.070)	0.207*** (0.043)	0.058* (0.035)	0.069 (0.044)	0.207*** (0.043)	0.064 (0.042)	0.073 (0.048)	0.207*** (0.043)
Educ: Junior or Senior Secondary	0.056 (0.048)	0.066 (0.055)	0.115*** (0.040)	0.030 (0.025)	0.043 (0.034)	0.115*** (0.040)	0.050* (0.030)	0.059 (0.037)	0.115*** (0.040)
Asset Index	-	-0.069*** (0.019)	0.053*** (0.017)	-0.010 (0.011)	-0.010 (0.012)	0.053*** (0.017)	-0.021 (0.013)	-0.021 (0.014)	0.052*** (0.017)
Cpisis proxy at province level			0.298*** (0.100)			0.310*** (0.117)			0.319*** (0.098)
Labor status of worker: Informal			0.156*** (0.035)			0.153*** (0.041)			0.151*** (0.038)
Constant	0.276*** (0.067)		0.285*** (0.022)	0.088* (0.040)		0.283*** (0.025)	0.148** (0.044)		0.281*** (0.022)
Observations	1,163	1,163	1,163	1,163	1,163	1,163	1,163	1,163	1,163
R-squared	0.029			0.008					

Robust standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

Source data: Turkey Welfare Monitoring Survey (May 2009)

Table 2.9: Robustness checks: Changes in Food Consumption Patterns (IV Regressions - Marginal Effects)

(Refer to Equation (2.7) in the empirical specification)

VARIABLES	Reduced Amount of Food Consumption			Substituted into cheaper food items			Had to "stretch" food consumption at home			Had to reduce the amount of food provided to children--		
	2SLS	IV Probit mfx	First stage results	2SLS	IV Probit mfx	First stage results	2SLS	IV Probit mfx	First stage results	2SLS	IV Probit mfx	First stage results
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lower earnings +	0.798*** (0.218)	0.578*** (0.061)		0.551*** (0.182)	0.465*** (0.084)		0.559*** (0.200)	0.490*** (0.109)		0.452** (0.228)	0.394** (0.189)	
Urban location	0.180* (0.093)	0.148** (0.068)	-0.237*** (0.058)	0.340*** (0.084)	0.322*** (0.062)	-0.240*** (0.058)	0.132 (0.083)	0.127* (0.074)	-0.235*** (0.058)	0.074 (0.097)	0.077 (0.083)	-0.222*** (0.067)
Educ: Illiterate or no schooling	-0.020 (0.120)	-0.020 (0.100)	0.176* (0.095)	0.125 (0.099)	0.115 (0.115)	0.178* (0.096)	0.292*** (0.097)	0.324** (0.134)	0.176* (0.095)	0.152 (0.140)	0.185 (0.145)	0.280** (0.118)
Educ: Primary School	0.052 (0.077)	0.041 (0.070)	0.208*** (0.043)	0.082 (0.068)	0.033 (0.067)	0.208*** (0.043)	0.111 (0.070)	0.121 (0.081)	0.207*** (0.043)	-0.011 (0.088)	0.064 (0.101)	0.282*** (0.056)
Educ: Junior or Senior Secondary School	0.062 (0.058)	0.054 (0.054)	0.115*** (0.040)	0.074 (0.055)	0.033 (0.049)	0.116*** (0.040)	0.091* (0.052)	0.108* (0.062)	0.115*** (0.040)	0.001 (0.058)	0.068 (0.079)	0.156*** (0.052)
Asset Index	-0.142*** (0.023)	-0.116*** (0.017)	0.050*** (0.016)	-0.131*** (0.021)	-0.114*** (0.017)	0.049*** (0.017)	-0.142*** (0.021)	-0.137*** (0.018)	0.052*** (0.017)	-0.149*** (0.028)	-0.151*** (0.023)	0.080*** (0.021)
Crisis proxy at province level			0.351*** (0.083)			0.370*** (0.086)			0.329*** (0.092)			0.305*** (0.116)
Labor status of worker: Informal			0.140*** (0.036)			0.133*** (0.040)			0.148*** (0.037)			0.165*** (0.049)
Constant	0.231*** (0.076)	0.275*** (0.020)	0.272*** (0.020)	0.489*** (0.064)	0.272*** (0.020)	0.272*** (0.020)	0.274*** (0.069)	0.279*** (0.021)	0.279*** (0.021)	0.122 (0.079)	0.122 (0.079)	0.290*** (0.027)
Observations	1,163	1,163	1,163	1,163	1,163	1,163	1,163	1,163	1,163	788	788	788

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

- Lower earnings defined as: household head has lower earnings in May 2009 than in Oct 2008 (sample limited to households where household head had a job in Oct 2008).

-- Sample limited to household that have children in age group 0-14 (and where household head was employed in October 2008)

Source data: Turkey Welfare Monitoring Survey (May 2009)

□

Table 2.10: Robustness checks Changes in Educational and Health Utilization Variables (IV Regressions - Marginal Effects)
(Refer to Equation (2.7) in the empirical specification)

VARIABLES	Education-related						Health-related					
	Withdrawn/postponed admission to school, college or kindergarten			Transferred children to cheaper public or private school			Reduced utilization of health services			Reduced utilization of preventive health services		
	2SLS	IV	First stage results	2SLS	IV	First stage results	2SLS	IV	First stage results	2SLS	IV	First stage results
(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	
Lower earnings	0.100 (0.098)	0.100 (0.177)		0.009 (0.064)	0.009 (0.070)		0.769*** (0.198)	0.606*** (0.066)		0.072 (0.138)	0.062 (0.156)	
Urban location	0.022 (0.043)	0.020 (0.034)	-0.210*** (0.073)	-0.001 (0.035)	-0.002 (0.029)	-0.209*** (0.073)	0.084 (0.091)	0.079 (0.059)	-0.232*** (0.058)	-0.033 (0.060)	-0.024 (0.055)	-0.233*** (0.058)
Educ: Illiterate or no schooling	-0.056 (0.060)	-0.032 (0.059)	0.301** (0.123)	0.013 (0.050)	0.005 (0.035)	0.301** (0.123)	-0.183 (0.117)	-0.106 (0.091)	0.176* (0.095)	0.026 (0.080)	0.045 (0.080)	0.175* (0.095)
Educ: Primary School	-0.039 (0.040)	-0.014 (0.042)	0.304*** (0.063)	-0.016 (0.034)	-0.015 (0.027)	0.303*** (0.063)	-0.077 (0.064)	-0.029 (0.053)	0.207*** (0.043)	0.074 (0.046)	0.087* (0.052)	0.207*** (0.043)
Educ: Junior or Senior Secondary School	-0.009 (0.028)	0.007 (0.030)	0.180*** (0.059)	-0.005 (0.029)	-0.005 (0.022)	0.180*** (0.059)	-0.036 (0.045)	-0.000 (0.044)	0.115*** (0.040)	0.040 (0.032)	0.055 (0.041)	0.115*** (0.040)
Asset Index	-0.031** (0.014)	-0.028 (0.020)	0.084*** (0.024)	0.000 (0.010)	0.001 (0.008)	0.085*** (0.024)	-0.067*** (0.021)	-0.050*** (0.015)	0.053*** (0.016)	-0.014 (0.015)	-0.014 (0.015)	0.053*** (0.017)
Crisis proxy at province level		0.307** (0.141)			0.294** (0.138)				0.292*** (0.084)			0.305*** (0.105)
Labor status of worker: Informal		0.150*** (0.056)			0.153*** (0.051)				0.158*** (0.033)			0.154*** (0.038)
Constant	0.000 (0.034)	0.296*** (0.032)		0.016 (0.023)	0.299*** (0.032)		-0.096 (0.067)		0.286*** (0.020)	0.123** (0.048)		0.284*** (0.023)
Observations	635	635	635	635	635	635	1,163	1,163	1,163	1,163	1,163	1,163

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Note: Education related regressions include only the sub-sample of households that have children between the ages of 6-14 inclusive. All regressions are limited to households where the household head was working in October 2008.

Source data: Turkey Welfare Monitoring Survey (May 2009)

Chapter 3

Protective Impact of the Green Card Non-Contributory Health Insurance Program in Turkey

3.1 Introduction

Free or subsidized health insurance programs targeted to the poor are often used in developing countries to provide access to basic health care. The main justification for such programs is rights-based, and rests on the belief that adequate medical care is a fundamental human right (Anand et al., 2004). However, potential distributional gains from such transfers are usually accompanied by large fiscal costs to the public budget as well as efficiency losses that may occur as a result of distortions in incentives for purchasing health insurance and health care. It is therefore important to carry out careful evaluations of the effectiveness of such programs, both in terms of their actual impact on health care demand and utilization, as well as their success in reaching the target populations.

Several such studies have been carried out in developing countries to look at the impact of publicly provided health insurance schemes for the poor. Trujillo et al. (2005) evaluate the impact of Colombia's subsidized health insurance program (SUBS) on health care utilization. The authors use a propensity score matching, as well as an instrumental variables method, to measure the impact of the demand-side subsidy on health care utilization. They use a data set that combines a unique household survey with community and regional data and find using both methods that Colombia's subsidized insurance program significantly increased health utilization among the country's poor and unin-

sured.

Pradhan et al. (2001) consider the impact of the Indonesian health-card program, which was implemented in response to the Asian economic crisis that hit Indonesia in 1997, and provided owners of health cards with subsidized care from public providers. The authors look at the impact of this program on outpatient care utilization and find that the program resulted in a net increase in utilization for poor beneficiaries. The authors note that for non-poor beneficiaries the program resulted in a substitution from private to public providers only.

Jütting (2004) focuses on a community-based health insurance program in rural Senegal. The main finding of the paper is that members of community-based mutual health organizations have a higher probability of using hospitalization services than non-members and pay substantially less when they need care. The targeting analysis in the paper shows that while the scheme attracted poor people, the poorest of the poor remained excluded.

This paper contributes to this literature by focusing on the expansion of a similar publicly provided free health insurance program in Turkey, the Green Card (*Yeşil Kart*) program, which aims to provide health benefits to the poor who are not covered through formal means of health insurance. Initially launched in 1992, the Green Card program saw a rapid expansion of beneficiaries and program benefits between 2003 and 2006. In this period, the number of beneficiaries for the card increased more than four-fold, from 2.5 million beneficiaries to 10.2 million beneficiaries. User benefits also expanded during this period, creating higher demand for the card by poor households: in 2004, Green Card holders started to benefit from outpatient as well as inpatient services at hospitals and as of January 2005, they became fully covered for outpatient prescription drugs. The expansion in the number of beneficiaries and benefits associated with the card, took place in parallel to significant increases in the budgetary allowance for the program. The budget for the Green Card program expanded from 780 million TL in 2004 to 3.65 billion TL in 2008.

Beginning in the final quarter of 2008, the Turkish economy was hit by the global financial events of late 2008. In the final quarter of 2008, growth plummeted to -6.5 percent. GDP shrank further in the first quarter of 2009 and continued to contract until growth resumed in the final quarter of 2009 to yield an estimated -4.7 percent GDP contraction for 2009. The crisis had a significant impact on households, mainly through reduced labor incomes. After remaining stable at levels below 10 percent for several years, the unemployment rate peaked at 16 percent in 2009 Q1. As discussed in the previous chapter (in Section 2.4.1), health care utilization also fell for about one-fifth of

the sample of households: 20.5 percent of households report reducing utilization of health care services and 18.7 percent of households mention utilizing preventive care services less since the onset of the crisis. The probability of reducing health care utilization was also higher among the poorer households as identified in Figure 2.6 Panel D. The Green Card program had already been in place, covering by the end of 2008 when the crisis hit, a large percentage of the poor in Turkey. The crisis period provided an occasion to test the protective impact of this large scale program, to see if the reduction in utilization of health care was across the board for the poor, or whether those who were covered by the Green Card were indeed protected from having to reduce their utilization.

The objective of this chapter, then, is to measure the effectiveness of the Green Card as a social safety net program for protecting the health care utilization of poor households during the financial crisis of 2008-09. The structure of the paper is as follows: Section 2 provides a conceptual framework for the paper in terms of theory and sets forth the empirical specification for the parametric estimation. Section 3 gives information on the data sets used in the empirical analysis. Section 4 provides information on the institutional set-up and targeting mechanism of the program, as well as highlighting the rapid increase in coverage. Section 5 focuses on the main results focusing on the impact of the program on protecting the health utilization of the poor in Turkey through the Global Financial Crisis in 2008-09. Section 6 concludes with main findings.

3.2 Conceptual Framework

3.2.1 The Model

The paper uses a simple household production model following the Grossman model for health demand. The model has a utility maximizing framework with indifference curves, constrained by the income level, price of health inputs and consumption activities, as well as the opportunities for transforming health inputs into health (Wagstaff, 1986) (McGuire et al., 1988) The individual's objective is to attain the highest consumption possibility contour, subject to his budget constraints and the health production function.

The Grossman model of health demand is considered below (as provided in McGuire et al. (1988)). The individual's objective is to maximize life-time utility. This is a function of Z_t , a composite consumption good, and h_t , the services which flow from the health stock. In other words H_t represents the healthy days derived from the stock of

health. The individual maximizes utility:

$$U = f(h_0, \dots, h_t; Z_0, \dots, Z_t)$$

The service flow, health days (h_t), is produced from the health stock (K_t^h), such that:

$$h_t = \Phi_t(K_t^h) : \Phi_t' > 0, \Phi_t'' < 0$$

Where Φ_t' may be considered as the marginal product of the stock of health as measured in healthy days. The stock changes over time may be shown by:

$$K_{t-1}^h - K_t^h = I_t^h - \delta K_t^h$$

Where I_t^h is new investment in health and δ_t is the rate of depreciation of the capital stock of health.

The individuals produce the gross investments in health and the other commodities in the utility function from the following households production functions:

$$I_t^h = I_t^h(X_t^h, T_t^h, E_t)$$

$$Z_t = Z_t(X_t^z, T_t^z, E_t)$$

Where X_t^h is health care and X_t^z is the market goods input in the production of Z; T_t^h is the time spent investing in health and T_t^z the time input for producing Z; E_t is the stock of human capital.

The life time budget constraint equates the present value of purchases to the present value of life cycle earnings plus initial asset endowments:

$$\sum_{t=0}^T \frac{P_t^z X_t^z + P_t^h X_t^h}{(1+r)^t} = \sum_{t=0}^T \frac{W_t + T_t^w}{(1+r)^t} + A_0$$

Where r is the opportunity cost of capital (the constant rate of interest), P_t^z and P_t^h are the prices of X_t^z and X_t^h respectively, W_t is the wage rate and A_0 is the discounted value of capital income.

Maximizing the utility function in the first line, subject to the constraints in the model and rearranging, the marginal condition for new health investment can be written as:

$$\frac{U_{\Phi_t} (1+r)^t}{\lambda} \cdot \frac{\Phi_t'}{MC_{t-1}^h} + \frac{W_t \Phi_t'}{MC_{t-1}^h} = r + \delta_t - \overline{MC_{t-1}^h}$$

Where $U_{\Phi_t} = \delta U / \delta \Phi_t$ which is the marginal utility of health time; λ is the marginal utility of wealth; Φ'_t is the marginal productivity of health as measured by healthy days; MC_{t-1}^h is the marginal cost of health investment in period t-1; and $\overline{MC_{t-1}^h}$ is the percentage rate of change in marginal costs between periods t-1 and t.

This equation sets at the margin, the user cost of health capital equal to the discounted marginal benefits of health. At the margin, benefits must equal costs in equilibrium; that is the total rate of return to an investment in health must equal the user cost of that capital as expressed by the price of gross investment. Thus reading the final equation in the model from left to right: the first term expresses the monetary rate of return (the investment benefit), the second term expresses the psychic rate of return (the consumption benefit), and the right hand side expresses the user cost as determined by the real own-rate of return ($r \cdot \overline{MC_{t-1}^h}$) and the depreciation rate.

The model is provided in Figure 3.1 as a four-quadrant diagram. Quadrant I gives the utility curves for health and other consumption, while Quadrant II provides the health production function with diminishing returns. The health production function shows how much health can be obtained for a given level of health input. In Quadrant III, the budget constraint is provided with a trade-off between health inputs and consumption on other goods. The slope of the budget constraint reflects relative costs. Key to the model is that health inputs do not translate one-to-one into health outcomes (or consumption) as a result of diminishing returns on the health production function. The model allows for the determination of the combination of health input activities and other consumption that the consumer may choose. Quadrant I transforms the information in Quadrants III through the 45 degree line of Quadrant IV. The concave curve on Quadrant I is the consumption possibility frontier, with equilibrium given in 'point a' in the initial conditions.

Faced with an income shock (or a macro shock that results in the anticipation of an income shock), the budget constraint shifts as provided in Panel A of Figure 3.1. In the absence of health insurance coverage, this is translated in Quadrant II into lower health (consumption) as a result of reduced health inputs into the health production function. The equilibrium moves from 'point a' to 'point b' in Panel A, whereby health demand is reduced along with the consumption of other goods. On the other hand, when the consumer is protected by non-contributory health insurance, the budget constraint in Quadrant III is convex whereby there is a kink at the point where insurance coverage ends. For a consumer who initially demands health care at 'point a' (assuming this is also the maximum coverage level for health insurance), when the budget constraint shifts with the income shock the amount of health inputs purchased remains the same.

While the income shock is translated into reduced consumption of other goods, health inputs remain protected. The equilibrium with health insurance protection, in the face of the income shock is at ‘point c’ on Panel B, where health demand (utilization) is higher than at ‘point b’ with the income shock (and with no health insurance). Hence, a non-contributory health insurance scheme is expected to protect health demand in the face of an income shock, with the level of health care utilization being closer in value in this scenario to the original level than in the case with no insurance.

3.2.2 Empirical Specification

The analysis in the paper compares the reduction in the health care utilization of Green Card holding households with households with no insurance coverage. The counterfactual in the analysis therefore is households that did not have access to any form of health insurance (whether through the Green Card or through mandatory SGK coverage). We model the different behavior of households with access to the Green Card and with no health insurance throughout the crisis using three different estimation techniques: (i) a non-parametric technique, (ii) parametric linear probability model and maximum likelihood *probit* regressions and (iii) propensity score matching.

When modeling the impact of a demand-side subsidy on health care utilization, one encounters the challenge of dealing with problems of “self-selection”. Comparing medical care use between program participants (the treatment group) and non-participants (the control group) may result in a biased estimate of the program’s effect. These groups may be different in terms of their characteristics, which may influence both their level of medical care utilization and their decision to participate in the program. With experimental data, this bias disappears because the random assignment of individuals to each group balances the observable and unobservable individual characteristics affecting health utilization.

In the absence of experimental data, this paper makes use of a unique household welfare monitoring survey collected during the financial crisis of 2008-09, and asks households retrospective questions about their health care utilization through the crisis. Using this “pseudo-panel”¹ retrospective questionnaire, it becomes possible to isolate household fixed effects and focus on the probabilities of “change” for each household in the utilization of health care services through the crisis.

¹It is important to note here that there may be serious measurement problems, such as “recall bias” in retrospective data sets, as they rely on perceptions and the memory of respondents.

The empirical specification for the parametric estimation in time t is:

$$y_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 N_t + \beta_3 N_t G_{it} + \beta_4 X_i + \beta_5 H_{it} + \beta_6 H_{it} G_{it} + u_{it} \quad (3.1)$$

Where

- y_{it} is the utilization of health services for household i in period t .
- G_{it} is the ownership of the Green Card for household i in period t .
- N_t is the dummy variable for the national level macro shock (the Crisis). The dummy takes the value of 1 in t_1 and 0 in t_0 in this setting.
- $N_t G_{it}$ is the interaction term for having access to the Green Card in period t and experiencing the macro shock.
- X_i summarizes household fixed characteristics and u_{it} is the household and time specific error term.
- H_{it} is the household level variable for household income.
- $H_{it} G_{it}$ is the interaction term for having access to the Green Card in period t and income at the household level

We only have two time periods in the data: $t=0$ in October 2008 and $t=1$ in May 2009, and we only observe the changes in health utilization behavior (dummy variable for reducing health care utilization) in t_1 , rather than levels in both periods. The same holds for income at the household level. The retrospective data allow us to track changes in income level at the household.

Hence the difference in equations for the two time-periods becomes:

$$\Delta y_{it} = y_{i1} - y_{i0} = \beta_1 (G_{i1} - G_{i0}) + \beta_2 (N_1 - N_0) + \beta_3 (N_1 G_{i1} - N_0 G_{i0}) + \beta_5 (H_{i1} - H_{i0}) + \beta_6 (H_{i1} G_{i1} - H_{i0} G_{i0}) + (u_{i1} - u_{i0}) \quad (3.2)$$

The dependent variable Δy_{it} is a binary variable in the data set taking a value of 1 if the household reports having reduced health care utilization (of curative and preventive care respectively). The coefficient β_1 gives the additional impact of obtaining access to the Green Card for those households that did not have access to it in t_0 . The sign of β_1 is expected to be positive. In the data set at hand, the variable for access to the Green Card in t_0 is not observed and it is also known that this period is not a period of

expansion for the Green Card². Hence, for simplification we make the assumption here that households that have access to the Green Card as of May 2009 already had access to the card in October 2008. The macro shock variable N takes the value 1 in May 2009 and 0 in October 2008 (as the severity of the crisis was most acute in labor statistics in the final quarter of 2008). In equation 3.2., we set $N_1 = 1$ in t_1 and $N_0 = 0$ in t_0 , and assuming that there has not been a change in the household's Green Card holding status between t_0 and t_1 ($G_{i1} = G_{i0}$), we derive a simplified form of the equation as follows:

$$\Delta y_{it} = \beta_2 + \beta_3 (G_{i1}) + \beta_5 (H_{i1} - H_{i0}) + \beta_6 G_{i1} (H_{i1} - H_{i0}) + (u_{i1} - u_{i0}) \quad (3.3)$$

where $E(u_{i1} - u_{i0}) = 0$

In the linear probability model (LPM) this is represented as:

$$E(\Delta y_{it} | G, x) = \beta_2 + \beta_3 (G_{i1}) + \beta_5 (H_{i1} - H_{i0}) + \beta_6 G_{i1} (H_{i1} - H_{i0}) \quad (3.4)$$

G_{it} stands for Green Card holder-ship by household i and in time period 0 or 1, N stands for the macro shock in the time period, and H_{it} represents an income shock experienced at the household level³. The coefficient β_2 measures the associated impact of the macro shock on the probability of reducing health care utilization. The coefficient is expected to have a positive value (with the macro shock being associated with a positive probability of reducing utilization of health care).⁴ β_3 coefficient can be interpreted as the protection provided by having access to the Green Card in period t_1 given the macro shock and β_6 is the coefficient for the protection provided to the household in the face of a household level income shock. The sum of β_3 and β_6 together can be interpreted as the average treatment effect of the Green Card in the face of the macro level shock and the idiosyncratic income shock at the household level taking place at the same time.

Normally, household characteristics drop out of the differenced equation as household-fixed effects. By retaining them in the model, the model allows for house-

²As of 2010, the number of green card holders was 9.5 million indicating that the total number of Green Card beneficiaries did not increase during 2008-2010. It is possible that there were new entries into the list of beneficiaries while some beneficiaries lost status, however for the purposes of this paper we will assume the beneficiaries in the sample that had access to the card in May 2009 (t_2) also had access to the card in October 2008 (t_1).

³We assume that $N_1 = 1$ in May 2009 and $N_0 = 0$ in October 2008 and that Green Card holdership status does not change between the two time periods. These two assumptions lead to the more simplified form of the equation.

⁴Note that the question used in the survey for the change in health utilization questions are "Have you had to reduce visits to the doctor since Oct 2008?" and "Have you had to reduce your use of preventive health care services since Oct 2008?". Hence, both questions when answered positively involve a reduction in the utilization of health care in the time period t_0 to t_1 .

hold characteristics to be associated differently with the change in utilization. In this way, by retaining household characteristics in the specification, the LPM model becomes:

$$E(\Delta y_{it}|G, x) = \beta_2 + \beta_3(G_{i1}) + \beta_4 X_i + \beta_5(H_{i1} - H_{i0}) + \beta_6 G_{i1}(H_{i1} - H_{i0}) \quad (3.5)$$

In the estimation, the household characteristics (X_i) include: (i) the household asset index; (ii) the educational attainment level of the household head; and (iii) household demographic composition (number of infants, children, adults and elderly in the household). All of these characteristics may potentially be correlated with health care utilization and demand, and many of them as proxies for poverty are also correlated with the Green Card variables. Hence, controlling for these characteristics we obtain a more unbiased and consistent OLS estimator for the partial correlation coefficient (β_3).

The main results for the parametric regression are provided using the LPM rather than a maximum likelihood (ML) estimator, acknowledging its shortfalls in estimation where the dependent variable is a binary outcome. The reason for the selection of the LPM is the importance in the estimation of the constant term (β_2), which represents the associated reduction in health care utilization as a result of the macro level shock, and indicates in this set up the probability of reducing health care utilization for those who are not covered by any form of health insurance. We would like to obtain an estimate of the size of this coefficient and compare the estimate of (β_3) on the protective impact of the Green Card against this coefficient. The estimated marginal effects following the maximum likelihood estimation models do not allow for the estimation of the constant term and are therefore less suitable for the purposes of this paper. However, as a robustness check, and in order to compare the results on the size of the protective impact of the Green Card (β_3) and (β_6) under the LPM and maximum likelihood estimation, robustness checks are subsequently run here using a ML *probit* model.

3.3 Data

3.3.1 Data Sources

The main data sets used in the analysis are (i) the Turkey Household Budget Surveys (HBS) from six consequent years (2003-08) and (ii) the Turkey Welfare Monitoring Survey Baseline data set (from May 2009).

HBS data sets are cross-sectional household surveys collected annually by the Turkish Statistical Institution (TURKSTAT). The main purpose of these data sets is to provide estimations of expenditure levels in various categories and allow for poverty calculations

from detailed consumption data. The samples are nationally (and urban/rural level) representative for each year of data and the survey sizes are 25,764 households in 2003, and about 8,640 households in subsequent years from 2004 to 2008. These data sets are chosen for this study as they provide information over time on households' access to health insurance — and *particularly* the Green Card.

The second main data set used for the analysis is the Turkey Welfare Monitoring Survey (TWMS) baseline data set. We have set up this survey instrument with the aim of monitoring the welfare of Turkish households through the crisis of 2008-09 and to measure the ways in which households cope with the economic turndown. The collection of the data set was financed collectively by the World Bank and UNICEF in Turkey. We fielded the survey in May-June 2009 with retrospective questions on welfare looking back to October 2008. We administered the urban sub-sample of the survey used in this paper in five major urban city centers of Turkey, including Istanbul, Ankara, Izmir, Kocaeli and Adana. The urban sample size is 2,102 households and the survey is representative at the level of the five urban city centers, which also make up 40 percent of the total urban population of the country⁵. The timing of the rapid welfare monitoring survey instrument is important in that the crisis hit households hardest in the last quarter of 2008 in terms of GDP and unemployment figures. We set up questions in the survey in such a way that households were asked to reflect upon their income and welfare levels as of May 2009 in comparison to October 2008, which can be assumed to be the onset of the macro shock in Turkey at the household level.

This is a household level survey that we designed as a rapid monitoring tool that would give immediate feedback to policy makers on the changes in the income and welfare level of households through the Global Financial Crisis in Turkey. The survey was fielded twice in the same households: in May 2009 (baseline) and in December 2009 (panel). The funding for the survey was provided by the World Bank and UNICEF and data collection was carried out by BAREM a local research institute. We have designed this survey with specialized modules that relate to coping strategies and access and utilization of safety nets. In this paper, only the baseline data from this survey is

⁵For 5 provinces in the sample that represent urban city centers (Istanbul, Kocaeli, Izmir, Ankara, Adana), a sample of 2,102 households was selected using stratified sampling such that 100 PSUs were selected at the 5 city center level (pooled) with over-sampling of poor neighborhoods, and with random sampling of households within each PSU. The data sampling process was carried out in collaboration with the Turkish Statistical Institute (TURKSTAT) and the weighted estimates of population averages in the urban sample, such as average education attainment rates, labor force participation rates, employment composition by sector, compare closely with estimates provided by TURKSTAT in the official Labor Force (LFS) and the Household Budget (HBS) Surveys for Turkey.

utilized. However, the baseline survey already had *retrospective* questions that asked households to compare their status of income, earnings, labor status, consumption and utilization of education and health services in May 2009 (t_2), with these levels in October 2008 (t_1). In the survey questionnaire, October 2008 was selected as the reference period for most of these comparison questions since it can be considered as the beginning/onset of the crisis in Turkey in terms of the macro figures.

3.3.2 Description of Variables

The HBS variables utilized in the analysis come from the individual and expenditures modules of the data set and the details on specific variables used are as follows:

1. *Access to Health Insurance*: The main variables used for analyzing the targeting and coverage of the Green Card program is the health insurance (*saglıks*) variable in the HBS individual module, which provides information on whether each individual in the household is covered through a mandatory insurance scheme, non-mandatory (*isteğe bağlı*) insurance scheme, or the Green Card.
2. *Expenditure deciles*: The targeting and coverage analysis is carried out using the nominal per capita expenditure deciles for households, constructed using the total nominal expenditures variable (*harcama*) in the data set, divided by the number of individuals in the household.⁶
3. Household and individual factor expansion weights: The HBS data sets use stratified two-stage sampling, and the paper adjusts for the weighting in the first stage of sampling and inflate the figures to population projection numbers using the household factor expansion weights.

The Turkey Welfare Monitoring Survey (TWMS) includes a health module, as well as questions in the “Coping Mechanisms” module that relate to the household’s utilization of health services. The survey also includes questions on the access of individuals to different types of health insurance, and it is possible to track their health utilization behavior through the period of the crisis by their access to health insurance and, in particular, the Green Card. While the TWMS baseline is a cross-sectional data set, it includes *retrospective* questions that ask household heads and their spouses whether

⁶The regionally deflated and adult equivalence and economies of scale adjusted consumption aggregates are not made available by TURKSTAT and in the absence of regional identifiers cannot be recreated, hence rather than constructing deciles around the real per adult equivalent consumption aggregate, the paper uses the nominal per capita expenditures for the construction of deciles.

they have had to adapt/change household behavior in order to cope with the crisis by utilizing less of health services. In this way, it becomes possible to manipulate the data as a “pseudo-panel” data set, whereby the characteristics of the household remain the same over the crisis period. We can therefore assess whether having access to the Green Card at the household level through this period was associated with “*less of a reduction*” in the utilization of preventive care and visits to the doctor, compared with a group of households that did not hold any form of health insurance.

In this paper, we use questions in the survey that relate to changes in health care utilization of households through the period in Turkey when the economic turndown—in terms of unemployment and GDP growth—was experienced most negatively: namely the period from October 2008 to May 2009. In particular, we consider the responses of households to the two questions in the baseline data: (i) “*Have you had to reduce visits to the doctor between October 2008 and May 2009?*”; and (ii) “*Have you had to reduce the utilization of preventive health services from October 2008 to May 2009?*”⁷ These variables are labeled as utilization of curative care and preventive care, respectively, in the analysis.

The asset index used among the control variables in the parametric estimation is a measure of household-level wealth based on housing characteristics and household durable goods. It is constructed using a principal components analysis following the Filmer-Pritchett asset index (Filmer and Pritchett, 2001) whereby wealthier households are identified with higher levels of the asset index. The asset index enters the parametric estimation as an independent variable in this analysis.

3.4 Institutional Background and Targeting of the Green Card

The Green Card program was initially set up in 1992 and has been a social assistance mechanism centrally financed through general revenues, by the Ministry of Health. Prior to 2002, the budget and coverage of the program remained small (Yildirim and Yildirim, 2011). Through the Health Transformation Program (HTP), launched in 2002, several fundamental changes were made in the health financing system in Turkey which impacted the benefits package of the Green Card and increased the demand for these cards in the time period analyzed. In essence, the program was scaled up significantly to cover more people with increased benefits. In 2005, Green Card holders were given access for the

⁷The variable names used in the analysis for health care utilization through the Crisis are “mo” and “ms” and can be found in the Coping Strategies module of the data set.

first time to outpatient care and pharmaceuticals making Green Card holdership more desirable than in earlier years. The applications for the program increased as a result of changes in the benefits package. The Ministry of Health has increased the budget allocated to the Green Card program from 780 million TL in 2004 to 3.65 billion TL in 2008. While the program made up about 16% of the budget for the Ministry of Health in 2004, this level has reached over one-third of the Ministry's budget in 2008.

3.4.1 Program Eligibility Criteria

While the Green Card scheme was financed from general taxes allocated through the Ministry of Health, the application process was evaluated and finalized by local committees and the District level. The Green Card is distributed through a community targeting mechanism that combines community discretion with eligibility rules determined by the central government. In this *hybrid* targeting scheme, centrally appointed *kaymakams* (district officers) are given discretion for the distribution of the card following eligibility rules determined by the central government. The applications are collected at the district level Green Card offices, which usually report directly to the centrally appointed district or provincial officers (*kaymakams* or *valis*). The ultimate decisions on the distribution of the cards are made by local committees chaired by the *kaymakam* (in districts) and the deputy governor in charge of the Green Card in the province center. In 2008, when field interviews were conducted by the author in local Green Card offices, the application and card allocation process was organized in the following manner:

Step 1: For districts and provinces with population exceeding 50.000 people, the application process was handled through a Green Card service center. The one-stop service center checked to see if the applicant was registered with any of the social security institutions (*SSK*, *Emekli Sandığı* or *Bağkur*) or if the person had any motor vehicles (ownership of a car would prevent the person from getting a Green Card).

Step 2: The total income of the household was calculated by adding the reported incomes of the individuals in the household to any estimated income from agricultural land holdings. The total household income was then divided by the number of people in the household. If the estimated income per capita was less than 1/3 of minimum wage (net of taxes) then the household members became eligible for the Green Card.

Step 3: The local committee decided whether or not qualifying persons (according to steps one and two above) should indeed obtain the Green Card. Even if the household was formally eligible, the committee could use discretion not to provide the card if it evaluated the person/s not to be poor. The household members who qualified each got

their own green booklet which registered all interactions with the health system from that point on.

This hybrid targeting mechanism that merged central criteria with local knowledge and assessment may have contributed to the successful targeting of program benefits as studied in the next section.

3.4.2 Coverage and Targeting of the Green Card

The analysis of HBS surveys in 2003-08 shows that health insurance coverage of the poor in Turkey has increased considerably in this time period, with the expansion in the coverage of both obligatory (formal sector) insurance schemes, as well as the Green Card. The coverage of obligatory insurance schemes (*SSK, Emekli Sandığı* and *Bağkur*) expanded from 40.6 million individuals (59 percent of the population) in 2003 to 50.1 million individuals (69 percent of the population) in 2008 according to HBS data. In the same period, the total number of individuals who report having access to the Green Card at the household level increased from 2.5 million individuals in 2003 to 10.2 million in 2006 and then declined to 9.5 million in 2008. As a result of the expansion of health insurance schemes in Turkey, the percentage of population in 2008 covered by some form of health insurance increased from 24 percent in 2003 to 82 percent in 2008.

The poor, who have traditionally *not* been covered by formal sector health insurance mechanisms, have benefited most significantly from the expansion of health insurance coverage, mainly through the expansion of the Green Card. While in 2003, only about 24 percent of the poorest decile was covered by some kind of health insurance plan (of which 12 percent was covered through the Green Card), while by 2008, 82 percent of this decile was covered by health insurance, 69 percent of which was covered by the Green Card. Figure 3.2 shows the rapid and progressive expansion of the Green Card scheme.

These household-level findings are consistent with administrative data sources: According to the statistics by the Ministry of Health, as of September 2008 the total number of Green Card holders in Turkey was about 9.4 million people. The Ministry of Health reports that there have been cancelations of about 6 million Green Cards in 2003-08, which may explain the drop in the total beneficiary numbers from 2006-07 to 2008. The Ministry of Health increased the budget allocated to the Green Card program from 780 million TL in 2004 to 3.65 billion TL in 2008. While the program made up about 16 percent of the budget for the Ministry of Health, in 2008 this level reached over one-third of the ministry's budget (see Table 3.1).

It is noteworthy that despite the rapid roll-out of the Green Card program from

2003 to 2008, there was no deterioration in the targeting performance of the program. On the contrary, an analysis of HBS data shows that the targeting performance of the Green Card improved over time in this expansion period. While in 2003, 55 percent of benefits accrued to the bottom quintile, this targeting performance improved over time with 64 percent of benefits reaching this group in 2005, 68 percent in 2007 and finally 71 percent of benefits reaching the bottom quintile in 2008. In international comparisons, we find that Turkey's Green Card program is better targeted to the poor than many targeted poverty programs from around the world. The targeting of the Green Card scheme in Turkey can be deemed a success by international standards. As of 2008, 71 percent of program benefits accrued to the bottom quintile of the distribution, while 90 percent of program benefits accrued to the bottom 2 quintiles (see Figure 3.3). In comparison, 60 percent of Chile's SUF cash transfers, 39 percent of Brazil's *Bolsa Escola* CCT program, 34 percent of Mexico's *Oportunidades* CCT program and 34 percent of Indonesia's *Kartu Sehat* health insurance program for the poor benefited the bottom quintile of the population in those countries (Lindert and Castaeda, 2005).

3.5 Empirical Results

Health care utilization of households through the recent economic turndown has been documented in the TWMS, which can be used as a data source on the strength and relevance of the safety net that the Green Card program provided through this period. If the poor are in fact protected by the presence of the Green Card, we would expect that their utilization of health services not to be affected in the face of an overall economic shock.

3.5.1 Summary Statistics

The paper models the different behavior of households with access to the Green Card and with no health insurance throughout the crisis. Before launching on this analysis, it is useful to provide some descriptive statistics for sub-groups in our sample by insurance category. The below analysis compares the reduction in the health care utilization of Green Card-holding households with households with no insurance coverage.

Table 3.2 Panel A provides summary statistics for household head characteristics for Green Card holders (treatment group) and other types of insurance holders and non-holders (which later becomes the control group) in the urban sample. Since the program is targeted to the poor, in the overall sample, we see that Green Card-holding

households on average have less educational attainment by the household head and are more likely to be employed in the informal sector, as of October 2008. The gender of the household head is also more likely to be female for Green Card-holding households. These means are statistically significantly different for the Green Card-holding group and the no insurance-holding group in the overall sample. In Table 3.2 Panel B, we see the same results for the sample of households in the poorest asset quintile only. Here the difference across insurance types among the poorest quintile of households is less pronounced: the difference in education attainment for the household head is not significantly different for the Green Card-holding and no insurance-holding group in the poorest asset quintile. The proportion of household heads employed in agriculture and industry are also similar across the two groups. The only difference remains in the proportion of household heads formally employed: while among Green Card-holding households this ratio is 4.3 percent, the ratio of informal workers among non-Green Card-holding households is 21.1 percent. This difference is to be expected since informal sector of employment is a prerequisite for eligibility to the Green Card program. Table 3.3 provides information on household demographics and assets for the different insurance groups for the whole urban sample and for the poorest asset quintile, respectively. Green Card holders differ from the other groups in the urban sample in that they live in larger households (average household size of 4.8 people in the urban sample of which 3 are children), with smaller space (in m²) per capita. Similarly, their likelihood of owning certain household items is lower than the other insurance groups. In the bottom asset quintile, however, these differences once again disappear for household size and for most household assets. This indicates that in the limited sample of the poorest asset quintile, the group of households with no health insurance and the group of households with the Green Card are similar to each other on observable characteristics.

3.5.2 Non-parametric Estimation

Using the TWMS urban data set, we then look at the below non-parametric comparisons:

$$\Delta y_t(x) = E(\Delta y|x, G_i = 1)$$

$$\Delta y_t(x) = E(\Delta y|x, G_i = 0, H_i = 0)$$

where G_i is the treatment variable for having access to the Green Card; H_i is the variable for having access to other health insurance at the household level (through formal sector health insurance *SGK* or private insurance); and x is log income per capita in

the household. The outcome variable Δy_t is a binary variable that represents reduction in health utilization between October 2008 and May 2009 and takes on two different variable definitions: (i) reduction in utilization of curative care; and (ii) reduction in utilization of preventive care.

Table 3.4 provides estimates of the probability of reducing utilization of curative care and preventive care for the whole sample and for the poorest per capita income quintile for those households that have access to the Green Card and those that do not have access, respectively, between October 2008 and May 2009. In the group of households that has no access to health insurance, the probability of reducing utilization through this period is 36.6 percent, while for Green Card holders the probability is 21.7 percent.⁸ Similarly, we observe a reduction in the utilization of preventive health care (in Panel B of same table): those who have no health insurance are 16 percentage points more likely to reduce utilization of preventive health care services compared with those holding a Green Card. Once again, the difference is statistically significant with (p value <0.01). Table 3.4 Panel B runs the same analysis limiting the sample only to the poorest per capita income quintile of the urban households. For this group, the difference in the means is larger at 18.8 percentage point's difference in means for curative and 26.4 percentage point's difference for preventive care. Both differences are statistically significant for the sample of poor households.

Figure 3.4 plots the non-parametric kernel regression estimates for the probability of reducing utilization of curative and preventive health services through the crisis period. The figure plots the conditional probabilities for reducing health care utilization for the Green Card-holding group ($G_i = 1$ in equation (1)) and the group of households with no health insurance coverage. The non-parametric kernel estimation confirms the results in Table 3.4 that are provided for mean differences across the insurance groups and also gives the distribution of the difference in probability of changing utilization. The x-axis in these plots is log per capita income and the analysis is run at the household level for the health care utilization variables and Green Card ownership. In this analysis, it is possible to observe that the difference in probabilities is largest among the poorer quintiles, where the poor households with no health insurance are most likely to reduce health care utilization — although if they have access to the Green Card their probability of reducing utilization drops significantly (to almost zero for the poorest households). Confidence intervals at the 90 percent confidence level are provided for each estimation. The finding is statistically significant for most income per capita levels at the 90 percent

⁸The difference of 14.8 percentage points between the two groups is statistically significant (with a p-value<0.01), using a Pearson Chi-2 test comparing two binomial distributions.

confidence level. The figure indicates that throughout the crisis, poor households were, overall, more likely to reduce health care utilization. However, if covered by the Green Card program, the program may have provided them with the protection needed to maintain health care utilization.

3.5.3 Parametric Estimation

Main Results

By imposing structure on the relationship between G_i and Δy_i , we estimate the average treatment effect (ATE) this time using a parametric regression. The parametric regression model using retrospective data on change in health care utilization as the dependent variable, is provided in Equation 3.3 and the LPM is represented in Equation 3.4. The LPM regression results are provided for the above specification in Table 3.5 for the two different dependent variables on health care utilization: in columns 1 and 3 for utilization of curative care and preventive care, respectively.

In the LPM regressions, the sample is limited to households that either have access to the Green Card or have no health insurance, hence the dropped category (and counterfactual) in the LPM regressions is the group where the household head has no health insurance in the urban sample. Such households on average had a 33.9 percent likelihood of reducing utilization of curative care and 24.7 percent likelihood of reducing preventive care in the period analyzed (as provided by the constant term in the regressions, and represented in Equation 3.4 as β_2). As expected, the β_2 coefficient turns out to have a positive, large and statistically significant value. For households that received a household level income shock in addition to the macro level shock, their probability of reducing utilization of curative health care increased by a further 18.9 percentage points (see Column 1), though their utilization of preventive care did not change (denoted by β_5 in Equation 3.4).

In the estimation, we consider the partial correlation coefficient of having access to health insurance through the Green Card. The category that is dropped out of the regression is the category for not having access to any kind of health insurance. The OLS regression yields a consistent estimate of the ATE as long as the expectation of the difference in the errors vanishes to zero.⁹

Households that had access to the Green Card were less likely to reduce utilization

⁹This is another way of saying; unobservable disturbances are the same in both time periods for treatment and control groups. In this context of health care utilization in Turkey, this means, the treatment (Green Card group) and control groups (no health insurance) have the same distribution on their error terms (before and after the crisis).

of curative care by 12.5 percentage points and preventive care by 15.8 percentage points. (represented by β_3 in Equation 3.4 , this can be interpreted as the interaction term between the macro shock of the crisis and access to the Green Card at the household level.). The interaction term between Green Card holder-ship and the income shock does not reveal statistically significant coefficients (β_6) in these regressions. This suggests that while Green Card households, overall, were less likely to reduce health care utilization compared with no insurance holders, the protective impact of the Green Card cannot be documented among those that received a household level income shock. In other words, for households that received an income shock in particular, having access to the Green Card did not reduce their likelihood of reducing utilization (this can be the result of a small sample size, where we do not have enough observations of households that received the income shock and had access to the Green Card at the same time, to establish a statistically significant result for this variable). The average treatment effect on health care utilization (protective impact) of the Green Card among those households that received an income shock can be calculated as the sum of β_3 and β_6 coefficients in Equation 3.4 . Since β_6 does not take on a statistically significantly different value than zero, this is simply the value of β_3 in these regressions.

Robustness Checks

In order to provide robustness checks on the results provided above, we control for household characteristics (X_i) as in Equation 3.5, allowing for a more flexible model whereby household characteristics may be associated with the change in health utilization differently in the two periods. The results of the LPM regression for the specification in Equation 3.5 are provided in Table 3.5 A in Columns 2 and 4, respectively, for curative and preventive health care utilization. Here, we consider again the partial correlation coefficient of having access to health insurance through the Green Card on changes in health care utilization by looking at the partial correlation coefficients β_3 and β_6 . The dropped category in these regressions are the households that have no health insurance and where the household head has no formal educational attainment (illiterate or holds no diploma). For this group, the likelihood of reducing health care utilization between Oct 2008 and May 2009 is 43.2 percent for curative care and 20.9 percent for preventive care as reflected by the constant term (β_2).

The results on Green Card protective impact are robust to the addition of these household level characteristics, where the size of β_3 remain negative and significant: minus 11.1 for curative care and minus 14.3 for preventive care with this specification.

These regressions make it possible to analyze the change in health utilization behavior by household characteristics in this time period: we observe for instance that for increased values of the asset index (for wealthier households) the probability of reducing curative health care utilization is lower. Household demographics also matter in determining health care utilization through the crisis: in households where there are infants (ages 0-3), and where there are elderly people (ages 60+) the probability of reducing curative health care utilization is lower. For each additional infant in the household, the probability of reducing curative health care utilization drops by 13.8 percentage points, and for each elderly person added to a household the probability of reducing curative health care utilization drops by 10.8 percentage points.

The marginal effects from the *probit* regression with the specification in Equation 3.4 are provided in Table 3.6, where the dependent variable is the probability of reducing health care utilization for preventive and curative care, respectively. The dummy variable for having access to the Green Card at the household level is associated with a reduction in the probability of reducing visits to the doctor for preventive care by 12.7 percentage points and the probability of reducing utilization of health services for preventive care by 17.1 percentage points compared to households that have no access to health insurance. (Table 3.6 Columns 1 and 3). Once again, the results are robust to controlling for household characteristics in the probit model as provided in Columns 2 and 4 of the same table.

The results using the linear probability model and the *probit* model with marginal effects both give similar conclusions that (i) access to the Green Card when interacted with the macro shock through the crisis (in β_3) is associated with a reduction in the probability of reducing health care utilization (both for preventive and curative care); (ii) that the household level income shock is associated with an increase in the probability of reducing health care utilization (β_6); and (iii) the interaction between the Green Card and the income shock at the household level does not take on a significant coefficient suggesting that the dominant channel through which the Green Card operates is a protection against the macro shock of the financial crisis. One explanation for this can be the fact that households adopt “precautionary” behavior in the face of the macro shock, reducing health care utilization. The Green Card counteracts this reduction in utilization to a certain degree in the overall sample (β_3). However, in the face of an income shock at the household level, the role of the green card is less clear: in the face of a household specific income shock, we do not observe a reduction in the probability of reducing health care utilization for households with the Green Card (β_6). It is possible to say that the parametric findings in this section, confirm the result in the non-parametric

estimation that the likelihood of reducing health care utilization declines with access to the Green Card.

3.5.4 Propensity Score Matching

Main results

An alternative approach to measuring the treatment effect of the Green Card on health care utilization is using propensity score matching. With this technique, we essentially (i) estimate each household's propensity to receive the binary treatment (of having the Green Card), using a *probit* or *logit* model, as a function of observable characteristics; and (ii) match the treated and untreated households on the basis of this propensity score, to compare their differences in the outcome variable (Rosenbaum and Rubin, 1983). In this methodology, we construct cells based on the propensity score, $p(x)$ and compute the expected value of the outcome variable for the treated and untreated observations with the same (or similar) propensity scores (calculating $E(y|w=1) - E(y|w=0)$ in each cell) and then aggregate over all propensity score cells.

The observations in the treatment and control group constructed in this way are comparable to each other since they are equally likely to be treated, although only some were treated. The difference between the two observations gives the effect of the treatment for that particular value of the propensity score (maintaining the selection on observables assumption). Repeating this exercise over many values of the propensity score and then aggregating over the whole sample gives the average treatment effect (ATE).¹⁰

Balancing tests were run to gauge comparability across the treatment and matched control groups, in terms of the list of independent variables used to determine the propensity score. The balancing tests compare the two matched samples using single nearest-neighbor matching. The t-tests for equality of means in the two samples are based on a regression of the variable on the treatment indicator. The results show that the treated and control groups are statistically not different from each other (with $pvalue < .01$) in 13 of the 19 selected indicators.

In order to carry out a different sensitivity analysis, we determine the propensity score using *logit* and *probit* regressions separately. The specification for the regressions determining the propensity score is provided Table 3.7. Household characteristics (household size, composition, housing conditions and assets) as well as the characteristics of

¹⁰The propensity score matching results are obtained using the `psmatch2` package in STATA. (Leuven and Sianesi, 2003)

the household head (gender, educational attainment and type of employment) are used as independent variables to determine the propensity score for accessing the Green Card. Figure 3.5 provides the kernel density plots for the propensity score for the treated and non-treated households in the sample using the *probit* and *logit* estimation. The x axis shows the propensity score in these graphs and it is possible to observe that the treated group in the sample have a higher propensity score for the treatment compared to the non-treated group.

In the main results, the treated observations are matched using one-to-one matching where a single control is used for each treatment observation (with replacement). The resulting average treatment effect from having the Green Card at the household is a reduction in the probability of reducing health care utilization in curative care of 20.8 percentage points and in preventive care 17.1 percentage points using the *probit* determined propensity scores. When *logit* propensity scores are used, the results are: minus 16.8 for curative care and minus 17.7 for preventive care (see Table 3.8 column1 and Table 3.9 column1).

Robustness checks

Next, the treated observations are matched using three other techniques including: (i) nearest neighbor matching; (ii) radius matching; and (iii) kernel matching. The size of the coefficient for the ATE is sensitive to the choice of matching technique and all results of these matching estimators are provided in Table 3.8 and Table 3.9 (columns 2-4) for the two different outcome variables on change in utilization. In nearest neighbor matching, the nearest three neighbors are selected as the control group; in radius matching all untreated observations within a certain radius (in this case caliper 0.2) are included in the control group and in kernel matching multiple controls are used for each treatment, with a weight that declines with the distance from the treatment observation. The standard errors of the estimators are obtained using bootstrapping (with 500 repetitions in each scenario). In order to provide one further robustness check, the data is trimmed in certain scenarios to increase common support and the results of the trimmed sample scenarios are also provided in the results.

Using these different methodologies, Table 3.8 provides results for the change in utilization of curative health care. The average treatment effect in these estimations, varies between 12.7 percentage points and 20.9 percentage points depending on: (i) whether a logit or probit function was used for the determination of the propensity score); (ii) whether trimming was used; and (iii) the matching technique. Similarly

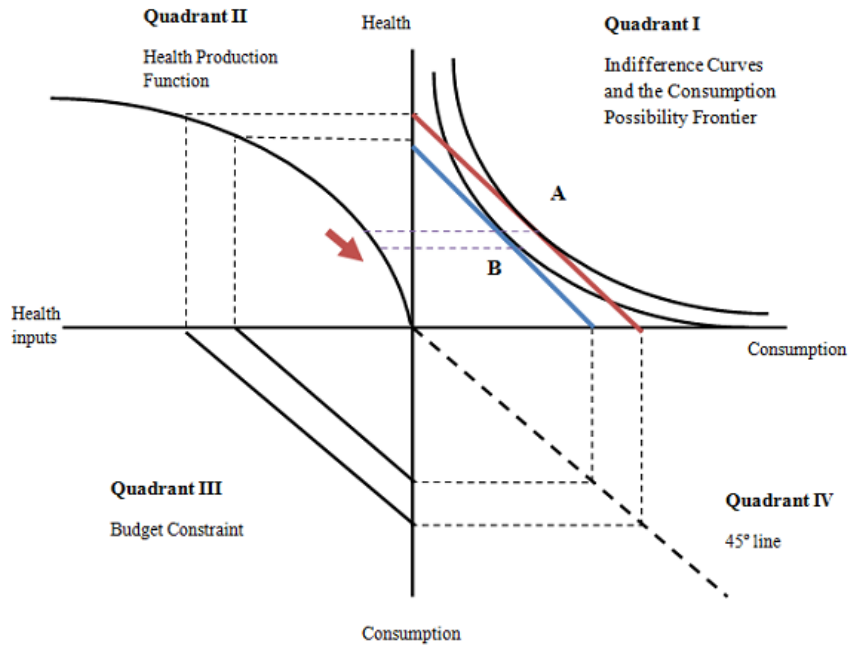
Table 3.9 runs the same analysis for the outcome variable on reduced utilization of preventive care between October 2008 and May 2009 and this table also reports that the average treatment effect of having the Green Card reduces the probability of reducing curative health care utilization by somewhere between 12.7 to 17.7 percentage points.

3.6 Conclusion

The analysis of household surveys indicates that in 2003-08 the rapid roll-out and successful targeting of the Green Card scheme increased the health insurance coverage among Turkey's poor. Having access to the Green Card was associated with a lower probability of reducing utilization of health care services through the crisis in the period from October 2008 to May 2009 in Turkey. Three different methodologies are followed in this paper to measure the impact of having access to the Green Card on protecting the health care utilization of the poor throughout the crisis. Both non-parametric and parametric estimates using the Turkey Welfare Monitoring Survey baseline data signal that the Green Card program was an effective and functional safety net, protecting the health care utilization of the poor during the crisis period. Propensity score matching estimates and robustness checks using four different matching techniques, as well as trimming to increase common support, also confirm that the Green Card had a positive and significant impact on protecting health care utilization of poor households from October 2008 to May 2009.

Figure 3.1: Conceptual Model for the Protection of Health Care Utilization with Insurance for the Poor

(a) Model of Health Demand with Income Shock (no insurance)



(b) Model of Health Demand with Income Shock (with insurance)

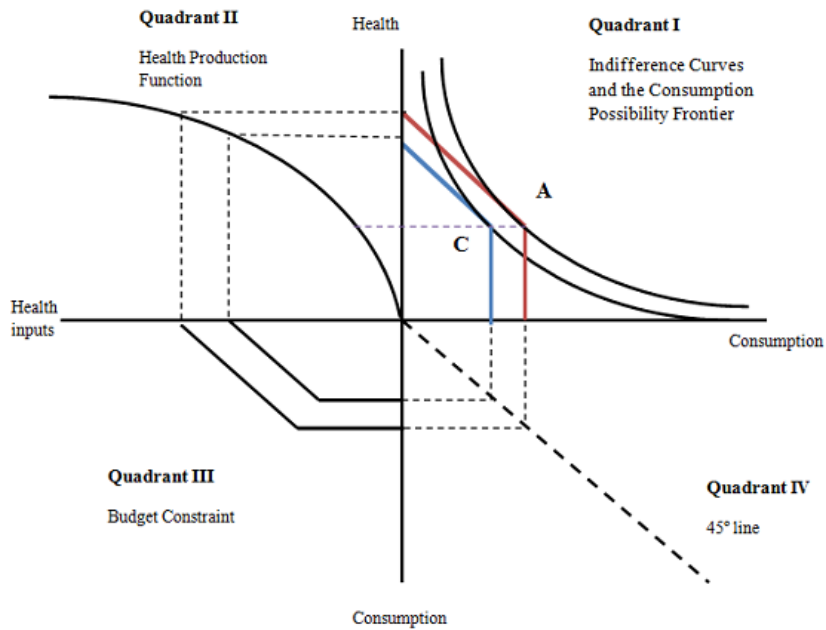
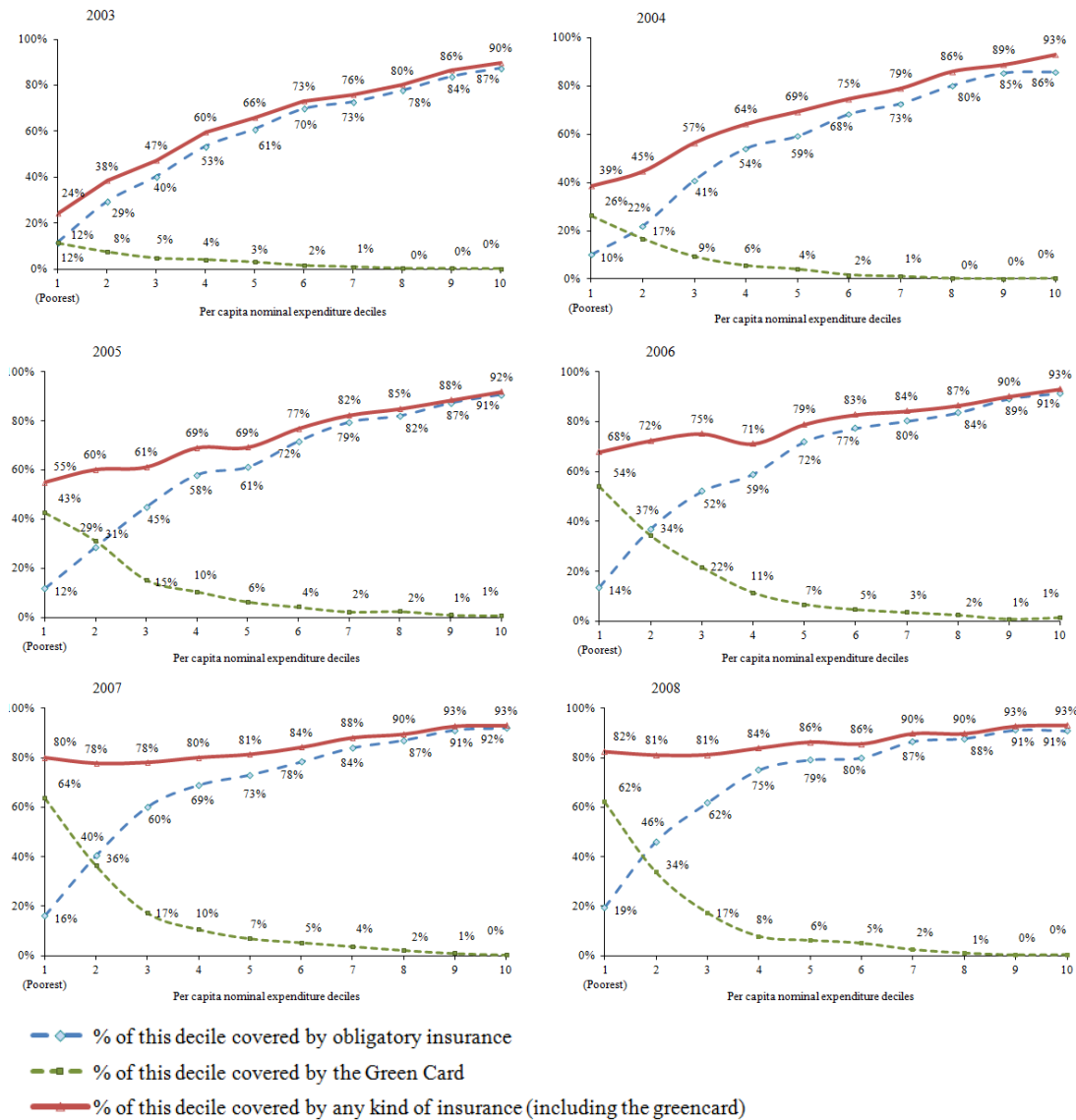


Figure 3.2: Health Insurance Coverage of the Poor Has Increased In Recent Years with the Expansion of the Green Card (2003-2008)

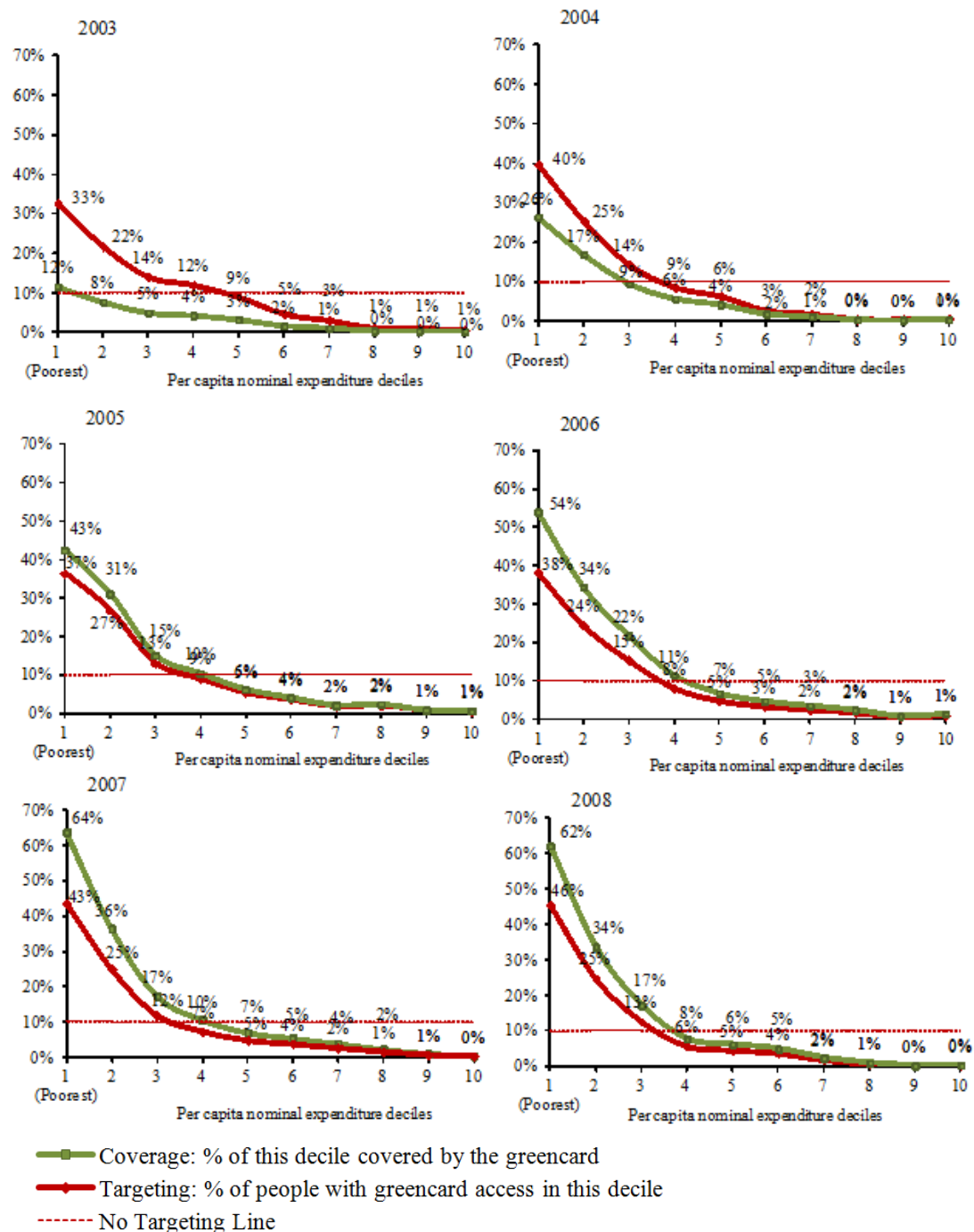
Percentage of households covered by health insurance, by per capita expenditure deciles



Source data: Turkey Household Budget Surveys (2003-2008) and author calculations.

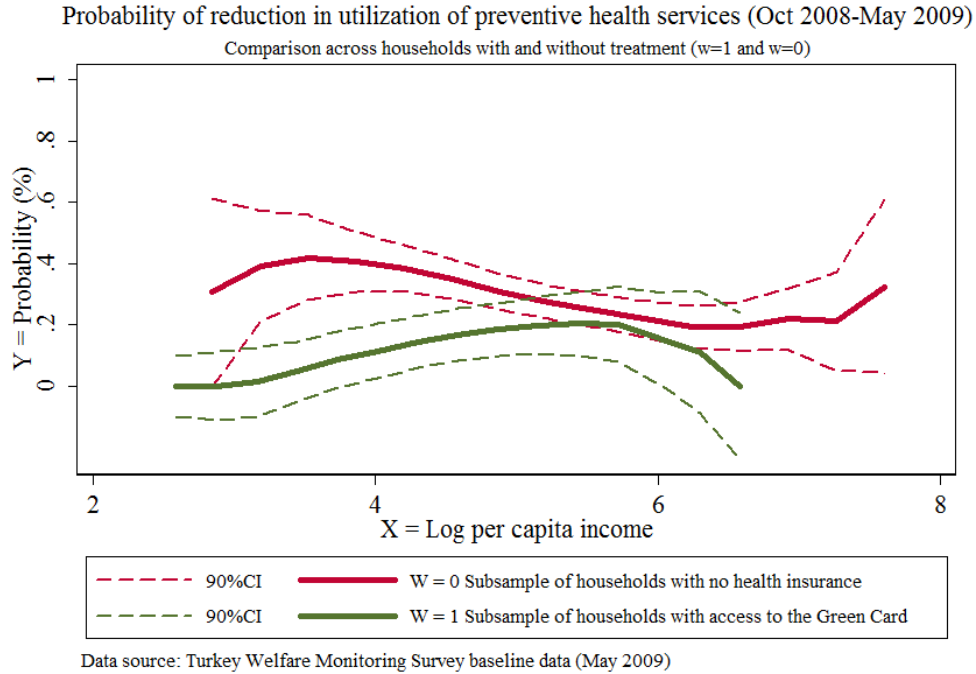
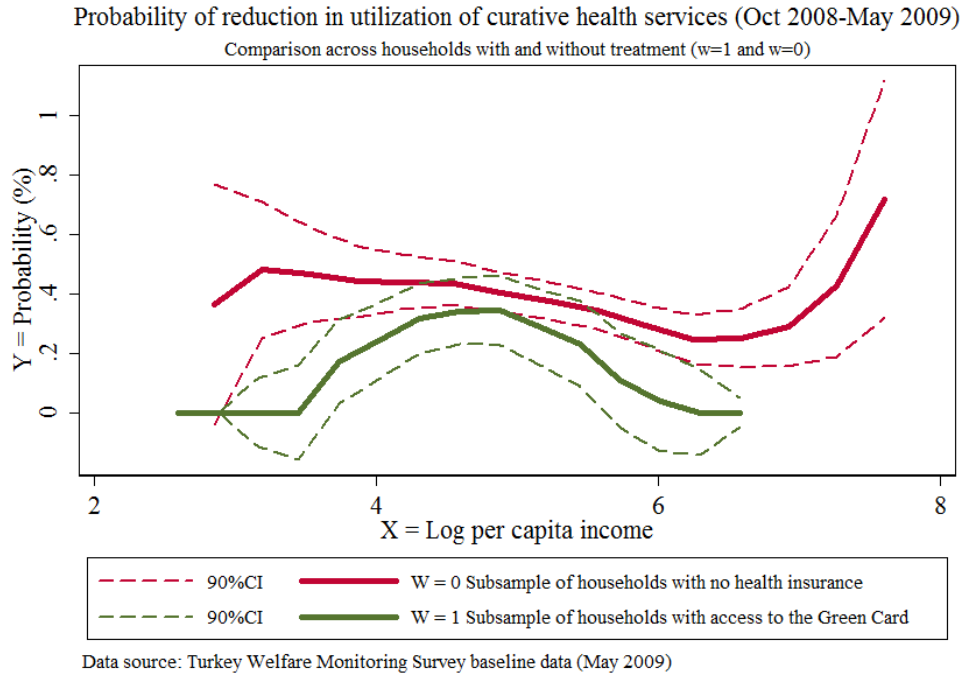
Figure 3.3: Targeting and Coverage of the Green Card Program (2003-2008)

Percentage of Green Card beneficiaries in each per capita expenditure decile



Source data: Turkey Household Budget Surveys (2003-2008) and author calculations.

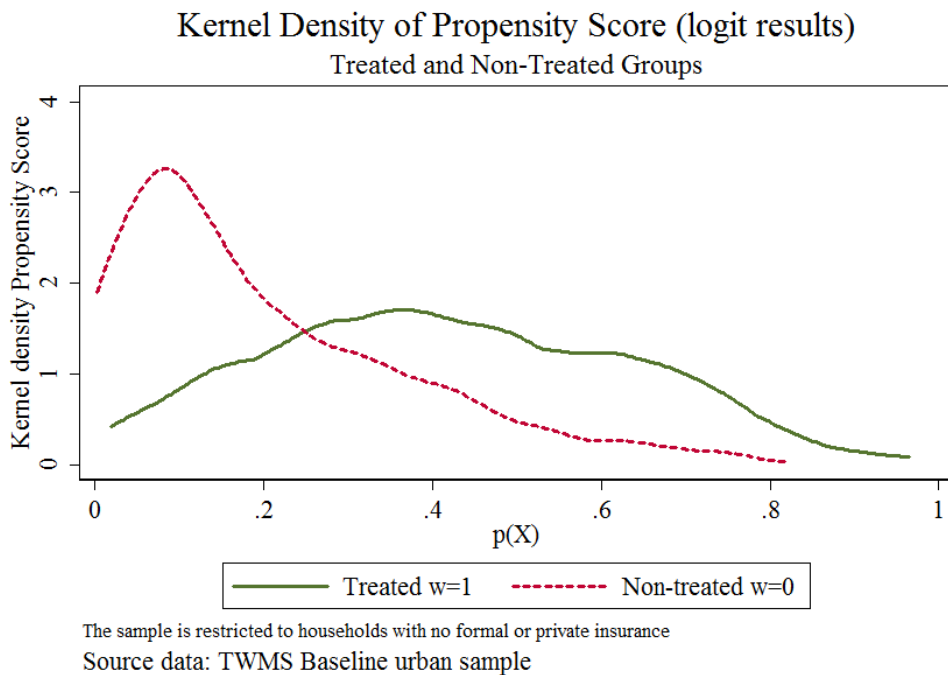
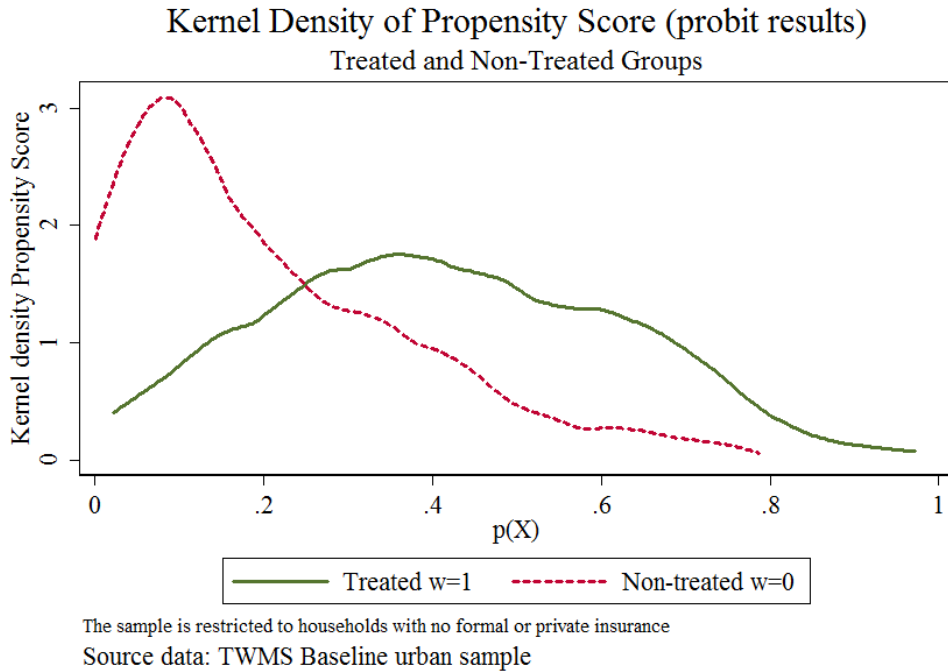
Figure 3.4: Non-Parametric Estimates for the Probability of Reducing Health Utilization through the 2008-2009 Economic Turndown



Source data: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

Figure 3.5: Propensity Score For Treated And Non-Treated Groups

(Using probit and logit Results For Determining The Propensity Score)



Source data: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

Table 3.1: Ministry Of Health Budget Figures (TL)

	2004	2005	2006	2007	2008
Personnel expenditure	3,045,408,000	3,322,865,750	4,549,680,000	5,445,940,000	5,459,423,000
Services and goods	563,820,000	565,693,000	659,361,000	420,907,000	939,874,000
Utilities	10,243,000	10,110,000	10,674,000	10,263,000	10,700,000
Capital expenditure	388,280,000	409,786,000	651,872,000	697,173,000	567,843,000
Green Card program	780,000,000	1,150,000,000	1,600,000,000	3,000,000,000	3,646,000,000
Capital transfer	0	4,520,000	5,884,000	7,172,000	4,230,000
Family medicine	0	0	0	0	200,000,000
TOTAL	4,787,751,000	5,462,974,750	7,477,471,000	9,581,455,000	10,828,070,000

Source: Leive (2008)

Table 3.2: Summary Statistics: Household Head Characteristics by Health Insurance Status

A. Whole Urban Sample

	Primary health insurance provider														
	SGK			Green Card			Private			None			Total		
	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%
Household head educational attainment															
Illiterate or no schooling (n=163)	6.1	[4.9,7.5]	21.3	[14.4,30.5]	0.0		8.2	[4.7,13.7]	8.8	[5.6,8.1]		6.8	[5.6,8.1]		
Primary School (n=923)	38.7	[35.8,41.8]	62.7	[52.0,72.3]	0.0		53.6	[46.1,60.9]	41.1	[38.4,43.9]		41.1	[38.4,43.9]		
Junior or Senior Secondary School (n=754)	37.7	[34.6,41.0]	16.0	[9.5,25.7]	21.4		32.4	[3.3,68.3]	36.3	[33.5,39.2]		36.3	[33.5,39.2]		
Higher Education (n=262)	17.5	[14.6,20.7]	0.0		78.6		5.9	[2.3,14.2]	15.8	[13.3,18.7]		15.8	[13.3,18.7]		
Total (n=2,102)	100.0		100.0		100.0		100.0		100.0			100.0			
Household head labor status (Oct 2008)															
Employed: Formal (n=926)	50.8	[47.5,54.0]	3.8	[1.4,9.8]	78.6		21.2	[15.4,28.5]	45.8	[42.8,48.7]		45.8	[42.8,48.7]		
Employed: Informal (n=259)	6.5	[4.5,9.2]	45.0	[34.3,56.1]	6.6		43.8	[0.6,45.1]	12.3	[10.3,14.7]		12.3	[10.3,14.7]		
Not working (n=917)	42.8	[39.6,46.0]	51.3	[40.4,62.1]	14.8		35.0	[2.0,59.2]	41.9	[39.1,44.8]		41.9	[39.1,44.8]		
Total (n=2,102)	100.0		100.0		100.0		100.0		100.0			100.0			
Household head sector of employment (May 2009)															
Agriculture (n=32)	1.7	[1.1,2.8]	10.4	[4.3,23.4]	0.0		3.7	[1.7,7.9]	2.2	[1.5,3.2]		2.2	[1.5,3.2]		
Industry (n=265)	22.6	[19.5,26.0]	14.8	[6.4,30.5]	0.0		20.9	[14.4,29.2]	22.1	[19.3,25.1]		22.1	[19.3,25.1]		
Construction (n=98)	6.4	[4.8,8.5]	24.9	[12.8,43.0]	0.0		11.8	[7.3,18.6]	7.5	[5.9,9.5]		7.5	[5.9,9.5]		
Services (n=804)	69.2	[65.4,72.8]	49.9	[33.5,66.2]	100.0		63.6	[54.2,72.1]	68.2	[64.7,71.5]		68.2	[64.7,71.5]		
Total (n=1,199)	100.0		100.0		100.0		100.0		100.0			100.0			
Gender of household head															
Female (n=379)	17.7	[15.6,19.9]	22.9	[15.3,32.9]	68.7		13.5	[9.3,19.3]	17.5	[15.6,19.6]		17.5	[15.6,19.6]		
Male (n=1,723)	82.3	[80.1,84.4]	77.1	[67.1,84.7]	31.3		86.5	[80.7,90.7]	82.5	[80.4,84.4]		82.5	[80.4,84.4]		
Total (n=2,102)	100.0		100.0		100.0		100.0		100.0			100.0			

Source: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

B. Poorest Asset Quintile in Urban Sample

	Primary health insurance provider														
	SGK			Green Card			Private			None			Total		
	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%	Mean %	95% CI	%
Household head educational attainment															
Illiterate or no schooling (n=53)	10.2	[6.4,15.9]	21.1	[12.7,32.9]	0.0	14.5	[6.7,28.6]	12.6	[8.9,17.4]						
Primary School (n=250)	62.1	[55.0,68.6]	59.9	[46.2,72.3]	0.0	56.8	[44.4,68.4]	60.5	[54.8,65.9]						
Junior or Senior Secondary School (n=104)	25.0	[19.4,31.6]	19.0	[10.3,32.5]	0.0	27.3	[18.2,38.9]	24.9	[20.4,30.1]						
Higher Education (n=9)	2.7	[1.4,5.5]	0.0		0.0	1.4	[0.2,9.0]	2.1	[1.1,4.0]						
Total (n=416)	100.0		100.0		100.0	100.0		100.0							
Household head labor status (Oct 2008)															
Employed: Formal (n=170)	55.8	[48.8,62.6]	4.3	[1.4,12.7]	0.0	21.1	[12.6,33.0]	41.1	[35.7,46.6]						
Employed: Informal (n=86)	10.0	[5.9,16.6]	48.2	[34.7,62.0]	0.0	38.0	[27.0,50.4]	21.5	[16.9,26.9]						
Not working (n=160)	34.2	[28.0,40.9]	47.5	[34.2,61.2]	0.0	40.9	[29.9,52.9]	37.4	[32.3,42.9]						
Total (n=416)	100.0		100.0		100.0	100.0		100.0							
Household head sector of employment (May 2009)															
Agriculture (n=16)	5.9	[2.8,12.1]	7.7	[2.4,22.1]	0.0	5.5	[2.0,14.3]	6.0	[3.4,10.4]						
Industry (n=62)	26.7	[20.1,34.4]	15.0	[6.0,32.7]	0.0	17.8	[8.8,32.6]	23.7	[18.4,29.9]						
Construction (n=28)	9.7	[4.8,18.5]	31.4	[15.4,53.5]	0.0	11.1	[5.0,22.6]	12.0	[7.7,18.3]						
Services (n=150)	57.7	[49.0,66.0]	45.9	[26.6,66.4]	0.0	65.6	[50.1,78.4]	58.3	[51.1,65.2]						
Total (n=256)	100.0		100.0		100.0	100.0		100.0							
Gender of household head															
Female (n=42)	7.9	[4.8,12.8]	21.6	[12.5,34.7]	0.0	9.6	[4.4,19.6]	9.9	[7.0,13.8]						
Male (n=374)	92.1	[87.2,95.2]	78.4	[65.3,87.5]	0.0	90.4	[80.4,95.6]	90.1	[86.2,93.0]						
Total (n=416)	100.0		100.0		100.0	100.0		100.0							

Source: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

Table 3.3: Summary Statistics: Household Size, Demographics and Asset Ownership by Health Insurance Status

	Whole urban sample											Poorest Asset Quintile										
	Green Card						No health insurance					Green Card						No health insurance				
	Obs.	Mean	Std. Err	95% CI	Obs.	Mean	Std. Err	95% CI	Obs.	Mean	Std. Err	95% CI	Obs.	Mean	Std. Err	95% CI	Obs.	Mean	Std. Err	95% CI		
Household size	92	4.77	0.22	4.33 5.21	268	4.15	0.11	3.94 4.36	58	5.81	0.25	5.31 6.30	96	5.69	0.18	5.32 6.06						
Number of children in HH (age <=14)	92	1.79	0.16	1.46 2.11	268	1.29	0.08	1.13 1.45	58	2.42	0.20	2.03 2.82	96	2.19	0.15	1.89 2.49						
Number of adults in HH (age >14)	92	2.98	0.14	2.70 3.27	268	2.86	0.08	2.71 3.01	58	3.38	0.20	2.99 3.78	96	3.50	0.16	3.18 3.82						
No of rooms per capita	92	0.79	0.04	0.71 0.87	268	0.95	0.03	0.89 1.02	58	0.57	0.02	0.53 0.61	96	0.60	0.02	0.57 0.64						
No of bedrooms per capita	92	0.48	0.02	0.44 0.52	268	0.56	0.01	0.54 0.59	58	0.41	0.01	0.38 0.44	96	0.43	0.01	0.41 0.46						
Housing size / capita (m2)	92	21.36	1.34	18.69 24.03	268	27.23	1.03	25.19 29.26	58	15.04	0.58	13.88 16.21	96	16.56	0.53	15.51 17.61						
<i>Likelihood of Owning Household Assets:</i>																						
Fridge	92	0.95	0.02	0.90 0.99	268	0.99	0.01	0.97 1.00	58	0.95	0.03	0.89 1.01	96	0.96	0.02	0.92 1.00						
Microwave	92	0.02	0.01	0.01 0.04	268	0.06	0.01	0.03 0.09	58	0.02	0.02	0.02 0.07	96	0.01	0.01	0.01 0.02						
Dishwasher	92	0.09	0.03	0.03 0.16	268	0.30	0.03	0.25 0.36	58	0.08	0.04	0.01 0.15	96	0.17	0.04	0.09 0.24						
DVD player	92	0.15	0.04	0.08 0.22	268	0.28	0.03	0.22 0.33	58	0.11	0.04	0.02 0.19	96	0.11	0.03	0.04 0.17						
Washing Machine	92	0.90	0.03	0.84 0.96	268	0.90	0.02	0.86 0.93	58	0.91	0.04	0.83 0.98	96	0.83	0.04	0.76 0.91						
TV	92	0.95	0.02	0.91 1.00	268	0.99	0.01	0.98 1.00	58	0.99	0.01	0.96 1.02	96	1.00	-	1.00 1.00						
Telephone	92	0.18	0.04	0.10 0.26	268	0.45	0.03	0.39 0.51	58	0.15	0.05	0.06 0.24	96	0.33	0.05	0.23 0.42						
Cell Phone	92	0.89	0.03	0.82 0.95	268	0.94	0.01	0.91 0.97	58	0.92	0.04	0.84 0.99	96	0.91	0.03	0.85 0.97						
Car	92	0.03	0.02	0.01 0.07	268	0.09	0.02	0.05 0.12	58	0.05	0.03	0.01 0.10	96	0.04	0.02	0.00 0.08						

Source data: Turkey Welfare Monitoring Survey (May 2009)

Table 3.4: Non-parametric Comparisons of the Probability of Reducing Health Care Utilization for Green Card holders and no health insurance holders

(Results of Pearsons Chi2 test with one degrees of freedom provided)

		Since October 2008, have you had to reduce the use of curative health services? (mo)			
		PANEL A: Whole Sample		PANEL B: Sample of the poorest quintile	
		Yes	No	Total	Total
Health insurance	Green Card	21.7%	78.3%	100.0%	77.1%
	No health insurance	36.6%	63.4%	100.0%	58.3%
	Difference	-14.8%			-18.8%
		Pearson chi2(1)=6.8343		Pearson chi2(1)=6.8996	
		Pr=0.009		Pr=0.009	
		Since October 2008, have you had to reduce the use of preventive health services? (ms)			
		PANEL A: Whole Sample		PANEL B: Sample of the poorest quintile	
		Yes	No	Total	Total
Health insurance	Green Card	9.8%	90.2%	100.0%	91.4%
	No health insurance	25.7%	74.3%	100.0%	65.0%
	Difference	-16.0%			-26.4%
		Pearson chi2(1)=10.2836		Pearson chi2(1)=16.355	
		Pr=0.001		Pr=0.000	

Source data: Turkey Welfare Monitoring Survey (May 2009) and author calculations

Table 3.5: Parametric results: Linear Probability Model (LPM) Results for the Probability of Reducing Health Care Utilization

(Sample limited to households where household head has a Green Card or has no health insurance coverage.)

	(1) Curative care	(2) Curative care	(3) Preventive care	(4) Preventive care
Health Insurance (Green Card) (b3)	-0.125** (0.0518)	-0.111* (0.0582)	-0.158*** (0.0425)	-0.143*** (0.0499)
HH received a negative income shock (demeaned) (b5)	0.189*** (0.0597)	0.188*** (0.0573)	0.0723 (0.0634)	0.0811 (0.0623)
Income shock(demeaned) X Green card (b6)	-0.142 (0.107)	-0.153 (0.104)	0.0438 (0.102)	0.0292 (0.101)
Constructed Asset index (household level)		-0.0583 (0.0385)		-0.0174 (0.0301)
HH head education: Primary School		0.107 (0.0893)		0.0479 (0.0619)
HH head education: Junior or Senior Secondary School		0.139 (0.0963)		0.0718 (0.0690)
HH head education: Higher Education		0.0591 (0.179)		0.169 (0.182)
Number of infants in HH (ages 0-3)		-0.0972** (0.0456)		-0.0544 (0.0450)
Number of children in HH (ages 4-14)		0.00899 (0.0158)		0.00443 (0.0170)
Number of adults in HH (ages 15-59)		0.0175 (0.0185)		0.0199 (0.0177)
Number of elderly in HH (ages 60+)		-0.0874* (0.0451)		0.00850 (0.0431)
Constant	0.339*** (0.0334)	0.432** (0.167)	0.247*** (0.0291)	0.209* (0.114)
Observations	360	360	360	360

Standard errors in parentheses

Source data: Turkey Welfare Monitoring Survey (May 2009).

Robust standard errors (clustered at the PSU level).

* p<0.10, ** p<0.05, *** p<0.01

Table 3.6: Parametric results: Maximum Likelihood Probit Estimation Results for the Probability of Reducing Health Care Utilization
Reporting marginal effects results of the probit estimation

(Sample limited to households where household head has a Green Card or has no health insurance coverage.)

	(1) Curative care	(2) Curative care	(3) Preventive care	(4) Preventive care
Health Insurance (Green Card) (b3) (d)	-0.127** (0.0542)	-0.116** (0.0583)	-0.171*** (0.0471)	-0.156*** (0.0505)
HH received a negative income shock (demeaned) (b5)	0.179*** (0.0562)	0.181*** (0.0545)	0.0623 (0.0537)	0.0720 (0.0525)
Income shock(demeaned) X Green card (b6)	-0.123 (0.117)	-0.145 (0.118)	0.111 (0.119)	0.0941 (0.118)
Constructed Asset index (household level)		-0.0606 (0.0403)		-0.0131 (0.0297)
HH head education: Primary School (d)		0.117 (0.104)		0.0476 (0.0724)
HH head education: Junior or Senior Secondary School (d)		0.156 (0.116)		0.0735 (0.0828)
HH head education: Higher Education (d)		0.0653 (0.221)		0.175 (0.200)
Number of infants in HH (ages 0-3)		-0.108** (0.0505)		-0.0638 (0.0519)
Number of children in HH (ages 4-14)		0.00810 (0.0162)		0.00319 (0.0168)
Number of adults in HH (ages 15-59)		0.0184 (0.0198)		0.0186 (0.0173)
Number of elderly in HH (ages 60+)		-0.121* (0.0630)		0.0110 (0.0476)
Observations	360	360	360	360

Marginal effects; Standard errors in parentheses

Source data: Turkey Welfare Monitoring Survey (May 2009). Robust standard errors (clustered at the PSU level)

(d) for discrete change of dummy variable from 0 to 1

* p<0.10, ** p<0.05, *** p<0.01

Table 3.7: Determination of The Propensity Score for Having The Green Card
Dependent Variable: The household head has the Green Card.

	(1) <i>Probit model</i>	(2) <i>Logit model</i>
Health Insurance (Green Card) (b3)		
No of people in household	0.194** (0.0808)	0.328** (0.143)
Number of children in HH (ages 0-14)	-0.0294 (0.0939)	-0.0624 (0.170)
(mean) NumOfRooms	0.116 (0.152)	0.208 (0.270)
(mean) NumOfBedRooms	-0.281* (0.154)	-0.478* (0.274)
(mean) HousingSize_inM2	-0.0106** (0.00474)	-0.0199** (0.00863)
(mean) fridge	-0.242 (0.485)	-0.364 (0.839)
(mean) Microwave	-0.274 (0.622)	-1.075 (1.558)
(mean) dishwasher	-0.536** (0.249)	-1.098** (0.524)
(mean) DVD_player	-0.171 (0.208)	-0.266 (0.394)
(mean) Wash_machine	0.788** (0.320)	1.391** (0.586)
(mean) TV	-1.363** (0.666)	-2.619** (1.233)
(mean) telephone	-0.638*** (0.200)	-1.187*** (0.390)
(mean) Cell_phone	-0.172 (0.283)	-0.228 (0.504)
(mean) Private_Car	-0.129 (0.348)	-0.367 (0.659)
HH head education: Primary School	-0.154 (0.232)	-0.253 (0.422)
HH head education: Junior or Senior Secondary School	-0.438 (0.279)	-0.769 (0.526)
HH head labor status: Employed: Formal	-0.894*** (0.322)	-1.696*** (0.650)
HH head labor status: Employed: Informal	-0.267 (0.179)	-0.423 (0.318)
HH head gender: Male	84 -0.261 (0.206)	-0.492 (0.349)
Constant	1.475* (0.814)	2.890** (1.457)
Observations	360	360

Standard errors in parentheses

Source data: TWMS sample limited to urban households that have no health insurance through SGK or private insurance.

* p_i0.10, ** p_i0.05, *** p_i0.01

Table 3.8: Propensity Score Matching Results for Reduced Utilization of Curative Health Services

Average Treatment Effect (ATE) by propensity score determination method and matching scenario:

	One-to-one ATE	Nearest ATE	Radius ATE	Kernel ATE
	(1)	(2)	(3)	(4)
Logit (No Trim)	-0.168* (-1.83)	-0.157* (-1.90)	-0.129** (-2.14)	-0.127* (-1.87)
Logit (Trim(5%) for common support)	-0.167* (-1.87)	-0.154* (-1.90)	-0.137** (-2.25)	-0.131* (-1.93)
Probit (No Trim)	-0.208** (-2.14)	-0.169** (-2.02)	-0.129** (-2.15)	-0.127* (-1.86)
Probit (Trim(5%) for common support)	-0.209** (-2.22)	-0.168** (-2.06)	-0.136** (-2.25)	-0.130* (-1.92)
N	351	351	351	351

Source data: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

Note: t statistics in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Bootstrapped standard errors are reported (with 500 repetitions for all estimators).

Table 3.9: Propensity Score Matching Results for Reduced Utilization of Preventive Health Services

Average Treatment Effect (ATE) by propensity score determination method and matching scenario:

	One-to-One ATE	Nearest ATE	Radius ATE	Kernel ATE
	(1)	(2)	(3)	(4)
Logit (No Trim)	-0.177*** (-2.60)	-0.163** (-2.35)	-0.128** (-2.48)	-0.133** (-2.37)
Logit (Trim(5%) for common support)	-0.179*** (-2.68)	-0.163** (-2.40)	-0.134*** (-2.59)	-0.136** (-2.43)
Probit (No Trim)	-0.171** (-2.37)	-0.161** (-2.33)	-0.127** (-2.47)	-0.134** (-2.40)
Probit (Trim(5%) for common support)	-0.173** (-2.46)	-0.162** (-2.38)	-0.132** (-2.56)	-0.137** (-2.46)
N	351	351	351	351

Source data: Turkey Welfare Monitoring Survey Urban Sample (May 2009)

Note: t statistics in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

Bootstrapped standard errors are reported (with 500 repetitions for all estimators).

Chapter 4

Agricultural Technology Diffusion in a Post-Conflict Setting: Evidence from an Experimental Study in Eastern Turkey

4.1 Introduction

4.1.1 Motivation

Adoption of newly introduced agricultural technologies by rural communities has strong implications for increasing economic welfare and reducing poverty in these settings and has therefore been a topic of interest among development economists. One of the earliest works looking at patterns of agricultural technology diffusion was by Griliches, who observed in his empirical assessment of the diffusion of hybrid corn in the United States, that there is a general “S-shaped pattern” of diffusion of new technologies “*where the rate of adoption is slow at first, accelerating until it reaches its peak at approximately the mid-point of development and then slowing again as the development approaches its final level*” (Griliches, 1960) He identifies three parameters that determine the shape of a diffusion curve: the date of beginning (origin), relative speed of adoption (slope) and final level (ceiling) and states that the observed patterns of adoption timing can be largely explained by the profitability of innovation to the individual farmer.

Following Griliches’ seminal empirical work, Feder and Slade (1984) have presented a theoretical decision model for adoption of new technologies, whereby the speed at which

farmers of different characteristics reach the level of ‘saturation’ (the ceiling) at different points in time and adoption patterns are differentiated mainly by land size and assets. All farmers make a decision to adopt the technology if they think it will enhance their profits or utility though there is a level of uncertainty associated with the returns of the technology. Farmers with more convenient access to information and better endowments (and thus lower risk aversion) are more likely to acquire higher levels of knowledge and adopt technologies sooner. Therefore in this model, farmers with more assets or with more human capital are expected to adopt a technology earlier than others. Over time, most farmers adopt the new technology and the differences in adoption levels disappear as the level of use converges to the ceiling.

Several other papers have also considered the role of social networks in the diffusion of agricultural technologies. Foster and Rosenzweig (1995) consider the impact of farmers own experience and their neighbors experience with high yielding seed varieties on adoption and profitability of new crops. Using a nationally representative panel survey of households in Rural India through the Green Revolution, they find evidence of learning spill-overs: farmers with experience neighbors are significantly more profitable than those with inexperienced neighbors and the former are likely to devote more of their land to the new technologies. Bandiera and Rasul (2006) consider farmer’s decisions to adopt a new crop, sunflower, in Mozambique and show an inverse U shaped relationship between the number of adopters in the network and the probability of each farmer’s adoption. In other words, they find that social effects are positive when there are few adopters in the network, though become negative when there are many. Munshi (2004) describes that the process of social learning breaks down if unobserved or imperfectly observed individual characteristics are important determinants of neighbors outcomes. Using data from the Green Revolution in India, he shows that social learning is slower in a heterogeneous population, where the performance of the new technology is sensitive to the neighbors unobserved characteristics. In such situations with heterogeneous populations, information flows less smoothly since individuals are unable to condition for differences between their own characteristics and the characteristics of their neighbors when learning from their experiences.

Some authors have modelled the role of social links, exclusion and networks in technology diffusion. Isham et al. (2002) extends the theoretical model of technology adoption by Feder and Slade (1984) by including characteristics of local social structures as an input into the household’s adoption decision. He introduces into the model the quantity of public information in the village which is affected by the village wide “cumulative proportion of adopters”, as well as “social capital” at the village level. The following

predictions come out of his formal model: the farmers that adopt more rapidly are those that (i) have more assets and obtain more private information, (ii) have neighbours that adopt and thus have more cumulative information around them, (iii) live in villages with higher levels of social capital and thus have better access to information, (iv) live in villages where agricultural extension services exist. He then takes this developed model to a data set collected in rural Tanzania and shows that the probability of adoption -in this case, of improved fertilizer- is positively correlated, as predicted by the model, with the size of land under cultivation (assets), cumulative adoption patterns in the village, ethnically based social affiliations and the availability of extension services.

The effect of the social engagement and affiliations of households in their adoption decisions is quite interesting to look at: In a much-cited book on the diffusion of technologies, Rogers (1995) presents a framework for thinking through types of adopters depending on their speed of adoption of the technology. He divides the S-shaped diffusion curve into five categories of people/households: (i) *the innovators*, (ii) *early adopters*, (iii) *early majority*, (iv) *late majority* and (v) *the laggards*. In this classification the last adopters, can either be “very traditional” or be “isolates” in the social system. In his words: “*If they are traditional, they are suspicious of innovations and often interact with others who also have traditional values. If they are isolated, their lack of social interaction decreases their awareness of innovations demonstrated benefits.*” It is not easy to argue the direction of causality when it comes to “exclusion”, since there may be many factors impacting both being excluded and the decision to adopt a technology late. In any case, correlations between exclusion and late adoption have previously been established.

4.1.2 Contribution

This paper contributes to an expanding literature on technology adoption, social networks and exclusion by looking at the impact of an agricultural extension program implemented in a post-conflict setting where issues of political and economic exclusion are abundant. By making use of a uniquely designed panel survey implemented in project and treatment villages before and after the program, the paper looks at the heterogeneous impact of the agricultural extension program on groups that are “laggards” or have been politically/economically or socially excluded from main stream information and agricultural technology. It looks at the changes in levels of utilization for some agricultural technologies and compares levels and rates of adoption across groups, focusing primarily on a “politically” excluded “non-Turkish speaking” minority group. It turns

out that the socially excluded and ethnically/economically excluded are not necessarily the same, and while the extension program may benefit those who are “politically excluded” (have low human capital, asset capital and are excluded in terms of language) – the program may be *less* effective in reaching out to those who are “socially excluded” in their community.

The main research questions answered in the paper are the following: (i) Has this specific agricultural extension program worked in terms of increasing adoption rates in the villages? Do we observe higher rates of adoption in places and technologies where the initial adoption rates were lower – in other words, does the baseline adoption level matter in the effectiveness of the agricultural extension program? (ii) What patterns are observed in the adoption of new agricultural technologies by community characteristics – do the excluded have higher or lower levels of adoption given the extension program? (iii) Does the kind of exclusion “political” vs. “social” exclusion matter in determining adoption rates?

The paper is structured as follows: Section 4.2 lays out the conceptual framework and testing strategy. Section 4.3 gives information on the data and context of the study. Section 4.4 gives the main results starting with descriptive statistics on the outcome variables in the baseline and posttest, then providing the main findings from the OLS estimation, and ending with robustness checks on the results. Section 4.5 concludes with main findings from the paper.

4.2 Conceptual Framework

4.2.1 The Model

In this paper, I use the conceptual framework provided by Isham et al. (2002) and look at differences in rates of adoption of agricultural technology in the presence of an extension program, and where a certain group in the population can be identified as an “excluded” minority and therefore may be experiencing difficulties in accessing information about an innovation. I consider the hypothesized adoption rates of the more advantaged (non-excluded) and disadvantaged (excluded) groups in the population, given the baseline adoption level of a technology and then look at the potential impact of a “treatment” that increases the availability of certain agricultural technologies in the villages.

A summary of the conceptual model is depicted in Figures 4.1a and 4.1b. The adoption pattern (cumulative distribution function for adoption) of the non-excluded group is depicted in blue, and the adoption pattern of the “excluded” group is in green,

where the CDF of the “non-excluded” group stochastically dominates the “excluded” group. In other words, in any time period before both groups reach “saturation point”, a higher percentage of the non-excluded group is expected to have adopted the technology. The S-shaped pattern of the adoption curve indicates that the rate of adoption of a technology depends very much on the initial (baseline) level of adoption for each group.

Figure 4.1a represents the early stages of adoption for a technology: here we expect to see that the more advantaged group has both a higher level of adoption, as well as a higher rate of adoption of the technology (a steeper slope on the CDF). In the early adoption stages, the excluded group may either not yet have started adopting the technology, or -in any case- would have lower levels of adoption compared to the non-excluded group. This delay may be a function of their expected returns to the investment or lack of resources/information about the technology and its validation. Figure 4.1b represents the later stages of a technology’s adoption, where the excluded group is still expected to have a lower level of adoption, but their rate of adoption (slope of the curve) may now be *higher* compared to the non-excluded group. The impact of the treatment in all cases would be an increase in the adoption rate for both groups, and if the policies have been successfully inclusive, bringing benefits to the poor, we would expect to see that the impact of the treatment would be higher for the excluded group.

4.2.2 Testing Strategy: The specification and interpretation

In order to test the model presented above, I set up the following empirical specification:

$$\Delta Y_i = \beta + \gamma Y_{i(t)} + \delta (T_{v(t+1)}) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \Delta u_i \quad (4.1)$$

Where t is the year when the baseline data is collected in the experiment and $t+1$ is the year for the post-test data. The dependent variable in the equations (ΔY_i) is whether a certain technology is adopted by a household between time t and $t+1$. The dependent variable takes the value of 0 or 1. For each household i , the probability of adopting a certain technology in time $t+1$ depends on: whether they had adopted the technology in the earlier period ($Y_{i(t)}$); whether they have received a treatment (in the form of an agricultural extension program) in time t , ($T_{v(t+1)}$); the interaction between treatment and the baseline adoption level ($Y_{i(t)} T_{v(t+1)}$), an interaction term between treatment and household characteristics which provides information on the heterogeneous impact of the treatment on different households ($Z_i T_{v(t+1)}$).

The treatment intervention for increasing the adoption of villagers to the new technology takes place between t and $t+1$. Given the experimental set-up of the study,

the treated group gets the intervention in $t+1$ while the control group does not. For the treated group: $T_{vt} = 0$ and $T_{v(t+1)} = 1$ and for the untreated group $T_{vt} = 0$ and $T_{v(t+1)} = 0$.

In this specification, β the constant term indicates the time trend in the diffusion of the technology in the absence of the treatment. We are able to measure this time-trend given the counterfactual measured by the control group in the time period of the treatment. β is expected to be positive if we assume there is on-going diffusion of the technology (increase in levels of use) outside of the treatment area. The coefficient γ is expected to be negative since the probability of adoption is –by definition– lower for a household that has already adopted the technology in a previous period.

If the treatment has had an impact on adoption rates in the project villages we should expect to see $\delta > 0$. The interaction term between initial levels of adoption and the treatment should yield a negative coefficient ($\zeta < 0$) since the treatment is likely to have a smaller impact on those who have already adopted the technology or in places where adoption rates are already high. To the extent that Z_i indicates variables of exclusion, we expect to see a positive coefficient on these variables (or the indexed exclusion variable) interacted with treatment, if the treatment has been “inclusive” and has reached the poor and excluded. A positive and significant coefficient for φ then indicates (where Z_i are household characteristics that define exclusion and poverty), a pro-poor and inclusive expansion of the technology as a result of the treatment.

Another specification includes baseline characteristics of households (Z_i) in the model. While normally, we expect household fixed effects to drop out of the model when we take the first difference, in this model we keep household characteristics, to allow the excluded and non-excluded groups to behave differently in their adoption patterns rates. The specification then becomes:

$$\Delta Y_i = \beta + \gamma Y_{i(t)} + \delta (T_{v(t+1)}) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \eta Z_i + \Delta u_i \quad (4.2)$$

This specification allows us to compare the adoption rates of the excluded and non-excluded groups in the absence of treatment. In this specification, we expect γ may take on a positive or negative value depending on the stage of adoption of the technology: in early stages of adoption the excluded may have lower rates of adoption (as in Figure 4.1 a in the conceptual framework diagrams) hence η would be expected to be negative for variables that proxy exclusion. For a technology that has already been around and been adopted by a larger percentage of the population, we may expect to see a steeper

adoption curve for the excluded (Figure 4.1 b), in which case η might take on a positive value¹.

A final specification is run looking at the impact of the treatment on the socially excluded:

$$\Delta Y_i = \beta + \gamma Y_{i(t)} + \delta (T_{v(t+1)}) + \zeta Y_{i(t)} T_{v(t+1)} + \varphi Z_i T_{v(t+1)} + \eta Z_i + \pi S_i T_{v(t+1)} + \Delta u_i \quad (4.3)$$

Here, the S_i variable is a dummy variable for not having social interactions in the village, and the coefficient on the interaction term between social exclusion and the treatment indicates whether the socially excluded groups in the village were more or less likely to benefit from the program.

To summarize, the following propositions come out of the conceptual model and are tested in the empirical specification.

Proposition 1: The impact of the treatment program is likely to be an increase in the adoption rate for all groups ($\delta > 0$) (if the program is successful).

Proposition 2: The treatment is likely to bring about a higher increase in adoption rates for a technology in the earlier phases of diffusion ($\zeta < 0$).

Proposition 3: To the extent that the program is inclusive in its reach, we expect to see that the rates of adoption are higher with the program among the excluded group (where exclusion can be defined in terms of political/economic exclusion or social exclusion). ($\varphi > 0$)

Proposition 4: For a technology that is in the early phases of adoption, we expect the excluded group to have a lower *level* of adoption in the baseline and a lower *rate* of adoption between t_0 and t_1 than the non-excluded group ($\eta < 0$).

Proposition 5: For a technology that is in the later phases of adoption, we expect the excluded group to still have a lower *level* of adoption in the baseline but we expect the excluded group to have a *higher* rate of adoption than the non-excluded group ($\eta > 0$).

¹While the results on exclusion are interesting to explore, it is important to note that there are likely to be issues of endogeneity related to omitted variables (as well as possibly reverse causality) here with the excluded not being able to adopt new technologies for other reasons that are not captured in the regression. So it is important to take these results related to exclusion with some caution and interpret them as associations rather than attribute causality to the interpretations.

4.3 Data

4.3.1 Origin of the Data

The data comes from a rural development program implemented by a Turkish NGO in the Bitlis province of eastern Turkey in primarily Kurdish-speaking villages. The eastern and south-eastern regions of Turkey, including Bitlis, have a long history of Kurdish ethnic insurgence dating all the way back to 1930's to the early days of the founding of the Republic of Turkey along lines of Turkish national identity. Conflict between the Turkish military and Kurdish PKK insurgents peaked in the mid-1990s, and the government decided to take measures to clear out and incinerate villages in the region that were taken to be sympathizers and supporters of the PKK (Randal, 1998). According to official statistics, between 1995 and 1998, the Turkish government emptied 3,000 villages, relocating close to 1 million people to urban centres in other parts of Turkey² (Baysal, 2008). In 2005, about 10 years after the relocation, the government started to allow villagers to move back to their homes (if/where they existed) and started a limited compensation program to rebuild destroyed villages. There was, however, a clear need to also bring economic/social livelihoods to this post-conflict area which had suffered for years from military tension and experienced negative growth rates, accompanied by high and stagnant levels of poverty.

The Özyeğin Rural Development Program was launched in January 2009, against this background of underdevelopment, forced migration and high levels of poverty. The project started as a pilot in 6 villages in the eastern Bitlis province of Turkey. At the launch of the Program, the project villages had high levels of poverty, and unemployment, particularly among the youth. When the program was launched, the unemployment rate and the percentage of population looking for jobs were high in the villages³. Because of lack of availability of local jobs, seasonal migration was rampant among young men in the baseline in 2008⁴. The program was set-up as a post-conflict village livelihoods revitalization project with the aim of “*empowering villagers to return to their villages with economic means to support themselves through agriculture in a sustainable way*”. In this regard, the pilot can be considered a post-conflict livelihoods and peace building

²According to official statistics, population affected by forced migration is 953,680, while it climbs up to 1.5-3 million according to non-governmental organizations.

³The percentage of working age male population (ages 15+) that were employed in project villages was 57.8 percent, while the unemployment rate has was 12.5 percent.

⁴About 14 percent of men in Project villages reported having to seasonally migrate outside of the province in order to find jobs within the past year. These men were mostly employed in the construction, services and manufacturing sectors and more than half of them worked in Istanbul.

project in the region. The Program was designed to reduce rural poverty in these villages by investing in the returns to the assets of the poor: mainly by means of investments in their productivity, through the extension of agricultural technologies to the villages⁵. In many ways, the technologies introduced by the NGO were not innovative or new, but these technologies that have long been used in other parts of the country were not used in this war-torn region.

Before the launch of the program, together with the NGO field team, I collected a baseline survey of households in the 6 treatment villages and also collected a non-randomized control sample from 6 villages in the neighbouring district. The baseline questionnaire included modules on use of agricultural technology, household economic welfare, use of health and education services, as well as a module on women's empowerment and use of maternal health care services. In December 2010, two years after the launch of the program, we ran a post-test in the same villages using a subset of the modules from the baseline survey. The quantitative survey was conducted as a census in the project and control villages (all households in the cluster of villages were interviewed). There were a total of 326 households in the baseline data, coming from 192 households in 6 treatment villages and 134 households in control villages. The panel survey was collected in 389 households since there were new households moving back in this period to the villages: the panel was collected from 227 treatment and 162 control households. In the analysis, only the 325 households that responded to both rounds of the survey were included in the sample.

Table 4.1 summarizes the characteristics of households in treatment and control villages in the baseline. It is possible to observe that the percentage of household heads with no formal education (illiterate or with no diploma) is higher (35 percent) in treatment villages compared to control villages where the same percentage is around 20 percent. In treatment villages there is a higher percentage of households that were forced migrants and moved back recently to the villages: the percentage of household heads in treatment villages that report they were forced migrants is 53 percent in the baseline, whereas this value is lower at 33 percent in control villages (difference is significant with $p\text{-value} < 0.01$). When we consider the asset profiles of the households in treatment and control villages, we can see similar profiles and the ethnic composition of the villages is also similar with mostly Kurdish speaking minorities living in these clusters of villages in Bitlis.

⁵In many ways, the technologies introduced by the NGO were not innovative or new, but their efforts in bringing these technologies that have long been used in other parts of the country in this war-torn region is what makes the program unique and important.

Table 4.2 provides balancedness tests comparing treatment and control villages and provides the t-tests for the differences in the means between treatment and control households across various household head characteristics. It is possible to see the differences in levels of education and the “forced migrant” status of the household head which come out as being significant differences between treatment and control samples.

The differences across treatment and control villages, at least in terms of forced migration status levels, is no coincidence: This is a direct function of the fact that the selection of villages was not random and the implementing NGO had already selected the treatment villages (based on need and the proportion of households returning to the village after forced migration in the 1990s) by the time the evaluation strategy was discussed. For lack of a completely randomized sample, the control villages were selected in the neighbouring district and are a cluster of villages that display similar characteristics: have a similar climate and agricultural crops and have a similar ethnic composition. In this regards, the control villages provide a comparison group for tracking the time trend for the outcome indicators ⁶

The Özyeğin Rural Development program impact evaluation provides an opportunity to set hypotheses related to the diffusion of agricultural technologies where there are certain sub-population groups that may be excluded in political/economic or social ways from mainstream access to information. The program attempted to reach out to the excluded groups to increase their adoption of certain technologies and use of public services. Given the panel and experimental structure of the survey, the data collected from this program evaluation allows us to look at technological diffusion rates for households at different baseline levels of adoption and with different characteristics. We can look at the heterogeneous impact of the agricultural extension program implemented by this NGO on different household types and test the propositions listed in the conceptual model.

4.3.2 Variables: Description of the variables

Three different outcome variables Y_i are considered in the paper: (i) whether the household has inoculated fruit trees in the past 12 months, (ii) whether the household has vaccinated livestock against diseases in the past 12 months, (iii) whether anyone in the household has used public agricultural consulting services (at the district level). The outcome variable ΔY_i is defined as a binary variable in the main results, whereby

⁶Given the differences in the baseline across treatment and control villages, it was a good idea to be controlling for baseline household characteristics in the empirical specification in order to reduce bias in the measurement of the treatment effect, and this is already how the model is set up (in Equation 4.2).

it takes the values 0 and 1. In the construction of the dependent variable, it is assumed that if a household has already adopted a technology in the past, they already have knowledge of it and would be able to apply it again, or that there is no return from the investment they have made. In this way, if the technology use takes on the value of 1 in t and then the household reports not using the same technology in $t+1$, then the model assumes they still have access to the technology, and the change in their technology use is set equal to 0 (rather than -1).

The Filmer-Pritchett asset index is constructed using principal components analysis and considering a list of housing characteristics and assets (Filmer and Pritchett, 2001). A higher value of the index indicates higher level of welfare (assets) for the household. The households in the sample (treatment and control villages) are split up into 5 equal groups of household quintiles, with the first quintile indicating the poorest 20 percent of households in terms of assets. The list of variables that are used for the construction of the asset index is listed in Table 4.3.

The exclusion variable in the regressions is constructed as a dummy variable and takes the value of 1 if the household head either (i) does not speak any Turkish, (ii) has not completed any formal schooling, (iii) if the household is in the poorest asset quintile. This variable is constructed as proxy for political and economic exclusion of the household. The regressions consider these variables separately (columns 1-2 in Tables 4.5-4.7) as independent variables and also look at the combined “political/economic exclusion” variable as an independent variable (columns 3-4 in Tables 4.8-4.10.)⁷.

Exclusion is defined in the paper in political/economic or social terms. The main exclusion variable used in the regressions is defined along political/economic lines: it is a constructed variable that takes a value of one if the household is either in the poorest asset quintile, the household head has no formal education or the household head does not speak the official language of the country (Turkish). The variables used in the construction are chosen deliberately as being poor, having low levels of education or not being able to speak the dominant language in the country as any (or all) of these factors may lead to not being able to fully participate in the economic and political life of the country. Language in particular is an important variable that determined political exclusion in the region, as Kurdish which is the predominant mother tongue for households in the sample is not recognized as an official language in the country and

⁷Due to high correlations across these variables, there is a problem with multicollinearity and we lose significance of these variables when they all enter the regression as separate independent variables. This is why an exclusion” proxy variable is constructed as a single proxy variable merging these three exclusion characteristics, in order to illustrate the heterogeneous impact of the program on the excluded.

is not taught in schools. We expect the politically/economically excluded group to have lower initial adoption levels as they may be less aware of technological enhancements (as a result of lower educational attainment and language barriers). Since all previous agricultural extension support by the government was provided in the Turkish language, we may expect to see a lower level of adoption among the Kurdish speaking minority. We also expect to see lower adoption rates among the asset poor, as they may be more risk averse in adopting new technologies, and hence may not benefit from the returns of new technological enhancements.

Social exclusion is defined as the household not having any social interactions with the rest of the households in the village. The data is collected in a social networks module that asks each household head in the village, which households they have “frequent” interactions with and which households in the village they have “rare/occasional” interactions with. The second kind of interaction is coded in the data as a “weak link” in the network. Such links are important for the transfer of information across households; hence we use this variable to construct the social exclusion variable for the household⁸.

4.4 Empirical Results

4.4.1 Descriptive Statistics

The descriptive analysis in Table 4.4 and Figure 4.2 provide some insights on the data before launching on the interpretation of the regression results:

First of all, adoption levels in the baseline between treatment and control villages did not vary: Agricultural technology use and utilization of public agricultural extension services vary at the baseline by household characteristics and the technology in question: In treatment villages where the intervention took place, 21.6 percent of households had inoculated fruit trees and 48.3 percent of households had vaccinated livestock in 2008 (compared to 23.1 percent and 50.8 percent respectively in control villages). The difference in adoption rates across the treatment and control groups was not statistically different in the baseline. The use of public agricultural services was also quite low in both project and control villages: 18.9 percent of treatment households and 19.7 percent

⁸Since weak social ties are particularly important for the diffusion of knowledge and information (Granovetter, 1973), in this paper we consider these types of social ties across households rather than strong ties that may be based on kinship and family relationships. Socially excluded households in the village, may be less likely to have heard of agricultural extension programs, and may therefore have lower levels of adoption in the baseline. They may also have a lower likelihood of benefiting from the NGOs intervention, since they have weak social interactions and may be unaware socially of the treatment that is taking place at the village level.

of control village households had utilized such consulting services in the past year when baseline data was collected (See Table 4.4).

Second, in the baseline, in both treatment and control villages, we find that the excluded group has lower adoption levels for all dependent variables. Figure 4.2 summarizes visually the adoption rates in treatment and control villages before and after the program, for the “excluded” and “non-excluded” households⁹. This pattern of the non-excluded having higher levels of adoption in the baseline holds for all three dependent variables in the analysis. This is in line with our expectation from the conceptual model Figures 4.1a and 4.1b where the cumulative distribution function for the technology adoption rates of the non-excluded group stochastically dominates the CDF of the excluded group.

Third, for both the excluded and non-excluded groups in treatment villages the adoption level increases in this time period, and in all cases the difference-in-differences between the treatment and control groups is positive. This is in agreement with Proposition 1 in the conceptual model. For the excluded group, however, the increase in adoption levels for inoculation of fruit trees as well as vaccination of animals is higher than for the non-excluded group, indicating that the policies implemented by the NGO were inclusive and helped reach out to the poor and lower educated members of the community on these two indicators (also in line with Proposition 2 in the conceptual model). However, the impact of the program on the excluded group, in terms of expanding reach to public services seems more limited: in terms of utilization of consulting services the program does seem to succeed in rates of access however not necessarily in an inclusive, pro-poor fashion. This is an interesting finding that will also be confirmed below in regression results.

Finally, it is important to note that the baseline adoption levels of these technologies are very different and therefore we should expect to see different diffusion patterns (and rates of adoption) among the excluded and non-excluded groups: While vaccination of animals was already adopted by close to half of the households in the baseline, inoculation of fruit trees and utilization of consulting services had only been adopted by about 1 in 5 households. We expect therefore that the diffusion patterns of the two technologies would be different after the treatment (following Propositions 4 and 5 in the conceptual framework respectively).

⁹The definition of exclusion is based on economic and political exclusion. The variable is defined as being either in the poorest asset quintile, having no formal education or not speaking the official language of the country (Turkish).

4.4.2 Main Results

The results of the OLS regressions for equations 4.1 and 4.2 are presented in Tables 4.5-4.7. In columns 1-2 the household characteristics for exclusion are taken as separate variables: these include the household being in the poorest asset quintile, the household head not speaking Turkish, and the household having no formal schooling or being illiterate. In Columns 3-4 of these tables, the exclusion variable is reduced to a dummy variable that takes on the value of 1 if any of the exclusion characteristics are in place. Column 5 in all of the tables runs the specification in Equation 4.3 that includes the “social exclusion” variable.

The samples in the regressions in this section were limited to households that could potentially benefit from the treatment. Note that while the total sample of households that responded to both rounds of the panel were 325 households, only 249 households (76.6 percent of the total sample) had fruit trees or could benefit from inoculation, and only 185 households (56.9 percent of total sample) had livestock and could benefit from an expansion in vaccination.

Inoculation of Fruit Trees: Early Stage Adoption

Table 4.5 provides results of the OLS regression for the dependent variable on inoculating fruit trees. Given that the inoculation of fruit trees was a technology adopted by 22 percent of households in the baseline (in treatment and control villages overall), we expect to see a pattern here of early adoption (See Figure 4.1a). In the results we find that $\gamma < 0$, indicating that higher levels of adoption in the baseline is associated with lower probability of adopting the technology during the treatment period. This is consistent with the model since we would only expect to see a positive coefficient on γ in the very early stages of adoption (as diffusion gains momentum). The treatment is associated with an increase in the rate of adoption by 26.2-31.4 percentage points depending on the specification (see Table 4.5 Columns 1-5). This fulfils proposition 1 in the conceptual framework ($\delta > 0$) and indicates that the program was successful in increasing the adoption rate in the treatment villages overall. For higher levels of initial adoption, the impact of treatment is smaller ($\zeta < 0$) as predicted by Proposition 2. (This result makes intuitive sense since with higher levels of adoption, there are a smaller number of households to have adopted the technology, and hence it becomes more difficult to diffuse a technology for the NGO.)

We test the inclusiveness of the NGOs efforts for reaching the excluded groups ($\varphi > 0$): in Column 2 and 4 the where specification follows Equation 4.2: we find that those

with no formal education are more likely to have higher adoption rates as a result of the treatment (Column 2) and those in the “excluded” category (as defined by either being in the poorest quintile, having no formal education or no speaking Turkish) are more likely to adopt the technology in this time period by 22.7 percentage points (See Column 4). The variable that interacts treatment with exclusion takes a highly positive and significant value hence it is possible to say that Proposition 3 in the model also holds for this technology and that diffusion of the technology has been inclusive. On the other hand, the excluded in general are less likely to have adopted the technology in this time period: in columns 2 and 4, we can observe that the coefficient on the variable for being in the poorest quintile, and the coefficient on the “exclusion” variable are both negative. The “excluded” (in Column 4) are 14.4 percentage points less likely to adopt the technology in this time period compared to the non-excluded. This finding is consistent with Proposition 5 in the conceptual model, that the excluded have lower rates of adoption (as well as lower levels of adoption) in the early phases of diffusion of a technology.

Finally, we also test for the impact of treatment on the socially excluded (in Column 5). The results show that for such socially excluded households, the efforts of the NGO are not necessarily inclusive: while those who are excluded on the economic/political dimensions, benefit favourably from the NGOs efforts, the socially excluded are less likely to have increased adoption levels as a result of the program (the coefficient on social exclusion is -0.173 with p-value<0.10).

Vaccination of Livestock: Later Stage Adoption

The second set of OLS results are related to the vaccination of animal livestock in the villages against diseases and are presented in Table 4.6. As described in Section 4.1, the baseline adoption levels for animal vaccination are higher at close to half of the villagers in the baseline using this technology. In this regard, it can be considered a technology already in the later stages of diffusion (See Figure 4.1b), by the time the NGO intervention starts. The baseline level of adoption takes on a strongly negative coefficient in these regressions: for higher levels of baseline adoption, we expect to see a much lower rate of adoption during the treatment period: ($\gamma < 0$). The impact of the NGOs efforts are not reflected on the results: the households located in the treatment villages are not more likely to adopt the technology and we also lose the results on the interaction terms between treatment and exclusion for this dependent variable: the treatment effect cannot be observed in these results in a statistically significant manner,

and the excluded are also not more likely to adopt the technology as a result of the NGOs efforts. (hence Propositions 1- 3 do not hold).

What we do observe is that for the excluded group the rate of adoption is higher (even without the treatment) and this is in accordance with Proposition 5 in the model, whereby we expect the excluded to have higher adoption rates and to catch up in the later stages of diffusion.

Use of Consulting Services: Early Adoption in the Case of Access to Public Services

The last set of results are presented in Table 4.7 where the dependent variable is whether anyone in the household has utilized publicly provided agricultural consulting services in the last year. In this case, the results closely resemble the early adoption period results for inoculation of fruit trees, though there is one difference: the treatment is not necessarily inclusive, particularly for the group that does not speak the official Turkish language. This intuitively makes sense since to make use of public services the ability to speak the official language would be essential.

Looking at these results in more detail: in the baseline we noted that about 20 percent of households were using these consulting services: hence we do expect the pattern of diffusion to be quite similar to the section on inoculation of fruit trees as the initial penetration rates are the same. In this set of results, again we find that baseline level of adoption is negatively correlated with adoption rates ($\gamma < 0$) and that treatment has a positive impact on adoption rates for all ($\delta > 0$), and treatment is less likely to be as beneficial in places with higher levels of initial adoption ($\zeta < 0$). In the case of use of public services though, we find that treatment was *not* more likely to benefit the excluded, rather the non-excluded group benefited disproportionately in this regard ($\varphi < 0$) (Column 4). The exclusion variable for not speaking Turkish took on a highly negative and significant coefficient in these regressions where not speaking the official language was associated with a 23.3 percentage point reduction in the probability of increased use of consulting services (with p-value < 0.05). Being excluded from social networks was once again associated with a lower level of increase in the adoption rate for these services.

4.4.3 Robustness Checks

In the current data set used for the study, there are a total of only 12 clusters (villages) and in the main results so far presented robust standard errors clustered at the village

level are presented. Cameron et al. (2007) suggests that in applications with few clusters (5-30), standard asymptotic tests can over-reject considerably. The authors provide a technique for using bootstrap methods to get asymptotic refinement on the results. In this paper, we run the same specifications using these bootstrapped standard errors (with 100 bootstrap repetitions in the calculation) as robustness checks.

Most results reported are robust to this asymptotic refinement, though not all. Tables 4.8-4.10 provide the OLS results with bootstrapped standard errors. While the treatment effect of the program and the interactions between baseline adoption levels and treatment are robust to the adjustment using bootstrapped standard errors, we lose significance on some of the exclusion variables (ηZ_i) in the robustness checks. For instance, while being in the poorest quintile of assets was associated with lower adoption rates for inoculation of fruit trees (with p-value<0.10) (in Table 4.5 Column 2), we find that this is no longer the case with bootstrapped standard errors (See Table 4.8 Column 2). The results on the inclusion/exclusion of the treatment (the interaction between exclusion variables and treatment) are still significant after the standard errors are adjusted.

As a second robustness check, I run the same specification using dependent variables that are defined as a change in behaviour variable and take the values -1, 0 and 1. If the household adopts the technology in t+1 and did not use the technology in t, the outcome variable takes the value 1. If the household used the technology earlier and then stopped using the technology the outcome variable takes the value -1. If there has been no change in behaviour for the household, then the outcome variable takes the value 0. Hence there are 3 categories the dependent variable can take: -1 for a decrease in use of technology, 0 for no change in adoption status and 1 for an increase in the use of the technology. The main results on the impact of treatment and disproportionate impact on the excluded group remain robust to this specification as well.

4.5 Conclusion

This paper considered the impact of an agricultural extension program in a post-conflict setting in eastern Turkey. It tested a model of agricultural technology diffusion by using an experimental panel survey that was conducted in project villages as well as control villages before and after program implementation.

The main propositions of the model were that if the extension program were successful, there would be an increase in the adoption rates of villagers in the treatment group, though the changes in adoption levels would vary by the phase of diffusion of the technology (early vs. late phases of adoption) and by the characteristics of the house-

holds (whether they were considered to be among an excluded or non-excluded group in the villages). We expected to see that for the technologies in the earlier phases of adoption, the excluded group would have lower levels and rates of adoption, while the non-excluded group (with higher assets, education and those who spoke the official language in the country) would have higher levels and rates of adoption. In the empirical findings, this was the case for two of the dependent variables: inoculation of fruit trees, as well as increased use of public consulting services. Both of these were used only by about one-in-five households in the baseline survey, and these technologies/utilization rates could be considered as being in the nascent stages of growth.

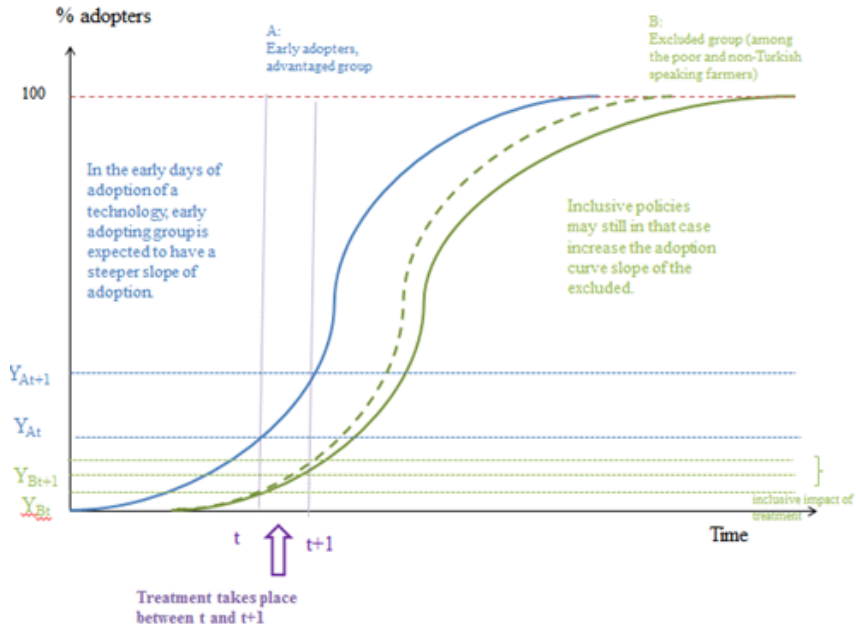
The extension program increased the adoption rates for inoculation of fruit trees by anywhere between 26.2 -31.4 percentage points. The impact of the program was higher among those with lower levels of initial adoption, and among the politically/economically excluded group. Among the excluded the likelihood of adoption was higher by an additional 22.7 percentage points as a result of the program. Consistent with the conceptual model, in the absence of the program though, the adoption rates of the excluded would have been lower for this technology in the earlier phases of adoption. The findings for the use of consulting services were similar (with strong impact of the program on overall adoption rates), however there was a difference in the reach of the program to the politically/economically excluded group: The program had no impact on improving access of the politically excluded to publicly provided agricultural services, while having a very strong and positive reach to the excluded group in the villages through its own private means (in the form of inoculation of fruit trees). This suggests that barriers to accessing mainstream information services is still limited in this post-conflict region particularly for those who do not speak the official language. The paper found that for vaccination of livestock, the impact of the program was negligible, and one could also not see a favourable impact of the program on the excluded. However, it was possible to see that the excluded group had higher catch-up rates in such a later-adoption stage technology (even in the absence of the program).

The paper also contrasted results of the impact of the program for the politically/economically excluded group vs. the socially excluded groups in the villages and it found systematically that those who were socially excluded in the villages could derive less benefits from the program and were less likely to adopt even when the NGO program could be defined as inclusive in reaching the poor and more disadvantaged. In other words, from this descriptive analysis, it seems that lack of social capital on the part of a household impacts their likelihood of benefiting from such services, more so than their lack of access to physical capital (as proxied by the asset index) or human

capital. This is an interesting descriptive finding of the paper that certainly merits further investigation.

Figure 4.1: Conceptual Model for Agricultural Technology Diffusion

(a) Earlier Stages of Adoption



(b) Later Stages of Adoption

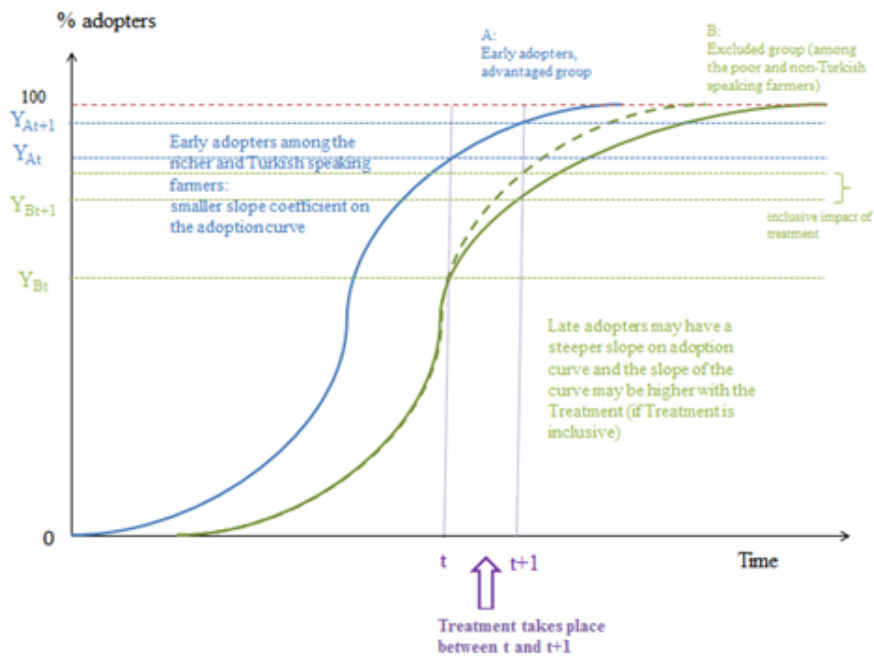
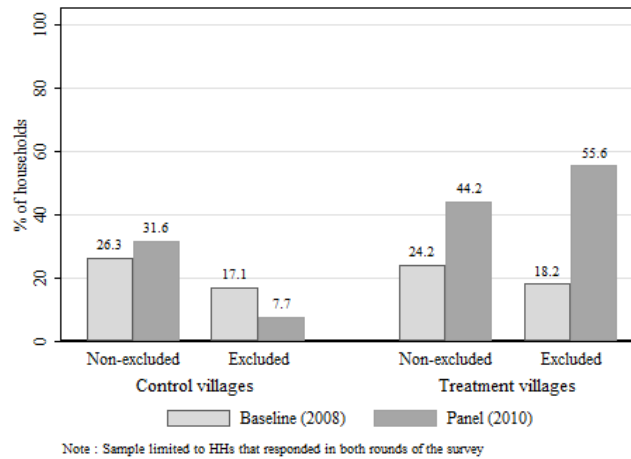
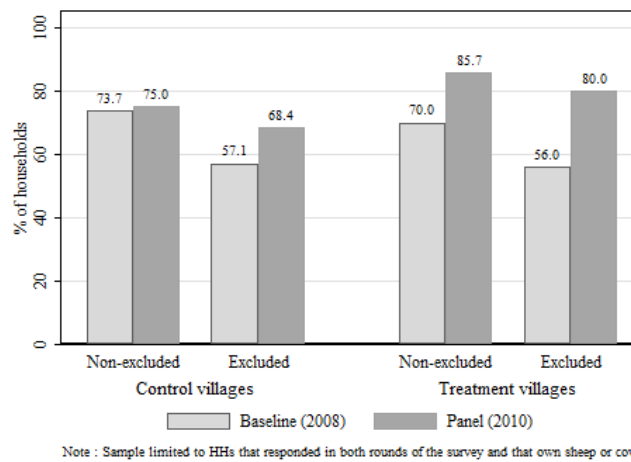


Figure 4.2: Changes in Agricultural Technology Adoption and Use of Consulting Services in Treatment and Control Villages

(a) Percentage of households that inoculated fruit trees



(b) Percentage of households that used preventive vaccination



(c) Percentage of households that visited the district or province agricultural offices

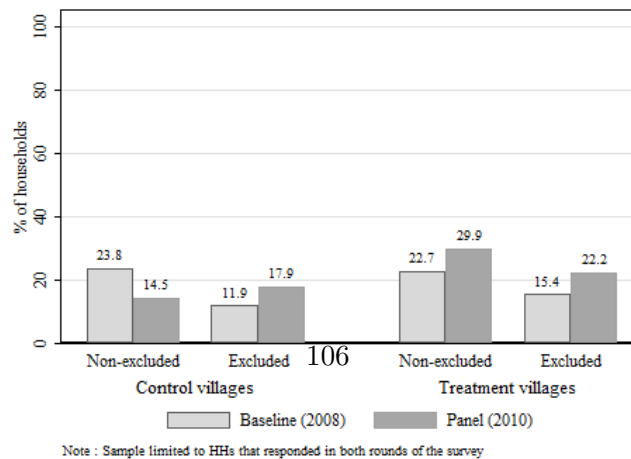


Table 4.1: Summary Statistics in Baseline for Treatment and Control Villages

	Household in Treatment Village					
	Control villages		Treatment villages		Total	
	Col %	95% CI	Col %	95% CI	Col %	95% CI
Asset Quintiles						
Asset Quint 1 (n=66)	24.1	[17.5,32.1]	17.6	[12.8,23.7]	20.2	[16.2,25.0]
Asset Quint 2 (n=65)	25.6	[18.8,33.7]	16.1	[11.5,22.0]	19.9	[16.0,24.6]
Asset Quint 3 (n=65)	18.0	[12.4,25.6]	21.2	[16.0,27.6]	19.9	[15.9,24.7]
Asset Quint 4 (n=65)	13.5	[8.7,20.5]	24.4	[18.8,30.9]	19.9	[16.0,24.6]
Asset Quint 5 (n=65)	18.8	[13.0,26.4]	20.7	[15.6,27.1]	19.9	[15.9,24.7]
Total (n=326)	100.0		100.0		100.0	
Educational Attainment of HH Head						
Illiterate or no diploma (n=91)	19.7	[13.7,27.4]	35.1	[28.6,42.3]	28.7	[24.0,33.9]
Primary school (n=192)	65.9	[57.4,73.5]	56.8	[49.5,63.8]	60.6	[55.1,65.8]
Basic education or Junior High School (n=18)	9.1	[5.2,15.4]	3.2	[1.5,7.1]	5.7	[3.6,8.8]
Senior High School or Above (n=16)	5.3	[2.5,10.8]	4.9	[2.5,9.1]	5.0	[3.1,8.1]
Total (n=317)	100.0		100.0		100.0	
Does not speak Turkish						
Speaks Turkish (n=307)	98.5	[94.1,99.6]	95.1	[90.9,97.5]	96.5	[93.9,98.1]
Does Not Speak Turkish (n=11)	1.5	[0.4,5.9]	4.9	[2.5,9.1]	3.5	[1.9,6.1]
Total (n=318)	100.0		100.0		100.0	
Was a forced migrant						
HH head was not a forced migrant (n=180)	66.9	[58.4,74.4]	47.2	[40.2,54.2]	55.2	[49.8,60.5]
HH head was a forced migrant (n=146)	33.1	[25.6,41.6]	52.8	[45.8,59.8]	44.8	[39.5,50.2]
Total (n=326)	100.0		100.0		100.0	
Exclusion variable)						
Non-excluded (n=189)	63.2	[54.6,71.0]	54.4	[47.3,61.3]	58.0	[52.5,63.2]
Excluded (n=137)	36.8	[29.0,45.4]	45.6	[38.7,52.7]	42.0	[36.8,47.5]
Total (n=326)	100.0		100.0		100.0	

Source: Bitlis Baseline data

Table 4.2: Balancedness Tests Comparing Treatment and Control Villages

Variable Name	Treatment	Control	T-test for difference in the means
Asset index	3.937	3.812	-1.111
	-1.027	-0.958	[0.267]
Poorest Quintile	0.176	0.241	1.423
	-0.382	-0.429	[0.156]
Richest Quintile	0.207	0.188	-0.427
	-0.406	-0.392	[0.670]
No formal Education	0.351	0.197	-3.029***
	-0.479	-0.399	[0.003]
Primary School	0.568	0.659	1.646
	-0.497	-0.476	[0.101]
Basic Education	0.032	0.091	2.228**
	-0.178	-0.289	[0.027]
Secondary School or higher	0.049	0.053	0.175
	-0.216	-0.225	[0.861]
Does not Speak Turkish	0.049	0.015	-1.619
	-0.216	-0.122	[0.106]
Forced Migrant	0.549	0.331	-3.969***
	-0.499	-0.472	[0.000]
Exclusion Variable	0.456	0.368	-1.575
	-0.499	-0.484	[0.116]

Notes: The standard deviations are provided below (Column 1-2) and the p-values for the t-test are provided in [bracket]. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source data: Bitlis Baseline Survey

Table 4.3: Household Characteristics and Assets Used in the Construction of the Asset Index

Household Assets	Refrigerator
	Oven
	Iron
	Microwave oven
	Laundry machine
	Dishwasher
	Radio
	TV
	Satellite
	Cable TV (Digiturk)
	Computer
	Landline phone
	Mobile Phone
	Bicycle
	Private Car
Minibus	
Household Characteristics	Number of Rooms
	Number of Living Rooms
	Number of Kitchens
	Number of Toilets
	Number of Baths
	Number of Animal Barns

Table 4.4: Summary Statistics for the Adoption of Agricultural Technologies

	Mean					
	Baseline Inoculation (%)	Baseline Vaccination (%)	Baseline Consulting (%)	Panel Inoculation (%)	Panel Vaccination (%)	Panel Consulting (%)
Asset Quintiles						
Asset Quint 1 (20%)	13.5	35.8	15.4	30.8	57.7	28.8
Asset Quint 2 (20%)	24.1	46.6	19.7	20.4	67.3	16.0
Asset Quint 3 (20%)	19.0	55.0	16.9	35.0	65.0	13.3
Asset Quint 4 (20%)	19.4	42.9	11.3	52.6	75.4	15.8
Asset Quint 5 (19%)	33.9	63.9	32.3	49.1	72.7	34.5
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5
Educational Attainment of HH Head						
Illiterate or no diploma (28%)	21.2	40.0	15.1	42.9	62.3	15.6
Primary school (60%)	21.5	52.8	20.0	34.1	68.9	21.2
Basic education or Junior High School (5%)	26.7	60.0	12.5	68.8	87.5	25.0
Senior High School or Above (5%)	38.5	53.8	46.2	30.0	50.0	50.0
Total (100%)	22.4	49.5	19.3	38.6	67.4	20.9
Does not speak Turkish						
Speaks Turkish (96%)	23.2	49.8	19.4	37.8	66.8	21.5
Does Not Speak Turkish (3%)	0.0	27.3	18.2	50.0	90.0	0.0
Total (100%)	22.3	49.0	19.3	38.3	67.7	20.7
Exclusion variable						
Non-excluded (57%)	25.3	56.8	22.7	37.7	72.2	22.1
Excluded (42%)	17.8	37.8	14.2	38.7	61.3	20.7
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5
Household in Treatment Village						
Control villages (40%)	23.1	50.8	19.7	23.5	62.6	15.7
Treatment villages (59%)	21.7	48.0	19.0	48.7	71.5	25.8
Total (100%)	22.3	49.2	19.3	38.1	67.8	21.5

Source: Bitlis Baseline data

Table 4.5: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Inoculation of Fruit Trees)
(Dependent variables: Increase in inoculation of fruit trees (0,1 binary variable))

	(1)	(2)	(3)	(4)	(5)
	inoculation	inoculation	inoculation	inoculation	inoculation
Baseline adoption level: Inoculation	-0.195*** (0.0182)	-0.203*** (0.0201)	-0.192*** (0.0189)	-0.206*** (0.0257)	-0.206*** (0.0258)
Household in Treatment Village	0.262*** (0.0305)	0.271*** (0.0288)	0.268*** (0.0306)	0.281*** (0.0285)	0.314*** (0.0182)
Baseline adoption level (Inoculation) x Treatment	-0.359*** (0.0470)	-0.351*** (0.0480)	-0.345*** (0.0410)	-0.331*** (0.0446)	-0.342*** (0.0471)
Poorest Asset Quintile X Treatment	-0.0491 (0.0580)	0.0279 (0.0666)			
No formal education x Treatment	0.0913 (0.0515)	0.180* (0.0926)			
Does not speak Turkish X Treatment	-0.0469 (0.151)	0.0179 (0.163)			
Poorest Asset Quintile		-0.0770** (0.0322)			
No formal education		-0.0891 (0.0768)			
Does not speak Turkish		-0.0648 (0.0597)			
Exclusion Variable x Treatment			0.0827* (0.0410)	0.227** (0.0745)	0.237*** (0.0743)
Exclusion				-0.144** (0.0621)	-0.144** (0.0623)
Social exclusion x Treatment					-0.173* (0.0911)
Constant	0.195*** (0.0182)	0.231*** (0.0363)	0.192*** (0.0189)	0.242*** (0.0398)	0.242*** (0.0399)
Observations	247	247	249	249	249

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.

* p<0.10, ** p<0.05, *** p<0.01

Table 4.6: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Vaccination of Livestock) (Dependent variables: Increase in vaccination of livestock (0,1 binary variable)) The sample for animal vaccination regressions is limited to households that own a sheep or a cow.

	(1) vaccination	(2) vaccination	(3) vaccination	(4) vaccination	(5) vaccination
Baseline adoption level: Vaccination	-0.850*** (0.0541)	-0.838*** (0.0590)	-0.850*** (0.0538)	-0.844*** (0.0518)	-0.844*** (0.0519)
Household in Treatment Village	-0.0188 (0.0314)	-0.0241 (0.0298)	-0.0149 (0.0303)	-0.0223 (0.0290)	-0.0189 (0.0220)
Baseline adoption level (Vaccination) x Treatment	0.0536 (0.0902)	0.0420 (0.0937)	0.0444 (0.0866)	0.0382 (0.0855)	0.0367 (0.0831)
Poorest Asset Quintile X Treatment	0.00358 (0.0890)	-0.0536 (0.0935)			
No formal education x Treatment	0.0268 (0.0368)	-0.0134 (0.0472)			
Does not speak Turkish X Treatment	0.101 (0.0631)	0.0250 (0.0746)			
Poorest Asset Quintile		0.0572* (0.0260)			
No formal education		0.0401 (0.0291)			
Does not speak Turkish		0.0759* (0.0389)			
Exclusion Variable x Treatment			0.0302 (0.0434)	-0.0397 (0.0469)	-0.0402 (0.0450)
Exclusion				0.0699*** (0.0176)	0.0699*** (0.0177)
Social exclusion x Treatment					-0.0206 (0.0580)
Constant	0.850*** (0.0541)	0.827*** (0.0610)	0.850*** (0.0538)	0.829*** (0.0538)	0.829*** (0.0539)
Observations	185	185	186	186	186

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.

* p<0.10, ** p<0.05, *** p<0.01

Table 4.7: OLS estimation for Increase in Use of Consulting Services
(Dependent variables: Increase in Use of Agricultural Consulting Services(0,1 binary variable))

	(1) consulting	(2) consulting	(3) consulting	(4) consulting	(5) consulting
Baseline consulting services utilization level	-0.133*** (0.0263)	-0.124*** (0.0275)	-0.131*** (0.0262)	-0.114*** (0.0210)	-0.114*** (0.0210)
Household in Treatment Village	0.0856*** (0.0253)	0.0885*** (0.0230)	0.0780*** (0.0246)	0.0690*** (0.0289)	0.0878*** (0.0361)
Baseline consulting services utilization level x Treatment	-0.105*** (0.0316)	-0.113*** (0.0327)	-0.109*** (0.0345)	-0.125*** (0.0308)	-0.115*** (0.0330)
Poorest Asset Quintile X Treatment	-0.00235 (0.0574)	-0.0906 (0.0753)			
No formal education x Treatment	-0.141** (0.0560)	-0.179 (0.111)			
Does not speak Turkish X Treatment	-0.0877* (0.0448)	0.145 (0.0939)			
Poorest Asset Quintile		0.0882* (0.0483)			
No formal education		0.0375 (0.0953)			
Does not speak Turkish		-0.233** (0.0824)			
Exclusion Variable x Treatment			-0.131*** (0.0356)	-0.223** (0.0769)	-0.214** (0.0753)
Exclusion				0.0917 (0.0682)	0.0917 (0.0683)
Social exclusion x Treatment					-0.114** (0.0471)
Constant	0.133*** (0.0263)	0.107*** (0.0266)	0.131*** (0.0262)	0.0982*** (0.0206)	0.0982*** (0.0207)
Observations	253	253	254	254	254

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust standard errors clustered at the village level.

* p<0.10, ** p<0.05, *** p<0.01

Table 4.8: Robustness checks: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Inoculation of Fruit Trees)
 (Dependent variables: Increase in inoculation of fruit trees (0,1 binary variable))

	(1) inoculation	(2) inoculation	(3) inoculation	(4) inoculation	(5) inoculation
Baseline adoption level: Inoculation	-0.195*** (0.0522)	-0.203*** (0.0570)	-0.192*** (0.0395)	-0.206*** (0.0541)	-0.206*** (0.0565)
Household in Treatment Village	0.262*** (0.0368)	0.271*** (0.0374)	0.268*** (0.0347)	0.281*** (0.0434)	0.314*** (0.0289)
Baseline adoption level (Inoculation) x Treatment	-0.359*** (0.0794)	-0.351*** (0.0754)	-0.345*** (0.0601)	-0.331*** (0.0622)	-0.342*** (0.0723)
Poorest Asset Quintile X Treatment	-0.0491 (0.0698)	0.0279 (0.0964)			
No formal education x Treatment	0.0913 (0.0631)	0.180 (0.118)			
Does not speak Turkish X Treatment	-0.0469 (0.150)	0.0179 (0.120)			
Poorest Asset Quintile		-0.0770 (0.0594)			
No formal education		-0.0891 (0.0924)			
Does not speak Turkish		-0.0648 (0.0937)			
Exclusion Variable x Treatment			0.0827* (0.0447)	0.227** (0.113)	0.237** (0.0938)
Exclusion				-0.144 (0.102)	-0.144 (0.0889)
Social exclusion x Treatment					-0.173* (0.0953)
Constant	0.195*** (0.0204)	0.231*** (0.0530)	0.192*** (0.0270)	0.242*** (0.0778)	0.242*** (0.0570)
Observations	247	247	249	249	249

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)

* p<0.10, ** p<0.05, *** p<0.01

Table 4.9: Robustness checks: OLS estimation for Increase in Adoption of New Technologies in Agriculture (Vaccination of Livestock)
 (Dependent variables: Increase in vaccination of livestock (0,1 binary variable)) The sample for animal vaccination regressions is limited to households that own a sheep or a cow.

	(1)	(2)	(3)	(4)	(5)
	vaccination	vaccination	vaccination	vaccination	vaccination
Baseline adoption level: Vaccination	-0.850*** (0.0801)	-0.838*** (0.0765)	-0.850*** (0.0858)	-0.844*** (0.0689)	-0.844*** (0.0773)
Household in Treatment Village	-0.0188 (0.0455)	-0.0241 (0.0320)	-0.0149 (0.0390)	-0.0223 (0.0325)	-0.0189 (0.0303)
Baseline adoption level (Vaccination) x Treatment	0.0536 (0.129)	0.0420 (0.0985)	0.0444 (0.109)	0.0382 (0.0913)	0.0367 (0.103)
Poorest Asset Quintile X Treatment	0.00358 (0.0906)	-0.0536 (0.0951)			
No formal education x Treatment	0.0268 (0.0360)	-0.0134 (0.0425)			
Does not speak Turkish X Treatment	0.101 (0.0789)	0.0250 (0.0747)			
Poorest Asset Quintile		0.0572 (0.0411)			
No formal education		0.0401 (0.0346)			
Does not speak Turkish		0.0759 (0.0500)			
Exclusion Variable x Treatment			0.0302 (0.0363)	-0.0397 (0.0548)	-0.0402 (0.0541)
Exclusion				0.0699** (0.0328)	0.0699** (0.0330)
Social exclusion x Treatment					-0.0206 (0.0551)
Constant	0.850*** (0.0801)	0.827*** (0.0800)	0.850*** (0.0858)	0.829*** (0.0750)	0.829*** (0.0830)
Observations	185	185	186	186	186

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)

* p<0.10, ** p<0.05, *** p<0.01

Table 4.10: Robustness checks: OLS estimation for Increase in Use of Consulting Services
(Dependent variables: Increase in Use of Agricultural Consulting Services(0,1 binary variable))

	(1)	(2)	(3)	(4)	(5)
	consulting	consulting	consulting	consulting	consulting
Baseline consulting services utilization level	-0.133** (0.0540)	-0.124** (0.0603)	-0.131** (0.0559)	-0.114*** (0.0371)	-0.114*** (0.0375)
Household in Treatment Village	0.0856* (0.0471)	0.0885*** (0.0300)	0.0780* (0.0470)	0.0690* (0.0408)	0.0878* (0.0497)
Baseline consulting services utilization level x Treatment	-0.105* (0.0568)	-0.113* (0.0627)	-0.109* (0.0632)	-0.125*** (0.0404)	-0.115* (0.0679)
Poorest Asset Quintile X Treatment	-0.00235 (0.0588)	-0.0906 (0.104)			
No formal education x Treatment	-0.141** (0.0555)	-0.179 (0.153)			
Does not speak Turkish X Treatment	-0.0877* (0.0480)	0.145 (0.0913)			
Poorest Asset Quintile		0.0882 (0.0892)			
No formal education		0.0375 (0.150)			
Does not speak Turkish		-0.233** (0.0929)			
Exclusion Variable x Treatment			-0.131*** (0.0390)	-0.223** (0.108)	-0.214* (0.114)
Exclusion				0.0917 (0.0966)	0.0917 (0.106)
Social exclusion x Treatment					-0.114** (0.0573)
Constant	0.133** (0.0556)	0.107* (0.0558)	0.131** (0.0559)	0.0982*** (0.0364)	0.0982*** (0.0365)
Observations	253	253	254	254	254

Standard errors in parentheses

Source data: Bitlis Baseline and Panel 1 Surveys. Robust bootstrapped standard errors clustered at village level using Cameron et al (2007)

* p<0.10, ** p<0.05, *** p<0.01

Chapter 5

Conclusion

This dissertation has brought together three papers using quasi-experimental and experimental methods to measure treatment effects of various shocks and poverty alleviation interventions on Turkish households.

The first paper considered the welfare impact of the 2008-2009 Global Financial Crisis on Turkish households. The paper first established a link between the macro level shock in the financial sector in the province and the changes in earnings at the household level and then using an instrumental variables strategy, established the link between the earnings shock and changes in consumption. The main findings in the paper were that the informally employed workers, and those with lower levels of education (lower than university level) were more likely to be hurt by the Crisis in the provinces where the survey was collected, and that food expenditures and consumption acted as a buffer, particularly for poor households, during the Crisis.

What may be some of the policy implications of the paper? Given that food consumption was the main buffer for these households and that we see the amount of food provided to children being reduced in the face of the income shock, it may be possible to consider in times of such Crises to expand in-kind distribution of food to children through school feeding programs for a limited time period. Such programs, can be an effective social safety net reducing the medium to long-term negative impact of the crisis on children's nutrition and physical/cognitive development, while also having an impact on school enrolment rates (Bundy et al., 2009). However, such programs can also be highly costly and administratively burdensome, hence it is important to make sure they are designed in a cost-effective and sustainable way and perhaps have a time-cap for the duration of the macro shock.

The analysis in the paper can be expanded in several ways in order to better analyse policy options. First of all, one could look at whether there have been changes to

household assets over time as a result of the income shock. While consumption may serve as a buffer in the short term in the face of the earnings shock, households may only begin to run down their assets in the medium term if the earnings shock persists (Fafchamps et al., 1998). The second round of the Turkey Welfare Monitoring Survey was collected as a panel survey in December 2009 (with retrospective questions going back to May 2009) and this survey data (following the same households over time) would enable us to answer questions regarding the changes in assets where the income shock persists for several months. The household assets module, as well as the module on household savings and debt in this survey questionnaire would be invaluable inputs in answering questions related to the medium term impact of the crisis on household assets.

A second way in which the analysis in the paper can be expanded, involves the use of the safety nets module in the data set. Such analysis would be quite descriptive in nature, though it would still be interesting to pursue: this module in the data has detailed information on the household's access to safety nets through public and private means. For instance, each household reports whether during difficult times they would be able to borrow from friends and relatives, and whether they have utilized this informal safety net in the past. A preliminary analysis of this module shows that informal safety nets (involving friends and family networks) are quite strong in the Turkish context, with 20.6 percent of households in the sample reporting they increasingly borrowed from friends and relatives and 7.4 percent reported they increasingly received help from friends and relatives through the Crisis. On the contrary, the public safety net is quite weak, with only 1 percent of households in the sample accessing social protection funds provided by government and municipalities in the same time period. This preliminary analysis of the safety nets module, also suggests that households that had access to informal safety nets had a lower probability of reducing (food) consumption through the crisis, even in the face of an income shock. This finding indicates that the informal safety net in Turkey may have been effective in *delinking* the income shock at the household level with changes in consumption and welfare. Hence, in a separate paper, it would be interesting to further analyze this data on use of informal safety nets through the Crisis and the effectiveness of such networks for reducing the welfare impact of the Crisis on households.

The second paper in the dissertation, assessed the protective impact of the Green Card non-contributory health insurance program in Turkey and concluded that having access to the green card was associated with a lower probability of reducing utilization of health care services through the Crisis. This result suggests that the Green Card was an effective safety net program in times of Crisis, though the cost-effectiveness of such

a program should also be evaluated separately in order to give a full-fledged assessment of the success and sustainability of the program.

To take these results forward, it would be interesting to look at a couple of other policy related research questions around the Green Card expansion in Turkey. In this time period we also observe a rapid reduction in the under-5 and maternal mortality rates in Turkey and a relevant and important question to ask is to what extent the Green Card program has contributed to these improved health outcomes. The main data source for such a study would naturally be the Demographic and Health Surveys collected in 2003 and 2008, the time frame for these cross sectional data sets would cover the rapid expansion period of the Card across Turkey. One could instrument for the household's access to the card by using the rate of expansion of the Green Card across provinces or districts from 2003 to 2007¹.

Another important question to ask is whether the Green Card has had the undesired impact of increasing “informal labour” in the country. Since the incentives in the program are such that only workers that are informally employed (and not paying taxes to government) can benefit from the program, those in the formal sector may be induced to taking informal (with more risk and higher pay) and substitute the benefits from the formal job by applying for the Green Card. In the field, there is some anecdotal evidence that this may be happening, and it would be interesting to pursue this question using the panel component of Turkish Labour Force Surveys².

The third paper in the dissertation focused on the impact of a post-conflict rural development program on agricultural adoption rates in Kurdish villages in eastern Turkey. The study showed that particularly for those technologies where the initial adoption rates were low, the agricultural extension program implemented by the NGO was successful in increasing adoption rates, and the politically and economically excluded groups benefited more favourably from the activities of the program. The results of the evaluation will be complete only after 5 years of full implementation (further data is to be collected at the end of 5 years of program activity in 2013), however even these preliminary results suggest that such projects can be useful in expanding income earning opportunities for villagers in this post-conflict zone. Once again, it is highly important to judge the cost effectiveness and sustainability of such a program, but it is possible to see that –at least

¹The rate of expansion of the Green Card is correlated with the treatment variable (access to the Green Card at the household level), though it should be uncorrelated with the error term in the equation, assuming it is related to child outcomes only through its impact on the households' access to the Green Card.

²These Labour Force Surveys do have panel components –necessary for such a study - though the panel identifiers are not always publicly shared by the Turkish Statistical Institute, it would be necessary to make a special request for such a data set.

in the pilot phases- the program has had some impact on beneficiary households.

The empirical analysis in this paper can be taken further in several ways: first of all, the “exclusion” variable used in the paper was a crude definition constructed using several existing variables in the data set relating to wealth (asset index), education and ability to speak the official language. While this serves as a decent proxy for exclusion in this region, it would be much better to have a more detailed – and preferably categorical - variable on exclusion. This could be collected using self-reporting, as well as using objective data on the number of visits to government offices, voting history and degree of engagement in political/social affairs.

Second, it would be good to repeat a similar analysis where the adoption levels are reported as continuous variables, where we can also take the quadratic form of the baseline adoption levels. This would enable us to emulate the S-shaped diffusion function and thus fit the functional form described in the conceptual model better. It would also be good to have larger sample sizes in the data, that would allow the construction of village level baseline adoption variables. Both of these independent variables would help explain the model better.

Finally, it would be interesting to further pursue the results presented in this paper on social exclusion and the inability of the program to reach the socially excluded (while being perfectly inclusive of the politically and economically excluded groups). It is obviously very difficult to set-up an experimental study that would give causal interpretations on this social exclusion variable (since such set-up would have serious ethical drawbacks), but it may be possible to have further qualitative measures of social exclusion included in the data that would perhaps make the correlation results associated with this variable more consistent and reliable.

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