



## Working paper 6/2012

**Background Risk of Food Insecurity and Insurance  
Behaviour: Evidence from the West Bank****Elisa Cavatorta, SOAS, University of London  
Luca Pieroni, University of Perugia**

**Abstract:** *This paper explores behavioural changes resulting from the presence of a back-ground risk. Due to markets incompleteness, not all risks are insurable. The literature suggests that, according to the structure of preferences, agents bearing a background uninsurable risk are less willing to bear other insurable risks and increase their demand for insurance. The empirical evidence of this effect is limited and, despite the relevance of this question, unexplored in developing countries. This paper fills this gap. It explores the effect of a background risk on the decision to buy health insurance using household data from the Palestinian Territories. We consider the risk of food insecurity as a background uninsurable risk. Using a bivariate probit model, we find that the propensity to buy health insurance is positively affected by the presence of a background risk of food insecurity. When allowing the back-ground risk to vary in intensity, we find that the propensity to insure is higher as the background risk becomes more intense. These results are robust to alternative indicators of background risk. The study shows that, in presence of background risks, there might be incentive changes towards the desirability of insurance that have implications for policy design.*

# Background Risk of Food Insecurity and Insurance Behaviour: Evidence from the West Bank

Elisa Cavatorta\*      Luca Pieroni†

This version: September 4, 2012

## Abstract

This paper explores behavioural changes resulting from the presence of a background risk. Due to markets incompleteness, not all risks are insurable. The literature suggests that, according to the structure of preferences, agents bearing a background uninsurable risk are less willing to bear other insurable risks and increase their demand for insurance. The empirical evidence of this effect is limited and, despite the relevance of this question, unexplored in developing countries. This paper fills this gap. It explores the effect of a background risk on the decision to buy health insurance using household data from the Palestinian Territories. We consider the risk of food insecurity as a background uninsurable risk. Using a bivariate probit model, we find that the propensity to buy health insurance is positively affected by the presence of a background risk of food insecurity. When allowing the background risk to vary in intensity, we find that the propensity to insure is higher as the background risk becomes more intense. These results are robust to alternative indicators of background risk. The study shows that, in presence of background risks, there might be incentive changes towards the desirability of insurance that have implications for policy design.

**Keywords:** Background Risk, Food Insecurity, Health Insurance, Bivariate Probit

**JEL Classification:** I11 015 C35

---

\*Corresponding author. Centre for Development, Environment and Policy, SOAS, University of London. *E-mail*: ec21@soas.ac.uk

†Department of Economics, University of Perugia. *E-mail*: lpieroni@unipg.it  
We are grateful to Ron Smith for his invaluable advice on earlier versions. We would like to thank Walter Beckert, Colin Rowat, Yunus Aksoy, Awad Mataria, Riadh Ben Jelili, Marijke Verpoorten and the conference participants of the 2010 African Econometric Society Conference in Cairo; the 2011 Global Economic Cost of Conflict Conference at DIW, Berlin; of the IFS internal seminars in London; the 2011 ERF Conference in Antalya, and the 2011 European Peace Science Conference in Amsterdam for stimulating discussions and helpful comments. We are indebted to FAO/WFP for sharing the data with us. The responsibility for any errors or omission is our own.

# 1 Introduction

Facing risks is a fact of life. They are central to many domains of individual capabilities and wellbeing: income, health, education, personal security and political freedom (Sen, 1985; Nussbaum & Sen, 1993; Becker *et al.*, 2005). Each of these spheres of life is subject to idiosyncratic risks such as illness, unemployment, drought, floods, earthquakes and conflict. These risks can severely impair individual capabilities and well-being.

In real life, individuals face multiple risks from living in particular locations. Some of these risks can be avoided or reduced by formal market insurance. But, due to markets incompleteness, other risks for which insurance markets and alternative systems of risk protection are missing, cannot be avoided. The term "background risk" originates from the interpretation that these unavoidable risks stay in the background. Little is known about people's reactions when facing both types of risks. Does the uncertainty originating from one unavoidable risk alter the risk-taking behaviour against other avoidable or insurable risks? The intuition suggests that risk-averse agents would behave in a more risk-averse manner in this situation. What is of concern is the overall exposure to risk.<sup>1</sup> Despite this behaviour seeming common sense, the literature lacks empirical evidence from developing countries.

This paper focuses on the behavioural changes resulting from the presence of uninsurable background risks. We argue that the presence of background risks influences the attitude toward other competing risks and the desirability of insurance against those insurable. Our findings suggest that individuals who are subject to higher background risk are more sensitive to the probabilities of avoidable risks. In other words, uninsurable background risks alter individuals attitude towards other, insurable, risks and affect positively the propensity to insure against them.

Despite the importance of such behavioural effects for policy, few studies have analysed empirically the effect of uninsurable risks on insurance decision against other risks. Understanding how the attractiveness of insurance may change due to a background risk is critical to policy designing insurance schemes and alternative risk protection programmes. Empirically, if background risk is an important determinant of individual behaviour toward insurable risks, neglecting it leads to incorrect inference when estimating a demand for insurance. The few studies looking at this issue focus on developed countries but, despite the relevance of the question in developing countries where missing markets are common, to our knowledge, none has

---

<sup>1</sup>Whether the aversion to risk in different contexts of life is stable is a debated question. The traditional view in economics assumes constant risk preferences across domains. This assumption is controversially debated in psychology (Slovic, 1972; Loewenstein *et al.*, 2001; Weber & Betz, 2002). In economics, a recent study by Barseghyan *et al.* (2011) reject the hypothesis of risk aversion being context-invariant using US insurance data.

investigated it yet.

In the Italian context, Guiso & Jappelli (1998) show that the demand for casualty insurance is positively affected by background risk, proxied by a subjective measure of earning uncertainty. In another study, Guiso *et al.* (1996) find that Italian households facing higher income risk hold fewer risky securities, concluding that higher income uncertainty reduces the demand for risky assets. This evidence supports the proposition that background risk should cause people to increase their demand for insurance against other risks where insurance is available or reduce their exposure to avoidable risks.

On the theoretical side, Pratt & Zeckhauser (1987) and Kimball (1993) formalise the notion that bearing one risk should make an agent less willing to bear another risk. This behaviour depends on the structure of preferences: Eeckhoudt & Kimball (1992) and Kimball (1993) show that decreasing absolute risk aversion and prudence are sufficient conditions for this behaviour. Gollier & Pratt (1996) establish that the same behaviour arises if temperance exceeds prudence.<sup>2</sup>

This paper contributes to this literature by exploring the effect of an uninsurable background risk on the decision to buy health insurance in a developing country. We also consider how the propensity to insure changes as the intensity of the background risk varies. To do so, we use an original household dataset - the 2009 and 2010 *Socio-Economic and Food Security Surveys* - conducted in the West Bank region of the Palestinian Territories, where the health insurance market exists but it has not universal public coverage.

The Palestinian Territories are an example of a risky environment. Palestinians have lived in a state of severe insecurities and war-like conditions since 1948. Years of political stalemate have led Palestinians to face serious conditions of economic insecurity, only partially mitigated by a heavy dependence on foreign resources and international aid. Malnutrition and food insecurity are among the most pronounced outcomes of such economic insecurity.<sup>3</sup> We use a subjective measure of food insecurity risk as a proxy for background uninsurable risk. Perception of food insecurity risk is a direct

---

<sup>2</sup>This property of preference is called "proper risk-aversion" by Pratt & Zeckhauser (1987) and "standard risk aversion" by Kimball (1993). Let  $u(w)$  be a standard utility function of wealth,  $w$ : decreasing absolute risk aversion -  $-u''(w)/u'(w)$  - says that an individual sensitivity to risks decreases with wealth. Decreasing absolute prudence -  $-u'''(w)/u''(w)$  - says that the precautionary saving motive decreases in intensity with wealth. Temperance is defined as a preference for disaggregation of risks and requires  $u''''(w) \leq 0$ . Further extensions on preferences properties required for background risk to induce more risk-averse behaviour involving stochastic dominance properties are presented in Eeckhoudt *et al.* (1996). Eeckhoudt & Kimball (1992) show that an agent's willingness to bear other risks in presence of a background risk decreases whether or not the two risks are correlated or independent.

<sup>3</sup>Banerjee & Duflo (2007) argue that there is a certain amount of choice among the poor regarding food consumption: spending the available budget on other commodities other than food may be a deliberate choice. However, it is unlikely that this phenomenon occurs widely among Palestinians in the West Bank, where people in the lowest quartile of total expenditure spend approximately 65 percent of their budget on food (the Socio-Economic and Food Security Survey, 2010).

reflection of uncertainty in initial endowment which is not formally insurable.<sup>4</sup> Other forms of self-protection, such as informal insurance networks, can be alternative responses to uninsurable background risk. Their importance relative to the demand for insurance against insurable risks is a topic left for further research.

To estimate the effect of a background risk on the decision to insure, our main empirical strategy uses a bivariate probit model. This choice takes into account that food insecurity risk and the decision to buy health insurance may depend on similar factors, such as individual resources, gender, work environment and geographical location. This induces a correlation between the background risk of food insecurity and the decision to buy health insurance through the observable variables.

The change in the desirability of insurance due to the background risk remains unobserved to the econometrician. This cross-risk effect results in the unobserved determinants being correlated. Our empirical approach allows the residuals to be correlated and interprets this correlation.

This paper contributes to the understanding of household behaviour in presence of background uninsurable risks. It draws from the theoretical literature on attitudes toward risk in presence of uninsurable risks (Pratt & Zeckhauser, 1987; Eeckhoudt & Kimball, 1992; Eeckhoudt *et al.*, 1996) and it contributes to the limited number of empirical studies on this topic (Guiso & Paiella, 2008). The paper develops work on background risk and demand for insurance by Guiso & Jappelli (1998) bringing empirical evidence from a developing country. The paper relates to the literature on complementarities between multiple risks to life as in Dow *et al.* (1999). The paper also relates to the literature on the value of life such as in Viscusi & Evans (1990) and Evans & Viscusi (1993), but it differs from it by differentiating between an insurable and an uninsurable risk. Lastly, this paper relates to the literature in development economics that studies risk and insurance in developing countries (see Dercon (2004) and references therein) . This literature generally focuses on one risk and the demand for insurance against that specific risk. Our aim is different because we focus on the spillover

---

<sup>4</sup>Limits of (formal)insurability against food insecurity risk (similarly to resource endowment uncertainty) are related to asymmetric information problems, such as moral hazard and adverse selection; the imprecision of risk assessment and the size of the loss and the possible existence of correlated risks. Moral hazard problem relates to the fact that incentives to prevent the occurrence of the risk would reduce, should a type of "food insecurity insurance" exists. Also, since losses from food insecurity may be difficult to verify and quantify, claims might be overstated, creating an ex-post moral hazard. A potential insurer would need to estimate the chances of the risk occurring to set some form of premium. Doing so it is extremely difficult, especially in a context such as the Palestinian Territories, where conflict related events and externally enforced restrictions may changes the risk landscape radically. Also, the risk of food insecurity partly depends on atmospheric conditions: despite forms of weather insurance exist in other developing countries, no scheme of weather insurance is available in the Palestinian Territories. Finally, food insecurity and health risk may be correlated in the long run. We do not claim that food insecurity is an independent background risk. However, it is plausible that this dependence is weak in the short-run. Indeed, the data do not show evidence of any association of this form.

effect across risks.

The paper is organised as follows. Section 2 presents a brief overview of the Palestinian health-care system and it explains the state and the causes of food insecurity in the Palestinian Territories. Section 3 develops the model used to examine how the propensity to buy health insurance changes in presence of background risk. Section 4 discusses the data used and their sources. Section 5 presents the empirical results: it first presents the results from a baseline model, then an extension and finally some caveats. Section 6 concludes and discusses the policy implications of our findings.

## 2 Health insurance and food insecurity in the West Bank

The health insurance market in the Palestinian Territories (West Bank and Gaza Strip) includes three main providers: the Palestinian Authority through the Palestinian Ministry of Health (MoH), the United Nations Relief and Works Agency (UNRWA) and a number of private insurance companies.<sup>5</sup> Despite national health programmes over the years have aimed to promote enrollment into the government scheme, health insurance coverage is still far short than universal. In 2010, yet 28.8% of households in the West Bank are not covered by any health insurance.

Health insurance is to a large extent a voluntary decision, except for government employees. Government employees are compulsorily enrolled in the government insurance scheme as part of their contract. Formally registered refugees, who are the people displaced and dispossessed during the Arab-Israelis wars and their descendants, are entitled to receive a free of charge health insurance coverage provided by UNRWA, subject to an application. As a result, most of refugees are covered by UNRWA health insurance scheme, to which a government insurance (or, possibly, a private scheme) can be voluntarily added. Excluding these categories, the percentage of households not voluntarily insured was 38.3% in 2010.

The fragmentation of the system is partly the result of political conditions and the reaction to emergency situations in the past, such as the inception of UNRWA health services. Partly because of this fragmentation, partly because of uncoordinated policies of funding and partly because of its enrolment rules, the financial viability of the health insurance system is extremely fragile. Mataria *et al.* (2009) and Abu-Zaineh *et al.* (2008) discuss these issues in details. In particular, the rule of open enrolment, that allow people to enroll into the system at any time, may enhance problems of adverse selection. Healthy people have the incentive to stay out of the system

---

<sup>5</sup>In remote rural areas, non-governmental organisations may deliver forms of primary health-care as part of their programmes, without formal health insurance schemes.

until they are sick. Secondly, since Palestinian are denied access to Israelis hospitals and capacity in local hospitals is constraint, increasing number of patients are referred abroad (primarily to Jordan). A practise that increases the financial burden of the health care in the West Bank. In this context, understanding the drivers of the propensity to formally insure has a direct influence for policy planning.

As Guiso & Jappelli (1998) show in the Italian context, insurance decision may be affected by the presence of other uninsurable risks. Clearly, this issue is relevant to Palestinians who face a severe risk of food insecurity, which is not formally insurable. The Food and Agriculture Organization (FAO) classifies about 22% of the Palestinian population in the West Bank as severely food insecure in 2010 and 12% vulnerable to food insecurity (FAO, 2010).

Food insecurity in the West Bank is due to an intertwined mix of impaired food accessibility, food availability and food utilisation. Economic accessibility is the most important dimension of food insecurity. Food access is constrained by low income opportunities (a consequences of low wages and salaries, high rates of unemployment and limited internal and external markets for goods, services and entrepreneurial activities) and artificially inflated food prices due to high transportation costs, limited local production and heavy dependence on Israeli imports. Food availability is constrained by low crop and animal production and limited expansion possibilities due to land access restrictions, water availability and a limited variety of alternative supplies due to the closure policy in place. Impaired food utilisation reflects insufficient macro-nutrient intake and unbalanced diets, partly related to cultural practises and partly to the relatively higher cost of nutritionally-rich food products.

Being food insecure is a persistent risk in the West Bank, which may affect individual behaviour towards other risks to life and the demand for risk protection against insurable risks. This is the question we now turn. The next section proposes a theoretical model to analyse the effect of the presence of a background risk of food insecurity on the propensity to buy health insurance.

### 3 The model

We first abstract from the background risk and suppose that the individual preferences can be represented by a von Neumann-Morgenstern non-separable utility function which depends on income,  $U(y) > 0$ , and utility is increasing in income and concave,  $U'(y) > 0$ ,  $U''(y) < 0$ . If the individual buys health insurance, she needs to pay an enrollment fee  $\pi$ . The utility with insurance is  $U(y - \pi)$ . If the individual does not buy insurance she may

have to pay the cost of hospitalisation in case of illness. Let  $c$  be the cost of health service and  $p$  the exogenous probability of illness. The expected utility under no-insurance is  $pU(y - c) + (1 - p)U(y)$ . Individuals will insure provided that the utility with insurance exceeds the expected utility with no-insurance:

$$U(y - \pi) > pU(y - c) + (1 - p)U(y) \quad (1)$$

The individual decision to insure depends on individual income and observable characteristics, risk aversion and unobservable beliefs of health risk incidence.

Let's now consider an uninsurable background risk. In our setting, the individual is subject to an idiosyncratic background risk of food insecurity which depends on some observable individual characteristics and the environment where the individual lives. The risk is uninsurable since no economically viable insurance market against the risk of food insecurity exists. This missing market adds an additional sources of randomness to the utility function. We aim to see whether the presence of an uninsurable background risk influences the probability of buying health insurance.

Let the utility function subject to an uninsurable background risk of food insecurity,  $\tilde{f}$ , be  $U(y, \tilde{f})$ . This risk has support  $\tilde{f} \in R_0^+$ . In this framework, the observed choice between insuring and not-insuring reveals which status provides the greatest utility, subject to the presence of a background risk and the budget constraint. The single utilities in (1) remain unobserved. That is, the indirect utility is the maximum of the two conditional indirect utility,  $EV^{insured}$  and  $EV^{uninsured}$  (which we abbreviate in  $EV^{ins}$  and  $EV^{uns}$  respectively):

$$EV(y, \pi, p, c, \tilde{f}, x) = \max[EV^{ins}(y, \pi, p, \tilde{f}, x), EV^{uns}(y, c, p, \tilde{f}, x)] \quad (2)$$

$$s.t. \quad e + s \leq y \quad (3)$$

where  $y$ ,  $\pi$ ,  $p$ ,  $c$  and  $\tilde{f}$  are defined previously and  $x$  is a vector of individual characteristics. The budget constraint is made of expenditure to buy goods and services,  $e$ , and savings,  $s$ . We assume that people buy insurance with their savings, thus  $s$  is equal to the price of insurance  $\pi$  if people decide to insure, or it is zero if people decide not to insure. This is a simplifying modeling assumption, which is in line with the evidence that individual savings in the West Bank are exhausted by deteriorating income-generating opportunities (FAO-WFP, 2009).

Under these assumptions, the unobserved elements of the utility function can be identified as individual-specific preference factors. Following McFadden (1981) we assume an additive separable random error for each insurance coverage state:  $\epsilon^{ins}$  in case of insurance,  $\epsilon^{uns}$  in case of no-insurance. The stochastic component allows for unobserved factors of choice.



Individuals decide to buy health insurance only if

$$\Delta \bar{EV} = \bar{EV}^{ins} - \bar{EV}^{uns} > 0 \quad (4)$$

where  $\bar{EV}$  indicates the deterministic component of  $EV$ . If  $\epsilon^i$  where  $i = ins, uns$  is assumed to be standard normal distributed, the probability to buy health insurance is

$$\begin{aligned} Pr(y_1^* > 0 | x) &= Pr(\Delta EV > 0 | x) \\ &= \Phi(x' \beta^{ins} + \epsilon^{ins} - x' \beta^{uns} - \epsilon^{uns} > 0 | x) \\ &= \Phi(x'(\beta^{ins} - \beta^{uns}) > \epsilon^{uns} - \epsilon^{ins} | x) \end{aligned} \quad (5)$$

The background risk of food insecurity, conditional to an arbitrary threshold, may simultaneously depend on similar factors,  $x'$ , inducing a correlation through the observable variables. Differently from the decision to buy a health insurance, food insecurity may not be interpreted as a choice variable, but it depends on the environment characteristics and these need to be jointly controlled for. However, what remains unobserved is the change in desirability of insurance due to a cross-risk effect. This induces a correlation through the unobservables. Assuming the disturbances are normally distributed, the choice to insure and the background risk of food insecurity can be simultaneously described by a bivariate probit in latent variables.

The empirical model is represented as follows

$$y_{1i}^* = \beta_1' x_{1i} + \epsilon_{1i} \quad (6)$$

$$y_{2i}^* = \beta_2' x_{2i} + \epsilon_{2i} \quad (7)$$

$$\{\epsilon_{1i}, \epsilon_{2i}\} \sim \Phi_2(0, 0, 1, 1, \rho)$$

where the values for  $y_{.i}^*$  are unobservable and related to the following binary dependent variables, on the basis of these conditions:

$$y_{1i} = 1 \quad \text{if} \quad y_{1i}^* > 0, \quad 0 \text{ otherwise}, \quad (8)$$

and

$$y_{2i} = 1 \quad \text{if} \quad y_{2i}^* > 0, \quad 0 \text{ otherwise}, \quad (9)$$

where  $y_{1i} = 1$  indicates that the individual is insured, which depends on personal and family characteristics, job sector and geographical factors included in  $x_{1i}$ .  $y_{2i} = 1$  indicates that the individual is food insecure, which depends on similar factors included in  $x_{2i}$ . The errors  $(\epsilon_{1i}, \epsilon_{2i})$  are assumed to have a standard bivariate normal distribution, with  $Cov(\epsilon_{1i}, \epsilon_{2i}) = \rho$ . The parameter  $\rho$  captures the unobservable change in attitudes toward insurance.

Following these assumptions, the probability of an individual to be in-

sured and food insecure is given by

$$\begin{aligned}
Pr(y_1 = 1, y_2 = 1 | x) &= Pr(y_1^* > 0, y_2^* > 0 | x) \\
&= Pr(-\epsilon_1 < \beta_1'x_1, -\epsilon_2 < \beta_2'x_2) \\
&= \int_{-\infty}^{\beta_2'x_2} \int_{-\infty}^{\beta_1'x_1} \phi_2(z_1, z_2, \rho) dz_1, dz_2 \\
&= \Phi_2(\beta_1'x_1, \beta_2'x_2, \rho)
\end{aligned}$$

where  $\phi_2$  and  $\Phi_2$  denote the density function and the bivariate standard normal distribution function, respectively. Estimation requires at least one exclusion restriction for identification (Angrist, 2009). and the method of Maximum Likelihood provides unbiased and efficient estimates (Zellner & Lee, 1965; Ashford & Sowden, 1970; Greene, 1998, 2008). The next section introduces the data on which we base our estimations.

## 4 Data and descriptive statistics

The empirical evidence is based on the household data provided by the *Socio-Economic and Food Security Surveys 2009 and 2010* conducted in the West Bank. The surveys were administered by the Food and Agriculture Organization (FAO), the Palestinian Central Bureau for Statistics (PCBS) and the World Food Programme (WFP) during the second half of 2008 and the second half of 2009. In addition to standard demographic variables, the surveys provide data on insurance coverage and an extensive module to elicit food insecurity. The sample design is a (two-stage stratified) cluster random sample representative of the Palestinian population. It includes 8971 households living in the West Bank and East Jerusalem. People living in East Jerusalem have access to the Israeli labour market, Israeli insurance system and have higher living standards. Given the differences with the population in the West Bank they are excluded from the estimation sample. After deletion of outliers and missing observations, the available sample includes  $N = 7935$  households in the West Bank.

Our health insurance indicator is a binary variable equal to 1 if the household head is covered by health insurance: 71.4% of the households have a health insurance, 28.6% have no health insurance. We do not differentiate by health insurance type in the empirical estimation.

Since government employees are subject to a compulsory health insurance and refugees are covered by UNRWA health insurance free of charge, we consider two samples: the sample including all households ( $N = 7935$ ) and a restricted sample excluding government employees and refugees ( $N = 4880$ ). We refer to the latter sample as 'voluntary insured' sample because these

households face a voluntary choice about insurance: 59% of households are covered by health insurance, 41% are not. Table A1.2 in the Appendix reports averages of socio-economic variables in the total sample and the restricted sample. Households in the total sample are 4 percent richer than households in the restricted sample. However, overall there are no significant socio-economic differences between the total and the selected sample, suggesting no evidence of sample selection bias.

To select the food insecurity risk indicator we refer to the definition contained in the Rome Declaration on World Food Security (1996) and the World Food Summit Plan of Action which defines food insecurity as the situation when people do not have adequate physical, social or economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life. The definition includes four main components: (i) adequacy of food supply or availability; (ii) stability of supply, without fluctuations or shortages from season to season or from year to year; (iii) accessibility to food or affordability; (iv) quality and safety of food.

The literature suggests a number of food insecurity indicators, each capturing different aspects of food insecurity and food insecurity risk.<sup>6</sup> We measure food insecurity risk by the Household Food Insecurity Access (HFIA) Prevalence. This is based on the frequency of occurrence of certain behaviours which result from an insufficient availability of food (such as being unable to eat because of lack of resources, eat a limited variety of food, going a whole day and night without eating); insufficient stability (such as having no food in certain days, going to bed hungry because food was not enough) and shortage (such as eating smaller meals than needed, eating fewer meals because food was not enough); insufficient quality (such as eating food one prefers not to eat) and household anxiety about food being sufficient (Coates *et al.*, 2007). Households are categorised in four levels of food insecurity as they experience those conditions more frequently. This classification generates a categorical variable, HFIA, coded as follows: 1 = Food secure; 2 = Mildly food insecure; 3 = Moderately food insecure; 4 = Severely food insecure. The HFIA indicator is preferred over alternative indicators because it includes questions related to all aspects (i)-(iv) above and asks about anxiety regarding the availability of food which is a direct reflection of the perception of risk of food insecurity.

---

<sup>6</sup>For example, perception-based versus standardised scale indicators often give different pictures. A common indicator of food insecurity is the number of calories consumed per day. When this indicator is possible to compute, it offers a precise and comparable measure of food security. However, the indicator tends to increase when food is externally provided by food-aid agencies. Despite condition (i) and (iv) above might be met in this situation, supply is not stable and the condition is not self-sustainable. The risk of food insecurity remains high in such a situation. Perception and behaviour based indicators capture subjective aspects of food security but they are necessarily context dependent. A discussion about the validity of food insecurity indicators based on self-reported behaviours and perceptions can be found in Coates *et al.* (2007) and Webb *et al.* (2006).

In the baseline analysis (section 5.1), we consider the background risk of food insecurity as a dichotomous condition. The background risk of food insecurity is a binary variable equal to 1 if the household is "severely food insecure" according to the HFIA indicator, 0 otherwise. Then, in section 5.2, we consider various levels of risk intensity.

Over the two years, the proportions of severe food insecure households are similar: about 22% of households are severely food insecure and 78% are not. Intermediate levels of food insecurity risk are also similar. The descriptive statistics suggest that the presence of a background risk of food insecurity influences positively the propensity to buy health insurance. Table 1 shows the unconditional joint probabilities of health insurance coverage and food insecurity status as measured by the HFIA binary indicator. The upper Table reveals that the joint probability of being food insecure and insured (16.1%) is three times higher than the probability of being food insecure and not insured (5.5%). This feature persists in the voluntary insured sample: 14% of food insecure households are insured while only 7.7% are not insured (bottom Table). If the probability to insure was only a function of the ability to pay for insurance, poorer individuals might be expected to insure less as they might be likely to substitute their expenditures for food consumption. Unconditionally, the hypothesis of independence of the two events is rejected by Pearson's Chi square tests. In the next section we show that, conditioning on other covariates, the two events remain significantly correlated. Control variable statistics and coding details are summarised in Appendix 1.

Given the linkages between malnutrition and health outcomes, we are concerned that food insecure people may sort themselves out into insurance schemes because they are more likely to be ill. We cannot exclude this effect being relevant in the long-run. However, we do not find significant differences in disease prevalence among food insecure and food secure people in the short-run, conditioning on age and gender.

In the second part of this analysis, we use the HFIA indicator to capture different levels of food insecurity and to study the propensity to insure as food insecurity intensifies. The HFIA indicator classifies 21.6% of households as severely food insecure; 13.7% as moderately food insecure; 8.6% as mildly food insecure and 56.1% as food secure. The findings are discussed in section 5.2.

We also experiment with alternative indicators of food insecurity based on reported household behaviours. The indicator "less food" indicates that the household reports to have consumed less quantity of food in the past weeks to stand financially. The indicator "food credit" indicates that the household resorted to buy food on credit to be able to eat. The indicator "less food for adults" indicates that adults have restricted their own consumption of food in order for children to eat. The indicator "meal reduced" indicates that the

household has reduced the number of meals per day during the past weeks to be able to stand financially. Results using these alternative indicators are presented in Tables 3 and 4 and commented in the next section.

## 5 Empirical results

### 5.1 Baseline model: dichotomous background risk

This section discusses the baseline model in which the background risk of food insecurity is a binary condition. The model is estimated by a bivariate probit model specified in equations (6) and (7). We model food insecurity and health insurance coverage jointly because similar observed factors may influence both outcomes.

The vector of control variables  $x_{ki}$  is a vector of household  $i$ 's characteristics and geographical factors. These include household total *monthly expenditure*, a proxy for income, which influences the ability to pay for insurance and to acquire food; *age* of the household head, which may affect the demand for insurance coverage and the vulnerability of food insecurity. We test (and reject) alternative non-linear specifications of expenditure and age. We include *education*, expressed as years of schooling, as education may increase information about health insurance schemes and open up access to better income opportunities and stable jobs, reducing the likelihood of food insecurity risk; we control for the different behaviour of *female-headed* household. Insurance decision is likely to depend on individual *health risk*: this is unobservable. Our strategy to address this problem is to include a variable indicating whether the households faced any severe health problems in the last 6 months. The *location of residence* (urban, rural or refugee camp) may influence the decision to insure and food insecurity through the availability of services. We include a set of *employment sector* dummies to capture the effect of compulsory insurance system and indirect support to cope with risks linked to the employment environment. We control for the ownership of a *crop* cultivated field, which may alleviate food insecurity risk through own-production of food. *Crop* has no effect on insurance decisions and it is an exclusion restriction. We include a set of dummy variables for *geographical areas* to capture unobserved heterogeneity of prices in different locations and a *time dummy* related to the data-collection year. Risk preferences are not observed directly, however we include as many as possible of its socio-economic determinants such as gender, age and wealth.<sup>7</sup>

The baseline estimates are reported in Table 2. Columns 1-2 in Table 2 refer to the whole sample. Columns 3-4 refer to the restricted sample of

---

<sup>7</sup>Despite height and parental background are found to be significant determinants of risk aversion in the health context, we need to omit these variables as metric data on height were not collected and parental education is available only for a small number of observations (Dohmen *et al.*, 2011).

voluntary insured households. The residual correlation based on the whole sample estimates is 0.077: while modest in size, it is statistically different from zero at 1% confidence level. The LR test statistics for the hypothesis that the two equations are independent has a  $p$ -value of 0.001: this suggests that there is a significant degree of interdependence between the two equations which creates a correlation between the residuals. In the sample of voluntary insured households, we obtain a stronger correlation (0.089) statistically significant at 1% level.<sup>8</sup>

The positive residual correlations indicate that households that experience more food insecurity than the model predicts, are also more likely to buy health insurance. In other words, we find a positive influence on health insurance coverage when background risk is present. Although the effect is measured through a correlation parameter, this effect is plausibly causal as it is natural to interpret health insurance decision as a choice variable and food insecurity as an exogenous variable from the point of view of the household. Our empirical finding is consistent with the theoretical literature on background risks: increases in the uninsurable risk raises the probability to insure against the insurable risks by increasing the attractiveness of insurance.<sup>9</sup>

Table 3 and Table 4 present the results computed with a number of alternative food insecurity indicators. In both the whole sample and the voluntary insured sample, the results confirm the positive and significant correlations detected in Table 2. The size of these correlations are approximately similar, ranging from 0.065 to 0.10.

To detect how the propensity to buy health insurance changes in presence of a background risk of food insecurity, we predict conditional probabilities for a number of household categories, based on the estimates in Table 2. These estimates are shown in Table 5. Column 1-2 present conditional probabilities of having health insurance given that the household is food insecure, that is  $Pr(y_1 = 1|y_2 = 1)$  in the system (6) and (7). Column 3-4 present conditional probabilities of having health insurance given that the household is food secure, that is  $Pr(y_1 = 1|y_2 = 0)$ . The probabilities are computed for a representative household with average income of her own category, headed by a 40 year old male, with a post-secondary school diploma, no serious disease in the past, living in a urban neighbourhood of Ramallah governorate and owns no crop field. Table 5 reports the conditional probabilities for dif-

<sup>8</sup>Table 2 presents the best fitting model from a battery of alternative specifications. Corrected classified observations in the health insurance equation are 67% (whole sample) and 60% (voluntary insured sample). Corrected classified observations in the health insurance equation are 61% (whole sample) and 62% (voluntary insured sample).

<sup>9</sup>The health insurance equation estimated on the whole sample cannot be interpreted as a pure demand for health insurance. As the decision to insure is not necessarily a voluntary decision in the whole sample, the coefficients of the health insurance equation in column (1) may capture supply as well as demand effects.

ferent employment categories, location of residence, occurrence of diseases in the past, female versus male-headed households and refugee status.

In presence of background risk of food insecurity, the probabilities of buying health insurance are higher. There is some variability in the propensity to insure across employment categories. A food insecure private sector employee has a predicted probability to buy health insurance equal to 0.53 while the probability falls to 0.20 for a food secure private employee with otherwise the same characteristics. The estimated probability to insure for government employees reflect their compulsory coverage so that are as high as 0.93 in presence of background risk of food insecurity and 0.63 without background risk, other things equal. A foreign government employee has a probability of 0.54 to insure with background risk and 0.26 without background risk. A charity sector employee has a probability to insure of 0.61 if subject to background risk and 0.42 otherwise. In the voluntary insured sample, the included employment categories maintain similar propensities. Overall, these estimates suggest that employment sector is an important determinant of the pattern of likelihoods to buy health insurance.

Table 5 shows that rural dwellers who are food insecure are more likely to buy health insurance than urban dwellers. The propensity to insure for rural households (in the private sector) is 0.57, while it is 0.53 for urban households (in the private sector). This pattern is reversed in absence of background risk of food insecurity: the propensity to insure for urban households scores 0.20, for rural households scores 0.17. As, on average, rural household income in the West Bank is lower than urban household income, these results suggest a change in the attractiveness of insurance for poor households in presence of background risk.

Having experienced some forms of disease in the past six months raises the probability to insure: for a private employee having experienced two forms of disease in the past, the propensity to insure increases from 0.53 to 0.67.<sup>10</sup> It seems that in presence of background risk, experiencing undesirable events makes insurance more desirable. Without background risk, having experienced a disease in the past does not increase the probability to buy health insurance (column 3) or the increase is small (column 4).

Female-headed households have a lower probability to buy health insurance (0.46) than comparable male-headed households (0.53) in presence of food insecurity. The propensity to insure of refugees reflect the free health insurance they are entitled to and it scores 0.84 for a refugee family in the private sector subject to food insecurity, 0.44 otherwise.

In conclusion, food secure households are on average less likely to buy

---

<sup>10</sup>The nature of the data do not allow to distinguish whether the insurance scheme was adopted only after the disease or it was in place before. Hence, we need to assume that the remaining individual heterogeneity depending on health riskiness after controlling for past diseases, family characteristics and geographical factors is negligible.

health insurance than food insecure households. Table 6 presents the odd ratios of these probabilities. In presence of background risk of food insecurity, the probability to insure is higher than without background risk for all categories of households. For example, the probability to buy health insurance for a private employee in presence of background risk of food insecurity is 2.6 times higher than the probability to insure without background risk. In the voluntary insured sample, the ratios are higher, revealing that the effect of background risk on the propensity to insure is stronger when compulsory insurance is left out.

## 5.2 Extension: continuous background risk

This section explores how the propensity to insure against the insurable risk changes with the size of the background risk experienced. The empirical evidence suggests that the propensity to buy health insurance increases with the level of background risk of food insecurity.

Letting  $f(\cdot)$  be a continuous function representing the intensity of food insecurity risk, our findings can be represented as follows:

$$f_{high}(E\bar{V}^{ins} - E\bar{V}^{uns}) > f_{low}(E\bar{V}^{ins} - E\bar{V}^{uns}) > 0 \quad (10)$$

The difference in expected utility with insurance and without insurance is higher when  $f(\cdot)$  is high than the difference in utility when  $f(\cdot)$  is low. This results in a higher propensity to insure when the background risk is intense.<sup>11</sup>

Table 7 and Table 8 present different approaches to investigate the propensity to insure for different levels of food insecurity. The HFIA indicator is an ordinal variable: hence, bivariate models are estimated with an implicit threshold that identifies  $y = 1$  and the counterfactual group  $y = 0$  that is strictly above (or below) that threshold. Using bivariate probit models, Table 7 shows how the residual correlations changes by changing that threshold. A severe food insecurity level results in a correlation of 0.077 and 0.089 in the voluntary insured sample (our baseline results). These correlations decrease for a moderate level of food insecurity (i.e. HFIA indicator ranging from 3 to 4 against mild level of food insecurity and complete food security) and are negative for food secure households (i.e. HFIA indicator=1 against all levels of food insecurity).<sup>12</sup>

<sup>11</sup>In principle, the value function can be given more structure. It can be thought that the propensity to insure may be steeper at extreme high values of food insecurity as severe food insecurity conditions deteriorate health, which makes health insurance more desirable.

<sup>12</sup>Using an indicator with mutually exclusive categories, such as the HFIA, implies that the category "food security" is not the complement of "food insecurity"; hence, the correlations needs not to be the same with opposite sign. In principle, one can identify the effect on each category by estimating the joint probabilities of four equations: the health insurance equation and three levels of food insecurity. This would lead to a four-variate probit model. Despite this is appealing, a four-variate model requires computationally intense methods for integration and we opted for the alternative methods described in this section.



An alternative way to let the food insecurity level to be free to vary is to estimate the propensity to insure by a probit model conditioning on the levels of food insecurity. This assumes food insecurity to be predetermined to the decision to insure. By construction, it imposes  $\rho$  to be equal to zero. This method is presented in Table 8, column 1. The estimated coefficients and (average) marginal effects indicate that mild and moderate food insecurity levels increase the propensity to insure, approximately by the same effect. Severe food insecurity has a stronger impact on insurance decisions.

An alternative method estimates food insecurity levels linearly by OLS. The propensity to buy health insurance is predicted using a probit regression conditioning on the same variables as in the baseline model. The correlation parameter  $\rho$  is estimated as the correlation between the two residual series. With this method, the values of the residual correlations in both sample are positive and significant (column 3): 0.044 in the whole sample, 0.059 in the voluntary insured sample. Estimating food insecurity by an ordered probit model leads to the same conclusions (column 4).

### 5.3 Caveats: endogeneity issues

The bivariate probit model presented in section 5.1 captures the simultaneous effect of a background risk of food insecurity on the propensity to insure, conditioning on a number of covariates. The model specification includes a set of controls which do not necessarily need to be exogenous to give unbiased predictions. As far as we are interested in the predicted probabilities and the correlation among the estimated disturbances,  $x'\hat{\beta}$  will give the minimum variance unbiased predictor without the assumption of covariates' exogeneity being necessary. However this limits on the causal interpretation of the effects of the covariates.

Potential endogeneity of covariates may arise due to unobserved consumer preferences. In the estimation on the whole sample, employment sectors may be endogenous because working in a specific sector may depend on unobserved characteristics. It is argued that more (less) risk-averse individuals may be more likely to choose a job in the public (private) sector (Pfeifer, 2011).<sup>13</sup> If this is true, the dummies for public and private sector may be endogenous and the coefficient is biased upwards (downwards). On this ground, our estimates can be considered an upper bound for the effect of government sector on the propensity to insure and a lower bound for the effect of private sector.

---

<sup>13</sup>Guiso & Jappelli (1998) point out that risk-averse individuals may end up being poorer because, for example, entrepreneurial activities or changes to better paid but uncertain jobs are less attractive for them. This may bias downwards the coefficient for expenditure in goods and services. The size of this effect is not straightforward because risk averse individuals will be sensitive to the variance of income rather than the level. Unfortunately, our data do not have information about this variability nor include potential instrumental variables for expenditure such as (expected) wages or imputed rent.

Finding good instruments to address the potential endogeneity of public and private employee status is not an easy task. Two potential candidates are the number of government employees in the family and the number of private employees in the family. We present an instrumentation strategy in Appendix 2. For the public sector, the Hausman test rejects exogeneity in the health insurance equation. For the private sector, the Hausman test does not reject the exogeneity assumption (Table A2.1). Hence, we address the endogeneity of public employees by estimating separately the health insurance equation by an IV probit regression, where we instrument public sector with the number of public sector household members, and the food insecurity equation by a probit regression. We then test the residual correlation. Table A2.2 shows these estimates. The results support our main finding: the correlation coefficient  $\rho$  is positive, somewhat smaller as expected, and significant at any conventional level.

## 6 Conclusions

This paper explores behavioural changes resulting from the presence of an uninsurable background risk. Due to markets incompleteness, not all risks are insurable. The theoretical literature suggests that, according to the structure of preferences, agents bearing an uninsurable background risk are less willing to bear other insurable risks and increase their demand for insurance. The empirical evidence of this effect is limited and focused on evidence from developed countries (Guiso & Jappelli, 1998). Despite the relevance of this question for developing countries, where missing markets are common, to our knowledge, this paper is the first to test empirically this behaviour in a developing country.

We use data from the Socio-Economic and Food Security Surveys conducted in the West Bank region of the Palestinian Territories. We analyse the role of food insecurity risk, an uninsurable background risk, on the decision to buy health insurance. The Palestinian health insurance market, which has no universal public coverage, allows to test this hypothesis.

We use a bivariate probit model to account for food insecurity and the decision to insure being determined by similar observable factors, such as socio-economic characteristics and geographical factors. The unobservable change in the desirability of insurance manifests in the residuals being correlated and we test this parameter.

We find robust empirical evidence that people more vulnerable to the uninsurable risk of food insecurity are more likely to buy health insurance. The predicted conditional probabilities of buying health insurance are higher in presence of the background risk of food insecurity. Comparing various types of households, we find evidence that rural households tend to insure

more than urban households in presence of background risk. While the opposite occurs without background risk.

Extending these results, we consider the possibility that the propensity to insure changes with the intensity of the background risk experienced. Our evidence suggests that there is a higher propensity to buy health insurance when the background risk is more intense. The results prove robust to alternative estimation techniques. We discuss concerns of potential endogeneity bias and we test the robustness of our findings via a feasible instrumentation strategy, given the data.

Our results are consistent with preferences being 'standard' risk averse (Kimball, 1993): risk-averse individuals facing uninsurable background risks limit their exposure to avoidable risks. Thus, this paper supports the argument that uninsurable and insurable risks are substitutes: increases in an unavoidable background risk alter individual attitudes toward insurable risks, increasing the desirability of coverage against them. Due to data limitations, we cannot test the 'standardness' of preferences directly in this article. We are aware that food insecurity is only one of many possible uninsurable background risks, such as unemployment risk and personal security due to conflict violence. Due to lack of data, we are unable to test the implications of the theory for these other types of background risks. This is left for further research. Overall, this analysis suggests that there is a cross-risk effect in various domains of life under risk.

These findings have implications for the development of health insurance programmes. Despite reducing food insecurity is certainly welcomed, policies changing the exposure to this background risk may reduce the propensity to buy health insurance. This may have negative consequences on the health insurance system, such as a reduced participation in health insurance plans. This type of myopic behavior may in turn create problems for the financial viability of the health-care system and thus impairs equity of access and quality of care. Welfare improving policies targeted to erase household vulnerability to food insecurity should include elements aimed to counterbalance the negative incentive on health insurance demand outlined in this analysis.

## References

- Abu-Zaineh, M., Mataria, A., Luchini, S., & Moatti, J.P. 2008. Equity in health care financing in the Palestinian context: the value-added of the disaggregated approach. *Social Science and Medicine*, **66**(11), 2308–20.
- Angrist, J.D., Pischke J.S. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton.
- Ashford, J.R., & Sowden, R.R. 1970. Multivariate probit analysis. *Biometrika*, **26**, 535–546.
- Banerjee, Abhijit V., & Duflo, Esther. 2007. The Economic Lives of the Poor. *Journal of Economic Perspectives*, **21**(1), 141–167.
- Barseghyan, Levon, Prince, Jeffrey, & Teitelbaum, Joshua C. 2011. Are Risk Preferences Stable across Contexts? Evidence from Insurance Data. *American Economic Review*, **101**(2), 591–631.
- Becker, Gary S., Philipson, Tomas J., & Soares, Rodrigo R. 2005. The Quantity and Quality of Life and the Evolution of World Inequality. *American Economic Review*, **95**(1), 277–291.
- Coates, J., Swindale, A., & Bilinsky, P. 2007. *Household Food Insecurity Access Scale (HFIAS) for Measuring of Food Access: Indicator Guide*. Tech. rept. Version 3. Food and Nutrition Technical Assistance - USAID.
- Dercon, Stefan. 2004. *Insurance Against Poverty*. WIDER Studies in Development Economics.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. 2011. Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences. *Journal of the European Economic Association*, **9**(3), 522–550.
- Dow, W. H., Philipson, Thomas, & Sala-i Martin, Xavier. 1999. Longevity Complementarities under Competing Risks. *American Economic Review*, **89**(5), 1358–1371.
- Eckhoudt, Louis, & Kimball, Miles. 1992. Background risk, prudence and the demand for insurance. *Chap. Part II, pages 239–254 of: Dionne, G. (ed), Contributions to Insurance Economics*. Kluwer Academic Press, London.
- Eckhoudt, Louis, Gollier, Christian, & Schlesinger, Harris. 1996. Changes in Background Risk and Risk Taking Behavior. *Econometrica*, **64**(3), 683–689.

- Evans, William N., & Viscusi, W. Kip. 1993. Income Effects and the Value of Health. *The Journal of Human Resources*, **28**(3), 497–518.
- FAO, PCBS, WFP. 2010. *Socio-economic and Food Security Survey 2010 - West Bank and Gaza Strip*. Report. Food and Agriculture Organization of the United Nations.
- Gollier, Christian, & Pratt, John. 1996. Risk Vulnerability and the Tempering Effect of Background Risk. *Econometrica*, **64**(5), 1109–1123.
- Greene, William. 2008. *Econometric Analysis*. 6th edn. Upper Saddle River (N.J.): Prentice Hall.
- Greene, William H. 1998. Gender Economics Courses in Liberal Arts Colleges: Further Results. *The Journal of Economic Education*, **29**(4), 291–300.
- Guiso, Luigi, & Jappelli, Tullio. 1998. Background Uncertainty and the Demand for Insurance Against Insurable Risks. *The GENEVA Papers on Risk and Insurance - Theory*, **23**(1), 7–27.
- Guiso, Luigi, & Paiella, Monica. 2008. Risk Aversion, Wealth, and Background Risk. *Journal of the European Economic Association*, **6**(6), 1109–1150.
- Guiso, Luigi, Jappelli, Tullio, & Terlizzese, Daniele. 1996. Income Risk, Borrowing Constraints, and Portfolio Choice. *The American Economic Review*, **86**(1), 158–172.
- Kimball, Miles S. 1993. Standard Risk Aversion. *Econometrica*, **61**(3), 589–611.
- Loewenstein, George F., Weber, Elke U., Hsee, Christopher K., & Welch, Ned. 2001. Risk as feelings. *Psychological Bulletin*, **127**(2), 267–286.
- Mataria, A., Khatib R. Donaldson C. Bossert T., Hunter, DJ., Alsayed, F., & Moatti, JP. 2009. The health-care system: an assessment and reform agenda. *The Lancet*, **373**(9670), 1207–1217.
- McFadden, Daniel. 1981. *Econometric Models of Probabilistic Choice*. Vol. Structural Analysis of Discrete Data and Econometric Applications. Cambridge, Mass.: MIT Press.
- Nussbaum, Martha C., & Sen, Amartya. 1993. *The Quality of Life*. Oxford: Clarendon Press.
- Pfeifer, Christian. 2011. Risk Aversion and Sorting into Public Sector Employment. *German Economic Review*, **12**(1), 85–99.

- Pratt, John W, & Zeckhauser, Richard J. 1987. Proper Risk Aversion. *Econometrica*, **55**(1), 143–54.
- Sen, Amartya. 1985. *Commodities and Capabilities*. Oxford: Oxford University Press.
- Slovic, Paul. 1972. Information Processing, Situation Specificity, and the Generality of Risk-Taking Behavior. *Journal of Personality and Social Psychology*, **22**(1), 128–134.
- Viscusi, W Kip, & Evans, William N. 1990. Utility Functions That Depend on Health Status: Estimates and Economic Implications. *American Economic Review*, **80**(3), 353–74.
- Webb, P., Coates, J., Frongillo, E. A., Rogers, B. L., Swindale, A., & Bilinsky, P. 2006. Measuring Household Food Insecurity: Why It's So Important and Yet So Difficult to Do. *Supplement to The Journal of Nutrition*, **5**(136), 1404–1408.
- Weber, E. U., A. R. Blais, & Betz, N. E. 2002. A Domain-Specific Risk-Attitude Scale: Measuring Risk Perceptions and Risk Behaviors. *Journal of Behavioral Decision Making*, **15**, 263–290.
- Zellner, Arnold, & Lee, Tong Hun. 1965. Joint Estimation of Relationships Involving Discrete Random Variables. *Econometrica*, **33**(2), 382–394.

Table 1: Joint Probabilities of Health Insurance Coverage and Food Insecurity Status.

**All Sample** ( $N = 7935$ )

	Not-insured	Insured	
Food secure	23.1	55.3	78.4
Food insecure	5.5	16.1	21.6
	28.6	71.4	100

Pearson's chi-square test (1) = 10.3640 (p-value=0.001)

**Voluntary insured** ( $N = 4880$ )

	Not-insured	Insured	
Food secure	33.2	45.1	78.3
Food insecure	7.7	14.0	21.7
	40.9	59.1	100

Pearson's chi-square test (1) = 14.1643 (p-value=0.000).

Notes - These are unconditional probabilities. Figures are expressed in percentages.

Table 2: Bivariate Probit estimates of Health Insurance coverage and Food Insecurity risk.

Dependent variable	All sample		Voluntary insured	
	(1)	(2)	(3)	(4)
	Insurance $Pr(y_1 = 1)$	Food Insecurity $Pr(y_2 = 1)$	Insurance $Pr(y_1 = 1)$	Food Insecurity $Pr(y_2 = 1)$
log expend	0.007 (0.027)	-0.276*** (0.028)	-0.012 (0.031)	-0.321*** (0.035)
head hh's age	0.005*** (0.001)	-0.006*** (0.001)	0.005*** (0.002)	-0.010*** (0.002)
female head-hh	-0.190*** (0.064)	-0.274*** (0.066)	-0.13* (0.074)	-0.040*** (0.006)
yrs school	0.010** (0.004)	-0.040*** (0.004)	0.012** (0.005)	-0.329*** (0.083)
refugee	0.925*** (0.044)	0.048 (0.039)		
disease	0.106*** (0.017)	0.117*** (0.016)	0.124*** (0.020)	0.101*** (0.021)
urban	-0.414*** (0.104)	-0.009 (0.072)	-0.456 (0.491)	-0.256 (0.591)
rural	-0.321*** (0.107)	0.117 (0.076)	-0.329 (0.492)	-0.094 (0.592)
private	-0.346*** (0.054)	-0.130** (0.056)	-0.327*** (0.061)	-0.135* (0.070)
government	1.057*** (0.100)	-0.226*** (0.079)		
foreign	-0.161 (0.134)	-0.227* (0.138)	-0.205 (0.157)	-0.376** (0.186)
crop		-0.100** (0.043)		-0.063 (0.050)
dummy time	0.107*** (0.037)	0.279*** (0.039)	0.315*** (0.043)	0.235*** (0.049)
constant	0.868*** (0.249)	1.872*** (0.241)	1.028* (0.558)	2.615*** (0.654)
Area fixed effects	yes	yes	yes	yes
N		7935		4880
MLL		-7863.4		-5506.5
$\rho_{\epsilon_1, \epsilon_2}$		0.077*** (0.024)		0.089*** (0.027)
LR ( $H_0: \rho = 0$ )		10.54***		10.81***
LR ( $\beta'_{2009} = \beta'_{2010}$ )		343.2***		210.8***
Corrected classified	67%	61%	60%	62%

Notes: Estimated coefficients. Robust standard errors are in parenthesis. Area fixed effects are included but not reported.  $\rho$  is the residual correlation parameter. The dependent variables are  $y_1 = 1$  if the household head has a health insurance, 0 otherwise;  $y_2 = 1$  if the household is classified as "severely food insecure" according to the HFIA classification described in section 4. *All sample* estimates include all households in the sample; *voluntary* estimates include only households voluntarily insured (i.e. excluding government employees and refugees). Excluded categories are camp resident and unemployed. Higher polynomial functions of expenditure have been tested and rejected. The time dummy refers to 2010. The likelihood ratio test (LR) of the hypothesis  $H_0: \rho = 0$  rejects the null hypothesis at 1% level in both samples. The LR test on equality of coefficients in the two periods rejects equality. This may be due to the coefficients being estimated quite precisely (e.g. mostly at 1% confidence level). Despite equality being rejected, the effects are qualitative similar in different years. The measure of goodness-of-fit is based on the percentage of corrected classified observations where the cutoff values for a predicted positive outcome are the unconditional marginal probabilities from Table 1. Covariate description is reported in Appendix 1.



Table 3: Bivariate Probit estimates of Health Insurance coverage and Food Insecurity risk by various Food Insecurity indicators - Whole Sample

	Dependent variables: Health Insurance (ins) and Food Insecurity indicator (as specified)							
	(1) ins	(2) less food <sup>1</sup>	(3) ins	(4) credit <sup>2</sup>	(5) ins	(6) less meals adult <sup>3</sup>	(7) ins	(8) meals reduced <sup>4</sup>
log expend	0.006 (0.027)	-0.206*** (0.025)	0.007 (0.027)	-0.047* (0.025)	0.007 (0.027)	-0.112*** (0.032)	0.006 (0.027)	-0.271*** (0.030)
head hh's age	0.004*** (0.001)	-0.006*** (0.001)	0.005*** (0.001)	-0.011*** (0.001)	0.005*** (0.001)	-0.017*** (0.002)	0.005*** (0.001)	-0.008*** (0.002)
female head hh	-0.191*** (0.064)	-0.285*** (0.058)	-0.191*** (0.064)	-0.450*** (0.059)	-0.190*** (0.064)	-0.541*** (0.090)	-0.191*** (0.064)	-0.385*** (0.073)
yrs school	0.010** (0.004)	-0.028*** (0.004)	0.010** (0.004)	-0.045*** (0.004)	0.010** (0.004)	-0.035*** (0.005)	0.010** (0.004)	-0.032*** (0.005)
refugee	0.924*** (0.044)	0.133*** (0.035)	0.924*** (0.044)	0.039 (0.035)	0.927*** (0.044)	-0.023 (0.045)	0.925*** (0.044)	-0.008 (0.043)
disease	0.106*** (0.018)	0.118*** (0.015)	0.106*** (0.018)	0.108*** (0.015)	0.106*** (0.018)	0.125*** (0.018)	0.106*** (0.018)	0.062*** (0.018)
urban	-0.414*** (0.104)	0.04 (0.066)	-0.415*** (0.104)	-0.322*** (0.064)	-0.413*** (0.104)	-0.102 (0.080)	-0.417*** (0.104)	-0.064 (0.078)
rural	-0.319*** (0.107)	0.041 (0.070)	-0.320*** (0.107)	-0.09 (0.068)	-0.318*** (0.107)	-0.007 (0.085)	-0.322*** (0.107)	-0.066 (0.083)
private	-0.345*** (0.054)	-0.101** (0.049)	-0.344*** (0.054)	-0.023 (0.048)	-0.343*** (0.054)	0.014 (0.065)	-0.344*** (0.054)	-0.143** (0.059)
government	1.058*** (0.100)	-0.220*** (0.068)	1.056*** (0.100)	0.114* (0.065)	1.058*** (0.100)	-0.004 (0.087)	1.058*** (0.100)	-0.246*** (0.085)
foreign	-0.164 (0.136)	-0.083 (0.123)	-0.158 (0.136)	0.218* (0.118)	-0.167 (0.135)	0.075 (0.151)	-0.164 (0.136)	-0.076 (0.148)
crop		-0.097** (0.039)		-0.100*** (0.038)		-0.07 (0.051)		-0.102** (0.049)
dummy time	0.106*** (0.038)	0.008 (0.035)	0.106*** (0.038)	-0.086** (0.034)	0.106*** (0.038)	0.058 (0.044)	0.106*** (0.038)	0.111*** (0.042)
constant	0.872*** (0.251)	1.661*** (0.222)	0.858*** (0.251)	1.329*** (0.216)	0.866*** (0.251)	1.026*** (0.275)	0.871*** (0.251)	2.072*** (0.265)
N	7935		7935		7935		7935	
MLL	-8751.9		-9095.7		-6803.5		-7004.4	
$\rho_{\epsilon_1, \epsilon_2}$	0.065***		0.091***		0.097***		0.078***	
se ( $\rho$ )	(0.022)		(0.021)		(0.028)		(0.026)	

Notes - Estimates are based on the all sample. [1] Indicator based on food quantity reduction:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household consumed less quantity of food to stead financially during the past weeks?". [2] Indicator based on use of credit to buy food :  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household purchased food on credit to stead financially during the past weeks?". [3] Indicator based on reduction of adult meals:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household restricted consumption by adults in order for children to eat during the past weeks?". [4] Indicator based on reduction of meals:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household reduced the number of meals eaten in a day to stead financially during the past weeks?". Area fixed effects are included but not reported. Standard errors are in parenthesis.

Table 4: Bivariate Probit estimates of Health Insurance coverage and Food Insecurity risk by various Food Insecurity indicators - Voluntary insured sample

	Dependent variables: Health Insurance (ins) and Food Insecurity indicator (as specified)							
	(1) ins	(2) less food <sup>1</sup>	(3) ins	(4) credit <sup>2</sup>	(5) ins	(6) less meals adult <sup>3</sup>	(7) ins	(8) meals reduced <sup>4</sup>
log expend	-0.012 (0.031)	-0.209*** (0.032)	-0.012 (0.031)	-0.082*** (0.031)	-0.012 (0.031)	-0.139*** (0.040)	-0.012 (0.031)	-0.286*** (0.038)
head hh's age	0.005*** (0.002)	-0.007*** (0.002)	0.005*** (0.002)	-0.014*** (0.002)	0.005*** (0.002)	-0.018*** (0.002)	0.005*** (0.002)	-0.011*** (0.002)
female head hh	-0.129* (0.073)	-0.382*** (0.076)	-0.129* (0.073)	-0.449*** (0.075)	-0.13* (0.073)	-0.517*** (0.112)	-0.13* (0.073)	-0.406*** (0.093)
yrs school	0.012** (0.005)	-0.032*** (0.005)	0.012** (0.005)	-0.044*** (0.005)	0.012** (0.005)	-0.036*** (0.007)	0.012** (0.005)	-0.037*** (0.006)
disease	0.124*** (0.020)	0.099*** (0.020)	0.124*** (0.020)	0.123*** (0.020)	0.124*** (0.020)	0.114*** (0.023)	0.124*** (0.020)	0.068*** (0.023)
urban	-0.458 (0.511)	-0.763* (0.444)	-0.464 (0.510)	-1.418** (0.565)	-0.442 (0.504)	0.073 (0.574)	-0.448 (0.506)	0.173 (0.604)
rural	-0.33 (0.512)	-0.778* (0.445)	-0.336 (0.511)	-1.175** (0.566)	-0.314 (0.505)	0.169 (0.576)	-0.32 (0.507)	0.176 (0.606)
private	-0.327*** (0.061)	-0.091 (0.061)	-0.326*** (0.061)	-0.064 (0.060)	-0.326*** (0.061)	0.013 (0.080)	-0.326*** (0.061)	-0.167** (0.073)
foreign	-0.206 (0.157)	0.093 (0.161)	-0.205 (0.157)	0.044 (0.157)	-0.205 (0.157)	0.239 (0.192)	-0.205 (0.157)	-0.003 (0.190)
crop	-0.086* (0.046)	-0.092** (0.045)	-0.08 (0.059)	-0.09 (0.057)				
dummy time	0.315*** (0.043)	-0.041 (0.044)	0.315*** (0.043)	-0.097** (0.043)	0.315*** (0.043)	0.048 (0.056)	0.315*** (0.043)	0.065 (0.053)
constant	1.028* (0.573)	2.483*** (0.522)	1.033* (0.572)	2.969*** (0.622)	1.012* (0.567)	1.039 (0.661)	1.017* (0.569)	2.144*** (0.679)
N	4880		4880		4880		4880	
MLL	-6021.1		-6219.3		-4843		-4984.5	
$\rho_{\epsilon_1, \epsilon_2}$	0.094***		0.092***		0.104***		0.089***	
se ( $\rho$ )	(0.025)		(0.024)		(0.031)		(0.030)	

Notes - Estimates are based on the sample of voluntary insured households. [1] Indicator based on food quantity reduction:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household consumed less quantity of food to steady financially during the past weeks?". [2] Indicator based on use of credit to buy food :  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household purchased food on credit to steady financially during the past weeks?". [3] Indicator based on reduction of adult meals:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household restricted consumption by adults in order for children to eat during the past weeks?". [4] Indicator based on reduction of meals:  $y_{2i} = 1$  if the household responds 'yes' to the question "Has the household reduced the number of meals eaten in a day to steady financially during the past weeks?". Area fixed effects are included but not reported. Standard errors are in parenthesis.

Table 5: Predicted Conditional Probabilities of Health Insurance by household characteristics.

Characteristics	(1)	(2)	(3)	(4)
	Pr(Health insured   food insecurity) $Pr(y_1 = 1 y_2 = 1)$		Pr(Health insured   non-food insecurity) $Pr(y_1 = 1 y_2 = 0)$	
	<i>All sample</i>	<i>Voluntary</i>	<i>All sample</i>	<i>Voluntary</i>
private	0.53	0.50	0.20	0.14
government	0.93	-	0.63	-
foreign	0.54	0.52	0.26	0.21
urban (private)	0.53	0.50	0.20	0.13
rural (private)	0.57	0.56	0.17	0.10
urban (foreign)	0.54	0.52	0.26	0.21
rural (foreign)	0.57	0.68	0.24	0.28
disease (private)	0.67	0.66	0.20	0.16
disease (government)	0.95	-	0.53	-
female-headed (private)	0.46	0.46	0.22	0.20
female-headed (government)	0.90	-	0.69	-
refugee (private)	0.84	-	0.44	-
refugee (government)	0.99	-	0.67	-

Notes: *All sample* estimates include all households in the sample; *voluntary* estimates include only households voluntarily insured (i.e. excluding government employees and refugees). Probabilities arguments select a representative household with average income of her own category, male-headed of 40 years old with a post-secondary school diploma, with no serious disease occurred in the past and living in a urban neighbourhood of Ramallah governorate, owning no crop field. Probabilities calculated on the total sample ( $N = 7935$ ) are computed with  $\rho = 0.077$ ; probabilities in the voluntary sample ( $N = 4880$ ) are computed with  $\rho = 0.089$ .

Table 6: Predicted Odds Ratios by Household characteristics

Characteristics	All sample	Voluntary
	$\frac{Pr(y_1=1 y_2=1)}{Pr(y_1=1 y_2=0)}$	$\frac{Pr(y_1=1 y_2=1)}{Pr(y_1=1 y_2=0)}$
private	2.65	3.57
government	1.48	-
foreign	2.08	2.47
urban (private)	2.65	3.84
rural (private)	3.35	5.60
urban (foreign)	2.08	2.47
rural (foreign)	2.38	2.42
disease (private)	3.35	4.12
disease (government)	1.79	-
female-headed (private)	2.09	2.3
female-headed (government)	1.30	-
refugee (private)	1.91	-
refugee (government)	1.48	-

Notes: Predicted odds ratios are the ratio of the conditional probability of a positive outcome when the conditioning variable is active to the conditional probability of positive outcome when the conditioning variable is inactive.

Table 7: Bivariate Probit statistics by various Food Insecurity risk levels

<b>All Sample</b>			
	Severe Food Insecurity HFIA = 4	Moderate Food Insecurity $3 \leq \text{HFIA} \leq 4$	Food Security HFIA = 1
$\rho$	0.077***	0.071***	-0.076***
se( $\rho$ )	(0.023)	(0.021)	(0.020)
% of $y_2 = 1$	21.6%	35.3%	56.0%
Controls	yes	yes	yes

  

<b>Voluntary insured sample</b>			
	Severe Food Insecurity HFIA = 4	Moderate Food Insecurity $3 \leq \text{HFIA} \leq 4$	Food Security HFIA = 1
$\rho$	0.089***	0.082***	-0.100***
se( $\rho$ )	(0.026)	(0.024)	(0.024)
% of $y_2 = 1$	21.7%	35.0%	56.6%
Controls	yes	yes	yes

Notes: The statistics refer to bivariate probit models with the same covariates as in Table 2. The full estimation results are available upon request. The dependent variables are  $y_1 = 1$  if the household head has a health insurance, 0 otherwise;  $y_2 = 1$  reflects the household level of food insecurity according to the HFIA classification described in section 4.  $\rho$  is the residual correlation parameter. Standard errors are in parenthesis.

Table 8: Evaluating the effect of varying food insecurity risk levels

	(1)	(2)	(3)	(4)
<b>All sample</b>				
$y_1$ Propensity to insure	$\Phi(y_1 = 1)$	Marginal effects <sup>1</sup>	$\Phi(y_1 = 1)$	$\Phi(y_1 = 1)$
$y_2$ Food insecurity			$y_2 = \beta'x$	$\Phi_O(y_2 = j)$
Mild	<b>0.105*</b> (0.061)	0.030 (0.017)		
Moderate	<b>0.099*</b> (0.050)	0.028 (0.014)		
Severe	<b>0.160***</b> (0.043)	0.045 (0.012)		
Controls	yes		yes	yes
N	7859		7935	7935
<i>pseudo R</i> <sup>2</sup> ( $y_1$ )	0.163		0.162	0.162
$\rho_{\epsilon_1, \epsilon_2}$	0		0.044***	0.043***
p-value( $\rho$ )			(0.000)	(0.000)
MLL ( $y_1$ )	-3937.3		-3977.0	-3977.0
<b>Voluntary insured sample</b>				
$y_1$ Propensity to insure	$\Phi(y_1 = 1)$	Marginal effects <sup>1</sup>	$\Phi(y_1 = 1)$	$\Phi(y_1 = 1)$
$y_2$ Food insecurity			$y_2 = \beta'x$	$\Phi_O(y_2 = j)$
Mild	<b>0.143**</b> (0.069)	0.052 (0.025)		
Moderate	<b>0.141***</b> (0.058)	0.051 (0.021)		
Severe	<b>0.190***</b> (0.049)	0.068 (0.017)		
Controls	yes		yes	yes
N	4842		4880	4880
<i>pseudo R</i> <sup>2</sup> ( $y_1$ )	0.060		0.058	0.058
$\rho_{\epsilon_1, \epsilon_2}$	0		0.059***	0.058***
p-value( $\rho$ )			(0.000)	(0.000)
MLL ( $y_1$ )	-3081.5		-3112.4	-3112.4

Notes - The effect of increasing levels of food insecurity on the propensity to buy health insurance are evaluated by a probit regression with predetermined food insecurity levels (column 2). This imposes the residual correlation  $\rho$  to be equal to zero. [1] Marginal effects are average marginal effects; standard errors are compute by the Delta-method and reported in parentheses. In column 3 food insecurity levels are predicted linearly by an OLS regression adjusting the extreme values. The propensity to insure is predicted by a probit regression. In column 4 food insecurity levels are predicted by on ordered probit regression. The propensity to insure is predicted by a probit regression.  $\rho$  is the residual correlation between the predicted probability of food insecurity levels and health insurance in each model. Since cut points from the ordered probit estimation in column 4 against the levels of  $y_2$  are approximately linear, the linear prediction is preferred. Control variables - as in the baseline specification - are included but not reported.

# APPENDIX 1.

Table A1.1: Data and variable description

	VARIABLE	DESCRIPTION	RANGE
Dependent variables	$y_{1i}$	Health-insurance coverage	Dichotomous variable, where 1 indicates the household has a health insurance, 0 if not
	$y_{2i}$	Food Insecurity indicator	
	HFIA	Household Food Insecurity Access Prevalence	Indicator from 1 to 4, where 1 is "food secure" and 4 is "severely food insecure". The indicator is summarised as a dichotomous variable equals to 1 if HFIA is 4, 0 otherwise
	<i>less food</i>	Household consumed less quantity of food	Indicator is a dichotomous variable equals to 1 if the household responds "yes" to the question "Has the household consumed less quantity of food to stead financially during the past weeks?"
	<i>food credit</i>	Household recurs to buy food on credit	Indicator is a dichotomous variable equals to 1 if the household responds "yes" to the question "Has the household purchased food on credit to stead financially during the past weeks?"
	<i>less food adult</i>	Adults in the household consume less food in favour of children	Indicator is a dichotomous variable equals to 1 if the household responds "yes" to the question "Has the household restricted consumption by adults in order for children to eat during the past weeks?"
	<i>meals reduced</i>	Household reduces the number of meals per day	Indicator is a dichotomous variable equals to 1 if the household responds "yes" to the question "Has the household reduced the number of meals eaten in a day to stead financially during the past weeks?"
Control variables	<i>log expend</i>	Household monthly expenditure	Continuous variable: in logarithm scale
	<i>head – hh's age</i>	Age of household head	Continuous variable: numbers of years
	<i>yrs school</i>	Years of schooling	Continuous variable: numbers of years
	<i>fem head – hh</i>	Female-headed household	Dichotomous variable: 1 if female-headed household, 0 if male-headed
	<i>refugee</i>	Refugee status	Dichotomous variable: 1 if household-head is a registered refugee, 0 otherwise
	<i>disease</i>	Severe illness that require a health services in the last 6 months	From 0 to 8. 0 (none) until 8 (8 different illnesses)
	<i>urban</i>	Urban dweller	Dichotomous variable: 1 if household live in urban areas, 0 otherwise
	<i>rural</i>	Rural dweller	Dichotomous variable: 1 if household live in rural areas, 0 otherwise
	<i>private</i>	Private sector employee	Dichotomous variable: 1 if household-head is employed in the private sector, 0 otherwise
	<i>government</i>	Government sector employee	Dichotomous variable: 1 if household-head is employed in the gov. sector, 0 otherwise
<i>foreign</i>	Foreign government, charity or int'l organisation employee	Dichotomous variable: 1 if household-head is employed by a foreign government, 0 otherwise	
<i>crop</i>	Ownership of crop-cultivated field	Dichotomous variable: 1 if household owns a crop-cultivated field, 0 otherwise	
Macro fixed effects	<i>gov#</i>	Area fixed effect	11 dummy variables

Table A1.2: Descriptive statistics

Variable	<b>Total sample</b>				
	Obs	Mean	Std. Dev.	Min	Max
expenditure (mth, NIS)	7935	2287	1445	50	11000
head age	7935	46.18	14.31	0	80
fem head	7935	0.10	0.30	0	1
years schooling	7935	9.21	4.63	0	26
refugee	7935	0.31	0.46	0	1
disease	7935	0.81	1.11	0	8
urban	7935	0.63	0.48	0	1
rural	7935	0.30	0.46	0	1
private sector	7935	.63	.48	0	1
government sector	7935	.10	.31	0	1
foreign organizations	7935	.02	.13	0	1
crop	7935	0.22	0.41	0	1
<b>Voluntary insured sample</b>					
expenditure (mth, NIS)	4880	2274	1538	50	13000
head age	4880	46.78	14.75	0	80
fem head	4880	0.10	0.31	0	1
years schooling	4880	8.68	4.50	0	26
disease	4880	0.79	1.09	0	7
urban	4880	0.67	0.47	0	1
rural	4880	0.33	0.47	0	1
private sector	4880	.72	.44	0	1
foreign organization	4880	.02	.12	0	1
crop	4880	0.27	0.44	0	1

## APPENDIX 2.

Table A2.1: Hausman Test of exogeneity

All Sample ( $N = 7935$ )		
	public	private
Insurance equation	31.32	0.02
	rejected at 10 %	not rejected
Food insecurity equation	2.42	18.40
	not rejected	not rejected

Hausman test -  $H_0$ : exogeneity assumption. The IV estimator is consistent under  $H_0$  and  $H_a$ ; the probit estimator is inconsistent under  $H_a$ , but efficient under  $H_0$ . Confidence level is set at 5% unless specified.



Table A2.2: Instrumentation strategy

Dependent variable	(1)	(2)
	IV Probit Insurance $Pr(y_1 = 1)$	Probit Food Insecurity $Pr(y_2 = 1)$
public (instrumented)	1.949*** (0.151)	-0.225*** (0.076)
log expend	-0.030 (0.027)	-0.275*** (0.027)
head-hh age	0.011*** (0.002)	-0.006*** (0.001)
female head-hh	-0.006 (0.068)	-0.273*** (0.063)
yrs school	-0.000 (0.004)	-0.040*** (0.004)
refugee	0.899*** (0.044)	0.047 (0.039)
disease	0.109*** (0.017)	0.117*** (0.017)
urban	-0.399*** (0.102)	-0.01 (0.072)
rural	-0.318*** (0.105)	0.116 (0.076)
private	0.106 (0.081)	-0.129** (0.053)
foreign	0.289** (0.147)	-0.225 (0.142)
time dummy	0.116*** (0.037)	0.279*** (0.038)
crop		-0.101** (0.043)
constant	0.515** (0.254)	1.871*** (0.240)
Area effect	yes	yes
N		7935
$\rho_{\epsilon_1, \epsilon_2}$		0.035***
Hausman test of exogeneity	31.32	2.42
FIRST STAGE: excluded instrument		
public in hhold	0.322*** (0.005)	

Notes: Estimated coefficients are based on the whole sample. Standard errors in parenthesis. Area fixed effects are included but not reported. The column 'First Stage' reports the excluded instruments.