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Do economic crises lead to health and nutrition behavior responses ? analysis using longitudinal data from Russia

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Analysis Using Longitudinal Data from Russia

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Abstract

Using longitudinal data on more than 2,000 Russian families spanning the period between 2007 and 2010, this paper estimates the impact of the 2009 global financial crisis on food expenditures, health care expenditures, and doctor visits in Russia. The primary estimation strategy adopted is the semi-parametric difference-in-difference with propensity score matching technique. The analysis finds that household health and nutritional behavior indicators do not vary statistically between households that were crisis-affected and households that were not affected by the crisis. However, the analysis finds that crisis-affected poor families curtailed their out-of-pocket health expenditures during and after the crisis more than poor families that were not affected by the crisis did. In addition, crisis-affected vulnerable groups changed their health behavior. In particular, households with low educational attainment of household heads and households with more elderly people changed their health and nutrition behavior response when affected by the crisis. The results are invariant to the propensity score matching techniques and parametric fixed effects estimation models.

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Do Economic Crises Lead to Health and Nutrition Behavior Responses? Analysis Using Longitudinal Data from Russia[1]

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1. Introduction

The recent global financial crisis hit the Russian economy very hard, leading its GDP to contract by 7.9 percent in 2009 after registering almost 7 percent GDP growth rates in the years prior to the crisis. Moreover, the pace of poverty reduction decelerated noticeably. While the impact of economic downturns on poverty has been studied, including using micro-simulation models (Bourguignon et al, 2008, Chen and Ravallion, 2009, Ferreira et al., 2008, Ajwad et al, 2012, Nikoloski 2011, Habib et al, 2012), research on the impact of economic crises on other aspects of human development, such as education and health behavior and outcomes, have received less attention in the literature. One reason for the nascent literature studying the crisis-human development nexus is that sufficiently detailed data, which allow households to be followed over a period of several years, is scarce. The data scarcity is particularly acute in emerging economies.

Economic shocks elicit conflicting health behavioral responses depending on whether the income or substitution effects dominate. During economic crises, the income effect directly reduces consumption of privately funded medical care, private insurance and healthy behavior, while it indirectly increases psychological costs and the likelihood of poor diets. In contrast, during crises, the substitution effect lowers the (opportunity) cost of time dedicated to healthy activities (exercise, breast feeding, etc.), increases the time available to invest in individual and household health, and reduces job-related accidents and stress.

This study analyzes the relationship between income shocks experienced during the 2009 economic crisis and health and nutrition behavior. The study, therefore, provides insights into household health and nutrition behavior during crises, specifically: (i) total household consumption of food; (ii) total household out-of-pocket health expenditure; and (iii) household doctors' visits. We use the Russia Longitudinal Monitoring Survey, which contains longitudinal data on over 2,000 Russian families spanning the period between 2007 and 2010.

We employ a difference-in-difference with propensity score matching technique to measure the impacts of the recent crisis in Russia on health and nutrition behavior. In addition, we carry out two separate robustness checks on our findings. The first check is propensity score matching (PSM).[2] The second check is to apply a parametric fixed effects model. We find that the results are substantively unchanged to the estimation methodology employed.

This paper contributes to the extant empirical knowledge of the crisis-human development nexus in a few, crucially important ways. The first contribution of this paper is that while past

[2] Rosenbaum sensitivity analysis is carried out as an integral part of the PSM technique.

studies generally relied on repeated cross sectional household survey data (McKenzie, 2003, EBRD, 2011, McCulloch, 2010, Dasgupta and Ajwad, 2012), this study analyses the crisis-human development nexus using longitudinal data in an emerging economy. As such, this is the first attempt to analyze the impact of crisis-induced income shocks in Russia by using longitudinal data and, thereby, to capture dynamic human behavior more accurately.[3] Longitudinal data reduce two potential sources of bias associated with cross-sectional data: (i) selection bias due to differences in observable factors between the crisis-affected and non-affected households, and (ii) selection bias due to endogeneity of being affected by an income shock. Longitudinal data has only been used in the context of advanced (OECD) countries in past research on the crisis-human development link (see for example Latif, 2010). The second contribution of this paper is that our methodology is not only able to analyze if there is a statistical significance between households affected and not affected by an income shocks, but is also able to discern if there is a statistical significance between the affected and not affected households before and after the crisis. As such we capture both, the impact of the crisis and the impact of an income shock sustained during the crisis year. The third contribution of the paper is that we go beyond analyzing the impact of the crisis on the average household in Russia, and we also study the impact on poor and vulnerable households separately. Performing the analysis on poor and vulnerable households separately is important because there is every reason to believe that a crisis will have a differential impact on these groups in comparison to the general population.

Our analysis of the crisis in 2009 in Russia shows that there was no statistically significant impact on average on food consumption, out-of-pocket health expenditures, and doctors' visits of income-shock affected households. However, we find robust evidence that poor (lowest quintile) households affected by an income shock spent less on health services, compared to households not affected by an income shock.[4] Furthermore we find evidence that vulnerable people affected by the crisis in 2009 altered their health and nutrition behavior. In particular, households with low educational attainment of household heads (less than secondary school completed) that suffered an income shock tended to decrease expenditures on both food and health services, while households that had a higher number of elderly people (older than 60 years) tended to curb the use of health services. These findings suggest a particular need to protect the health and

[3] While there are some studies that have looked at the impact of the process of transition as well as the impact of the 1998 crisis on health outcomes, it is worth mentioning that these studies rely on pooled longitudinal data and they usually span only 2 years.

[4] By the same token, when the analysis is conducted to a restricted sample of the two upper quintiles of the population (4th and 5th), we see that households that are affected by the crisis but are more affluent tend to spend more on health services.

nutritional needs of the poorest and most vulnerable in the population, but not necessarily the entire population.

This paper is organized as follows. Section 2 reviews the most relevant literature in the area of health and economic crises, whilst section 3 describes the data used in the analysis. Section 4 takes stock of some descriptive statistics of variables used in the analysis. Section 5 presents the empirical strategy used in the paper together with three separate robustness checks. Section 6 presents the results and Section 7 briefly relates the findings to those reported in past work. Section 8 concludes.

2. Literature review

2.1 Crises and health – general overview

For poor people, negative income shocks associated with crises may push food consumption below subsistence levels and, in so doing, may impact directly on nutritional and health-related outcomes. Indeed, increases in the incidence of malnutrition have been documented across numerous episodes of crises (Agenor, 2002, Shkolnikov and Mesle, 1996, Walton and Manuyelan, 1998, Waters et al., 2003). In Peru, the deterioration of publicly provided health services and lower quality diets resulted in worsening child health in the 1990s (Paxson and Schady, 2005). In Mexico, Cutler et al. (2002) found that the crisis of the late 1980s imposed a heavy burden, especially on the younger and older members of the population. In Indonesia, following the 1997-98 Asian crisis, households, particularly poorer households, were faced with diminished purchasing power and allocated a smaller percentage of their total budgets to heath care (Waters et al., 2003).

There are also numerous examples of indirect effects. Reduced incomes, psycho-social factors associated with unemployment, loss of status and uncertainty generated by crisis conditions result in heightened stress levels which could further exacerbate undesirable health outcomes (Cornia and Paniccià, 1995, Marmot and Bobak, 2000, Shapiro, 1995, Shkolnikov et al., 1998, Zoohori et al., 1998). Stress may additionally be associated with the break-up of social networks, of family dissolution and the need to form new social interactions following a crisis (Rose, 2000, Rose and McAllister, 1996). Stress is further associated with promoting unhealthy behaviors, such as increased tobacco or alcohol consumption, which in turn impact health outcomes relating to cardiovascular disease, deaths from external causes, suicides and homicides.

Economic and financial crises are often associated with budgetary pressures, where frontline health services are squeezed (Lara et al., 1997, Wibulpolpraser, 1999), though data on health spending and its efficiency are notoriously hard to unpack. Nevertheless, the extant evidence points to the fact that fiscal pressures associated with economic crises may lead to shortages in government provided services and products. In Indonesia for example, where total (real) public sector health spending fell by an estimated 9% in 1996-7, and a further 13% in 1997-8, shortages of antibiotics, iron supplements and contraceptive pills emerged in the public sector (Waters et al., 1997).

While the net outcome on health is likely to be country specific, some general patterns do emerge. Recessions in developed countries, where the substitution effect tends to dominate, generally lead to better aggregate health outcomes (World Bank, 2008). For example, in the US, economic downturns are associated with declining infant mortality (Ferreira and Schady, 2008, Gerdtham and Ruhm, 2002, Ruhm, 2000) while in Western Europe, reductions in traffic accidents and lower use of alcohol and tobacco can lower overall mortality (WHO, 2009). Stuckler et al. (2009) found no evidence that mortality rates increased during European crises, although increases in unemployment were found to be associated with short-term increases in violent deaths, including suicide. Meanwhile, in lower-income and middle-income countries, declining income has more typically been associated with deteriorating health outcomes (Brainerd, 1998, Brainerd and Cutler, 2005, Cornia and Paniccià, 2000, Cutler et al., 2002, Ferreira and Schady, 2008).

2.2. Crises and nutrition

Existing research finds overwhelming evidence that crises are bad for nutrition outcomes. Based on cross-country data, recent studies have found that lower GDP per worker and income per capita are, respectively, associated with higher frequency of low birth weight and underweight children in preschool (Berhman, 2004, Haddad et al, 2003). At the micro-level, a positive relationship between economic status and health status is well documented (Case et al, 2002, Pongu et al, 2004). Studies from developing countries also suggest that declines in household economic status, due, for instance, to national economic downturns or natural disasters such as rainfall shocks, drought, or floods, may adversely affect child mortality and nutritional status (Paxon and Schady, 2005, Jensen, 2000, Yamano et al, 2004). In Cameroon, studies found declining child nutrition in the 1990s mirroring the trends in under-5-mortality rates that rose from 126 to 152 per 1000 between 1991 and 1998 (Barrere, 1992, Libite, 2004). In a review of studies related to the effects of economic shocks, Ferreira and Schady (2008) conclude that economic crises tend to have negative effects on health and nutrition outcomes for children in poor countries but typically have positive effects for children in rich countries.

The price and the income effect is the main channel through which crisis impact upon households. Evidence from the Asian economic crisis in the late 1990s as well as from Africa consistently shows that as prices increase, households first reduce consumption of more expensive food items, typically animal source foods (meat, poultry, eggs, fish, and milk), and fruit and vegetables that are good sources of high-quality nutrients. This is followed by a reduction of the size and frequency of meals (Fuere et al, 2000, Bloem et al, 2005, Thorne-Lyman et al, 2010, Koumou, 2008, Block et al, 2004). World Food Programme's household-level food security assessments conducted in 2008 in a number of countries around the world found similar evidence as well as reductions in health care visits or health expenditures, increased school drop-outs, and sale of assets (Sanogo, 2009).

Individual country case studies have looked at the impact of crises on nutrition in: Indonesia, Jamaica, South Africa and Cameroon. Over the last twenty years, another strand of country studies has emerged, which has been solely focused on Russia. Using official Goskomstat for 1991 and 1992, Cornia (1994) concludes that there is only a small correlation between household resources (measured by income or expenditure) and caloric intake. Zohoori et al (2001), Popkin et al (1996), Vella (1997) and Dore et al (2003) use RLMS data to examine caloric intake and other measures of nutrition. These studies report little variation in aggregate levels of nutrition intake and nutritional status over time.

However, the absence of a robust link between economic crises and nutrition in the papers above might be a result of the methodological and data shortcomings. Indeed, as some of the authors point out, the nexus between the two variables is a complex one, thus involving various coping strategies that are usually not captured by some of the extant surveys. Moreover, it may well take a few years for a clear pattern to emerge – something that is almost impossible to do when a cross-section dataset or a two-year longitudinal data is used for analysis. Indeed, Vella (1997) and Popkin et al (1996) both use two year longitudinal datasets. Furthermore, as pointed by Popkin et al (1996), it is possible that some of their results are driven by differences in samples. In particular, it seems paradoxical that, in 1994, elderly people were poorer than before, spent a smaller proportion of their income on food, and yet had not lost weight. Finally, almost all of the papers above caution that their findings are preliminary and that further study of the crisis/nutrition nexus is needed in order to shed further light.

3. Data

In this study, we employ the Russia Longitudinal Monitoring Survey (RLMS). The RLMS is a series of nationally representative surveys designed to monitor the effects of reforms on the health and economic welfare of households and individuals in the Russian Federation. These effects are measured by a variety of means: (i) monitoring individuals' health status and dietary intake, (ii) measuring household-level expenditures and service utilization, and (iii) collecting relevant community-level data, including region-specific prices and community infrastructure data. Data have been collected 19 times since 1992. The RLMS consists of household and individual level data.

For the purpose of this exercise, we construct a longitudinal dataset composed of 2,191 families who are followed from 2007 through 2010.[5]

There are a few ways of defining households that were affected by an income shock. Dasgupta and Ajwad (2011) for example, use questions from a specially designed Crisis Response Survey to determine which families were more affected by income shocks than others. Similar approaches are applied in additional work in the field. For example, Andow and Koppe (2011) use a questionnaire revolving around job losses and prospective job losses, to estimate the households that were affected by the 2009 crisis in England and Scotland. EBRD (2011) argues that the wage reduction is the main channel through which crisis-affected households could be identified.

We define crisis-affected households as those households whose real incomes fell between 2008 and 2009 (as GDP contracted by 7.9 percent in 2009) by more than a given threshold. Given the size of the sample, as well as the distribution of the total household income, our preferred threshold is 30 percent of monthly household income (between 2008 and 2009). Therefore, any family that experienced a monthly income reduction of more than 30 percent between 2008 and 2009 is designated as crisis-affected. Conversely, the remaining families are classified as 'not-affected'. By ascribing large negative changes in household incomes to the impact of the crisis, we may be including some households that are affected by idiosyncratic shocks (families losing income due to voluntary job losses unrelated to the crisis, death of a member in the family etc.). However, this attribution is unavoidable and past work has been unable to separate crisis-affected households from households affected by shocks unrelated to the crisis (Cunningham

[5] We construct our dataset using guidance provided in the RLMS website.

and Maloney, 2000, EBRD, 2011, Arrondel et al, 2010, Thomas et al, 1999, Corbacho et al, 2003). Given this definition, 452 families are classified as 'crisis-affected'.[6]

We focus on three indicators that are available in the data and provide insights into nutritional and health seeking behavior in the Russian Federation: (i) total food consumption; (ii) total out-of-pocket health expenditure; (iii) number of doctor's visits.[7]

4. Descriptive statistics

Based on the definition above, we divide households into two main groups – those 'crisis-affected' and 'not affected' by income shocks. As mentioned above, there are 452 families in the sample that were affected during the 2009 crisis in Russia. This section presents summary statistics of our main variables of interest for both crisis-affected and not-affected households.

There are a few important conclusions that stem from the descriptive statistics presented in Table 1. First, the average monthly expenditure of the entire sample fell by about 2,000 rubles (US$66) (in real terms) during the crisis in 2009 relative to average monthly expenditures in 2008. While expenditures in households that did not suffer income shocks grew steadily, real expenditures of crisis-affected households fell dramatically in 2009. Second, food expenditures of the non-affected households grew in 2009 relative to 2008, while food expenditures of crisis-affected households fell sharply in 2009. Third, out-of-pocket health expenditures declined during the crisis in 2009 among households that suffered an income shock but grew among households that were not affected. Finally, there appears to be no uniform pattern between households affected and non-affected by an income shocks on doctor visits. In fact, and surprisingly, the total number of doctors' visits fell in 2008, the year prior to the crisis, while it increased in 2009 during the crisis year.

[6] In addition to the above method of identifying affected households, we also use an alternative measure, namely unemployment by any member of the household to determine which households were affected by the crisis. Households are crisis affected if they suffered a significant drop in: (i) the total number of household members that were employed; (ii) the percentage of household members employed in household, while also controlling for changes in the size of the household (due to births, deaths, migration, etc.). Whilst this is a narrower definition of a crisis affected household, we find a significant overlap between the 'affected' families derived by the both methods.

[7] The RLMS also contains household's self-assessment of their health status and some anthropometric indicators. We omitted the self-assessment questions because those questions bring up a series of caveats might are exacerbated during pessimistic periods such as crises. We omitted the anthropometric measures because of the small sample size across the longitudinal survey.

Table 1. RLMS: Selected health and nutrition variables

Total expenditure (in roubles)				
	2007	2008	2009	2010
income shock	14597.05	21039.59	12214.22	13081.52
non-income shock	10614.79	11659.98	11841.92	12331.89
sample average	11448.86	13594.98	11922.06	12491.12
Total food expenditure (in roubles)				
	2007	2008	2009	2010
income shock	4811.995	5895.166	4422.716	5205.508
non-income shock	4076.366	4095.325	4159.266	4472.185
sample average	4230.441	4466.629	4215.97	4627.951
health care expenditure (in roubles)				
	2007	2008	2009	2010
income shock	455.4994	551.2735	414.8871	513.1008
non-income shock	440.6567	455.4952	501.4874	494.6954
sample average	443.7655	475.2541	482.8477	498.6049
Doctors visits				
	2007	2008	2009	2010
income shock	9.312712	7.505747	8.557823	8.744292
non-income shock	9.083679	7.393584	8.593731	7.898586
sample average	9.137302	7.417315	8.586074	8.077966

Source: RLMS and authors' calculations

5. Methodology – Propensity score matching

5.1. Difference-in-difference with propensity score matching

In order to estimate the impact of an income shock sustained during a crisis year, we employ a difference-in-difference propensity score matching estimator (see Heckman et al, 1999), which extends simple before-after comparisons to determine the treatment effect based on the presumption that the outcome variable can also change over time due to reasons unrelated to income shocks. Such an approach requires longitudinal data and builds on the assumption of time-invariant linear selection effects. Following Heckman et al (1998), we implement a conditional difference-in-differences estimator. This method combines a propensity score matching approach with the difference-in-difference empirical strategy.[8] This technique relaxes the linear assumption when controlling for observables relative to standard difference-in-difference modeling and controls for unobservables by exploiting the longitudinal dimension of the data. This further feeds into Smith and Todd (2005), who show that the difference-in-differences matching estimator performs the best among non-experimental matching based estimators.

[8] As such, this method builds on propensity score matching (PSM). It is explained in the next section (as this is our robustness check).

When longitudinal data on participants and non-participants before and after an intervention are available, average treatment on the treated (ATT) can be estimated using a method of difference-in-differences with matching. The basic idea of matching is to find a control group that has similar distribution of X as the treatment group. Matching is combined with difference-indifference estimation to allow intervention selection to be based on unobserved variables. However, this method requires the unobserved variables be time-invariant.

Let Y_{0F} denote pre-intervention outcome. After the intervention, let Y_{1S} and Y_{0S} denote potential outcomes in states of intervention and no-intervention, respectively. ATT after the intervention is defined as:

$$ATT=E(Y_{1S}|X, D=1)-E(Y_{0S}|X, D=1) \quad (1)$$

The difference-in-differences with matching method relies on an assumption that conditional on X, difference in outcome expectations between the participants and nonparticipants is time-invariant:

$$E(Y_{0F}|X, D=1)-E(Y_{0F}|X, D=0)= E(Y_{0S}|X, D=1)-E(Y_{0S}|X, D=0) \quad (2)$$

Then, ATT can be identified, since:

$$ATT=E(Y_{1S}|X, D=1)-E(Y_{0S}|X, D=1) -[E(Y_{0F}|X, D=1)-E(Y_{0F}|X, D=0)] + [E(Y_{0S}|X, D=1)-E(Y_{0S}|X, D=0)]$$

$$=[E(Y_{1S}|X, D=1)-E(Y_{0S}|X, D=0)] - [E(Y_{0F}|X, D=1)-E(Y_{0F}|X, D=0)] \quad (3)$$

ATT is also identified, since:

$$ATT=\int_{X|D=1} ATT\ dF\ (X|D=1). \quad (4)$$

The matching estimator is based on equation (3). It is equal to difference-in-differences in outcomes between the treatment and control groups before and after the intervention.

5.2. Propensity score matching

As already mentioned above, our first robustness check is propensity score matching (PSM), which in fact, is a basis for conducting a difference-in-difference with matching. There are several seminal studies that have pioneered the use of PSM in the empirical literature (e.g., Rosenbaum and Rubin 1983; Dehejia and Wahba 2002; Heckman et al., 1998; Caliendo and Kopeinig 2005; Smith and Todd 2005).

Estimation of the average treatment effects on the treated group using matching methods relies on two key assumptions. First, that the conditional independence assumption (CIA), which implies that selection into the treatment group is solely based on observable characteristics (selection on observables). Second, that the common support or overlap condition is satisfied. The common support is the area where the balancing score has positive density for both treatment and comparison units. No matches can be made to estimate the average treatment effects on the ATT parameter when there is no overlap between the treatment and non-treatment groups.

When both of these conditions are satisfied, the average treatment impact (ATT) is calculated as follows:

$$ATT=E(Y1-Y0|D=1)=E(Y1|D=1)-E(Y0|D=1)$$

Following past studies, we carefully choose covariates to be included in the first step, namely the propensity score estimation. Heckman et al. (1997) show that omitting important variables can increase the bias in the resulting estimation. Bryon et al. (2002) also recommend against over-parameterized models because including extraneous variables in the adoption model will reduce the likelihood of finding a common support. Rosenbaum and Rubin (1983), Dehejia and Wahba (2002), and Diprete and Gangl (2004) emphasize that the crucial issue is to ensure that the balancing condition is satisfied because it reduces the influence of confounding variables.

While doing the matching, we rely on the usual diagnostic tests such as: the post matching reduction in bias, the likelihood ratio test of the joint significance of all covariates and the pseudo-R2 from probit of treatment status on covariates after matching on matched sample. After matching, there should be no systematic differences in the distribution of covariates between the treated and control groups; as a result, the pseudo-R2 should be low and the joint significance of all covariates should be rejected.

Propensity score estimation, per se, is not enough to estimate the ATT of interest. Because the propensity score is a continuous variable, the probability of observing two units with exactly the same propensity score is, in principle, zero. Various matching algorithms thus have been proposed in the literature to overcome this problem. Asymptotically, all matching algorithms should yield the same results. However, in practice, there are trade-offs in terms of bias and efficiency involved with each algorithm (Caliendo and Kopeining, 2005). We therefore implemented three matching algorithms: 1) one-for-one matching, 2) nearest neighbor matching, and 3) kernel matching. These methods numerically search for "neighbors" that have a propensity score for non-treated individuals that is very close to the propensity score of treated individuals. We omit further details here for brevity and refer to the literature on matching methods (e.g., Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002; Heckman et al., 1998; Caliendo and Kopeinig, 2005; Smith and Todd, 2005).

We include covariates that satisfy the following conditions: (i) the covariates are not affected by the income shocks; (ii) are time invariant or are relatively stable over time; (iii) are derived from the same source and from the same environment (Caliendo and Kopeining, 2008, Heckman et al, 1999). Hence, we include the following covariates to predict the household's propensity of being crisis-affected: demographic variables, educational attainment of household heads, size of the household, and households' asset index (the asset index is created and calculated following Filmer and Pritchett, 2000).

5.3. Fixed effects model

As a final robustness check we run fixed effects parametric regressions. As noted above, the longitudinal dataset allows us to implement fixed effects and thus, to account for the omitted variable bias. A key concept of the fixed effects is the existence of time-invariant characteristic that may influence the outcome variable. If one accounts for the existence of this time-invariant characteristic, then any changes in the outcome variable must be due to variables other than these fixed characteristics.

5.4. Identifying vulnerable groups

To identify vulnerable groups we follow the approach taken by Glewwe and Hall (1998) and we regress the percentage change in household consumption on various vulnerability characteristics. Table 2 reports the results. The results show that female headed households, households with large number of children (higher than 3), large households, and households whose head has a low level of educational attainment are particularly vulnerable to shocks. Households with a higher number of elderly people are less susceptible to shocks, which, although counterintuitive at first, is explained by significant transfers (either in a form of pensions or social assistance).[9]

[9] Nevertheless, when doing our analysis, we still confine parts of it to the households with higher number of elderly people.

Table 2. Households characteristics correlated with vulnerability (t-statistics from single variable regressions)

Characteristic	Vulnerability (% change in consumpion, 2008 to 2009)
Female headed household	-1.06
Number of children in the household	-0.33
Size of the household	-1.48
Number of elderly in the household	2.44
HH head has a low level of education	-3.33

A positive (negative) t-statistics indicates a less (more) vulnerable household.

6. Results

Our analysis has three parts: (i) we analyze the impact of the income shock on the entire sample; (ii) we restricted the analysis to the lowest quintile of the population (in order to analyze the impact of the income shock on the poor);[10] (iii) we restrict our analysis to other vulnerable groups.

Before elaborating our main results, Table 3 presents an overview of the main descriptive statistics used in the analysis.

Table 3. Descriptive statistics

	Households affected by income shock			Non affected		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Household size	1762	2.970488	1.579336	6531	2.56117	1.437643
Male head of household	1808	0.8451327	0.361878	6956	0.744681	0.436072
Pct of employed in household	1762	0.512231	0.352159	6531	0.446603	0.369057
Asset index	1148	0.1510217	0.973648	4745	-0.0594	0.997216
Education level of the household head	1427	4.674142	1.85662	5184	4.49537	2.03727
Age of the household head	1501	52.71086	13.52604	5934	57.51196	14.73281
Log of real health expenditure	1183	5.70942	1.267061	4838	5.669439	1.206375
Log of real food expenditure	1786	8.210205	0.861647	6688	8.067133	0.78741
Number of doctor visits	1627	10.25937	6.214223	6167	8.865737	5.517154

Tables 4, 5 and 6 present our difference-in-difference propensity score matching results.[11] Table 4 reports the results conducted on the entire sample. There are a few empirical regularities that emerge from Table 4. First, we see that there is no statistically significant difference between the crisis-affected and the non-affected group in the baseline scenario. This regularity holds for all three variables of interest: food expenditure, health expenditure, and doctors' visits. Second, the follow up scenario, namely, the year of the crisis and after, follows a similar empirical regularity.

[10] As a robustness check we also conduct the analysis on the upper quintile (as well as a combination of the two upper quintiles). The results of these robustness checks are available on request.

[11] We use one-to-one matching as a basis for the difference-in-difference matching procedure. The diagnostic tests for the propensity score matching (PSM) exercise that is a basis for the difference-in-difference PSM are presented in Appendix 1.

Finally, the difference-in-difference results are not statistically significant suggesting that, when the entire sample is taken in consideration, crisis induced shocks have no effect on the variables of interest.

Table 4. Difference in Difference propensity score matching

	Base line			Follow up			
Outcome variable	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Log of food expenditure	7.144	7.187	0.043	7.208	7.172	-0.036	-0.078
Std. Error	0.037	0.049	0.037	0.035	0.045	0.033	0.049
t	191.44	8.02	1.16	8.94	5.5	-2.36	-1.6
P>t	0	0	0.246	0	0	0.274	0.109
	Base line			Follow up			
	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Log of health expenditure	5.459	5.572	0.112	5.61	5.574	-0.036	-0.148
Std. Error	0.052	0.08	0.072	0.049	0.072	0.064	0.096
t	104.44	6.86	1.56	8.53	3.67	-2.2	-1.54
P>t	0	0	0.119	0	0	0.578	0.123
	Base line			Follow up			
	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Doctors' visits	3.238	3.185	-0.053	3.421	3.444	0.022	0.076
Std. Error	0.054	0.072	0.056	0.052	0.065	0.047	0.072
t	59.82	2.5	-0.96	6.79	4.53	1.56	1.05
P>t	0	0	0.339	0	0	0.63	0.295

Table 5 presents the results when the sample is restricted to households in the lowest quintile. For the poorest, health expenditures are reduced significantly when the household is affected by an income shock. Here we see statistically significant results in both the follow up scenario as well as in the difference-in-difference matched score, suggesting that the crisis has an impact on the out-of-pocket health expenditure of the poorest quintile of the population.

Table 5. Difference in Difference propensity score matching - lowest quintile only

	Base line			Follow up			
Outcome variable	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Log of food expenditure	6.922	6.785	-0.137	6.954	6.85	-0.104	0.033
Std. Error	0.096	0.123	0.094	0.091	0.111	0.073	0.117
t	72.11	5.81	-1.46	7.28	7.12	0.32	0.28
P>t	0	0	0.144	0	0	0.155	0.776
	Base line			Follow up			
	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Log of health expenditure	5.247	5.34	0.093	5.469	5.128	-0.341	-0.434
Std. Error	0.184	0.248	0.195	0.175	0.221	0.15	0.244
t	28.47	5.62	0.48	6.51	3.6	-2.8	-1.78
P>t	0	0	0.634	0	0	0.024**	0.076*
	Base line			Follow up			
	control	trated	diff (BL)	control	treated	diff (FU)	Diff-in-diff
Doctors' visits	3.218	3.156	-0.062	3.356	3.335	-0.021	0.041
Std. Error	0.136	0.177	0.139	0.13	0.158	0.103	0.171
t	23.58	2.87	-0.44	4.28	3.55	0.33	0.24
P>t	0	0	0.657	0	0	0.837	0.812

Table 6 presents the difference-in-difference propensity score matching for selected vulnerable groups.[12] The message that the table sends is unequivocal – there is a strong and robust link between income shocks and reduction in health expenditure (and in certain instances food expenditure) for vulnerable households. Indeed, the results suggest that households headed by people with low educational attainment tend to decrease both health and food expenditure as a result of events with a negative socio-economic impact. A similar finding emerges for households with larger number of older people.

Table 6. Difference in differnce propensity score matching for selected vulnerable groups

Group: Housheolds with headed by low educated head							
Outcome Variable	Control	treated	Diff(BL)	Control	treated	Diff(FU)	DIFF-IN-DIFF
Log of food expenditure	7.323	7.498	0.176	7.345	7.358	0.012	-0.163
Std. Error	0.105	0.114	0.058	0.106	0.111	0.05	0.076
t	69.55	8.86	3.04	7.53	6.05	-3.06	-2.15
P>t	0	0	0.002***	0	0	0.806	0.032**
Group: Housheolds with headed by low educated head							
Outcome Variable	Control	treated	Diff(BL)	Control	treated	Diff(FU)	DIFF-IN-DIFF
Log of health expenditure	4.667	4.884	0.218	4.791	4.671	-0.12	-0.337
Std. Error	0.211	0.229	0.119	0.213	0.223	0.106	0.158
t	22.16	5.62	1.83	5.25	3.5	-2.95	-2.14
P>t	0	0	0.067*	0	0	0.261	0.033**
Group: Housheolds with large number of aged people							
Outcome Variable	Control	treated	Diff(BL)	Control	treated	Diff(FU)	DIFF-IN-DIFF
Log of health expenditure	5.258	5.501	0.243	5.468	5.407	-0.061	-0.304
Std. Error	0.102	0.151	0.126	0.093	0.135	0.109	0.164
t	51.77	6.86	1.93	7.5	3.46	-2.55	-1.85
P>t	0	0	0.053*	0	0	0.574	0.065*

12 We only report results that are significant. The rest of the results are available from the authors upon request.

Propensity score matching (PSM)

Our initial robustness check is to conduct a propensity score matching (PSM) exercise. Table 7 presents the results of the propensity score matching method conducted on the entire sample. As indicted above, the details of the diagnostic tests for the entire sample and for the lowest quintile of the population are included in Appendix 1. For the three health and nutritional behavioral indicators, crisis-affected households are statistically identical to households that are not-affected by income shocks. In other words, households affected by income shocks in Russia in 2009 are similar to households that were not affected by shocks in 2009 in terms of health and nutrition behavior.

Table 7. Propensity score matching for selected health/nutrition variables

Method	Variable	treated	controls	mean value difference	S.E	tstat
One to one	Log of health expenditure	5.747664	5.755762	-0.0080978	0.068909	-0.12
	Log of food expenditure	8.157818	8.117031	0.04078673	0.036269	1.12
	Doctors' visits	9.26112	9.248764	0.01235585	0.515522	0.02
Nearest neighbour	Log of health expenditure	5.747664	5.709498	0.03816611	0.059659	0.64
	Log of food expenditure	8.157818	8.143538	0.01427951	0.032899	0.43
	Doctors' visits	9.580688	9.475529	0.10515873	0.451107	0.23
kernel	Log of health expenditure	8.157818	8.136856	0.02096177	0.03046	0.69
	Log of food expenditure	5.747664	5.719412	0.02825214	0.056214	0.5
	Doctors' visits	9.26112	9.233267	0.02785298	0.412412	0.07

*** signficance at 1 per cent, ** signficance at 5 per cent while * signficance at 10 per cent level of signficance. All models estimated using the following control variables: household size, gender of the household head, asset index, education level and percent of household members that are employed. Post-matching dignostic tests point to successfulness in the process of matching.

Table 8 presents findings from the PSM when restricted to the lowest quintile (the poor). In contrast to the results above, we find a statistically significant negative difference in health and nutrition behavioral indicators between crisis-affected and not-affected households, which closely mirror the finding from our difference-in-difference propensity score matching estimation above. When using both, one-to-one matching as well as nearest neighbor matching, we find a statistically significant difference in the amount of money spent on out-of-pocket health expenditure between the crisis-affected and not affected households. Therefore, the results reveal that crisis-affected poor households change their health behavior during the 2009 crisis in Russia.

Table 8. Propensity score matching for selected health/nutrition variables for the lowest quntile

Method	Variable	treated	controls	mean value difference	S.E	tstat
One to one	Log of health expenditure	5.262132	5.58269495	-0.3205632	0.1515604	-2.12**
	Log of food expenditure	7.949427	8.04660606	-0.0971788	0.0867171	-1.12
	Doctors' visits	7.143564	5.95544554	1.18811881	0.9220845	1.29
Nearest neighbour	Log of health expenditure	5.202165	5.50183442	-0.29966907	0.1400657	-2.14**
	Log of food expenditure	7.859147	7.88457056	-0.02542403	0.0851229	-0.3
	Doctors' visits	6.628253	5.97992565	0.64832714	0.852917	0.76
kernel	Log of health expenditure	5.202165	5.40008288	-0.19791754	0.1304266	-1.52
	Log of food expenditure	7.859147	7.9645441	-0.10539757	0.079272	-1.33
	Doctors' visits	6.628253	6.85735593	-0.22910314	0.7212048	-0.32

*** signficance at 1 per cent, ** signficance at 5 per cent while * signficance at 10 per cent level of signficance. All models estimated using the following control variables: household size, gender of the household head, asset index, education level and percent of household members that are employed. Post-matching dignostic tests point to successfulness in the process of matching.

Fixed effects model

Table 9 presents the fixed effects model. In this specification, our crisis-dummy variable is 1 during and after the crisis year (2009), while it takes values of 0 for the years prior to the crisis. The results for the entire sample are similar to those found when estimated using the non-parametric technique above, namely that there was no statistical difference between crisis-affected and not affected households. However, when restricted to the sample of households in the lowest quintile, we find that crisis-affected low income households reduced their health expenditures more than low income households that were not affected by income shocks.

Table 9. Panel fixed effects of the selected variables of interest

	Entire sample			Lowest quintile only		
Log of food expenditure	-0.137 (0.450)			-0.115 (0.134)		
Log of health expenditure		-0.178 (0.108)			-0.530**(0.285)	
Doctors' visits			1.311 (0.958)			-1.417 (2.124)
Number of observations	3776	2800	3757	804	581	801
Number of groups	1142	1030	1141	364	282	362
Year dummies	YES	YES	YES	YES	YES	YES
R2	0.0347	0.0214	0.0307	0.027	0.051	0.0505

All models estimated with robust standard errors. *** denotes singficance at 1 % level of signficance, ** denotes signficane at 5% level of significance, while * denotes signficance at 10 % level of signficance. All modles estimated with control variables used for the propensity score matching: age of the head of the households, whether or not the household is headed by a male, education level of the head of the household, size of the household as well as the asset index for each housheold (results of the control variables are not reported but are conistent with the results obtained with the semi-parametric modelting techniques. Robust standard errors are reported in parantheses.

Finally, we repeat our analysis on the vulnerable groups only, which are reported in table 10. The results presented in table 10 echo the findings conducted with semi-parametric approach, namely that certain vulnerable groups are particularly vulnerable to economic shocks and adopt coping strategies that could potentially have a harmful impact on human capital development.

Table 10. Panel fixed effects for selected vulnerable groups and selected variables of interest

	Female headed households			Households headed by head with lower education			Households with large number of older people		
Lof of food expenditure	-0.088 (0.075)			-0.092* (0.054)			-0.067 (0.069)		
Log of health expenditure		-0.222 (0.192)			-0.241* (0.158)			-0.157 (0.190)	
Doctor's visits			-0.022 (0.141)			-0.012 (0.081)			-0.065 (0.111)
Number of observations	1268	964	1227	2014	1467	1934	1602	1232	1550
Number of groups	422	375	420	643	566	638	539	481	534
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.036	0.0708	0.0141	0.038	0.0292	0.018	0.047	0.037	0.0067

All models estimated with robust standard errors. *** denotes significance at 1% level of significance, ** denotes significance at 5% level of signficance, * denotes signficance at 10% level of significance. All models estimated with control variables used in the propensity score matching exercise: age of the head of household, whether or not the household is headed by male (where appropriate), level of education of the head of the households (where appropriate), as well as an asset index. The results of the control variables are not reported but are consistent with the results obtained in the propensity score matching. Robust standard errors are reported in parantheses.

7. Discussion

We find that on average, Russian households affected by the 2009 crisis where no different to households that were not affected by the crisis in terms of household's health and nutrition behavior. The finding is not very surprising given Russia's wealth and ability among many households to move towards home production of food, during and in the aftermath of the crisis. Previous research also failed to find robust and significant impacts of crises on nutrition in Russia. Stillman and Thomas (2004) for example find that nutritional status appears to be resilient to variation in household resources. Gross energy intake, adult body mass index (BMI), and child stature all change very little as expenditure deviates from its long-run average. In contrast, they find a positive, significant and substantively large effect of longer-run resources on energy intake, two indicators of diet quality, adult body mass index (BMI), and child stature. Their study suggests that fluctuations in income might have a more significant effect in long than in short run. Dore et al (2003), while assessing dietary trends for children in low and high income households during this politically and economically unstable period from 1994 to 2000, find that low income children maintained a steady energy intake per kilogram weight throughout the study period, whereas intake for high income children increased energy intake per kilogram weight significantly. Their results suggest that Russian households were able to conserve their diet structure for children by using what appear to be food-related behavioral mechanisms during periods of economic crisis.

On the other hand, our analysis does confirm a strong link between crisis-affected poor households and out-of-pocket health expenditure, which is in line with the existing literature. Frankenber et al (1999) and Cutler et al (2002) find that, in general, households that are crisis-affected reduced healthcare utilization in Indonesia and in Mexico during crises because of out of pocket expenses.

Moreover, our results also suggest that there is a strong link between vulnerability and out-of-pocket health expenditure (and, in certain instances, food) especially in the periods of crisis. Certain vulnerable families (such as those with household heads with low educational attainment) tend to be particularly affected during periods of economic distress and are, occasionally, forced to adopt potentially harmful coping strategies, such as reducing food and out-of-pocket health expenditure. The long-term consequence of these coping strategies could be damaging to the household's human capital accumulation, which is particularly worrisome because poor and vulnerable people are more dependent on human capital over other types of capital for their long term welfare.

8. Conclusions

Financial and economic crises influence human development in various ways and can have a long term impact on household welfare. In this paper, we analyze the impact of the 2008-2010 global financial crisis on selected health and nutrition behavioral variables among Russian households.

Our analysis of the crisis in 2009 in Russia shows that there was no statistically significant impact on the average household on food consumption, out-of-pocket health expenditures, and doctors' visits of crisis-affected households. However, we find robust evidence that poor (lowest quintile) crisis-affected households spent less on health services, compared to poor households not affected by an income shock.[13] Furthermore we find that vulnerable people affected by the crisis in 2009 altered their health and nutrition behavior. In particular, households with low educational attainment of household heads that suffered an income shock tended to decrease expenditures on both food and health services, while households that had a higher number of elderly people tended to curb the use of health services. These findings suggest a particular need to protect the health and nutritional needs of the poorest and most vulnerable in the population, but not necessarily the entire population.

The findings underscore the need to study crisis impacts for sub-groups, despite the finding that the overall health and nutritional behavioral responses may not vary between households that were and were not affected by income shocks. In addition, the study reveals the value of using longitudinal household survey data to analyze the impact of crises.

[13] By the same token, when the analysis is conducted to a restricted sample of the two upper quintiles of the population (4th and 5th), we see that households that are affected by the crisis but are more affluent tend to spend more on health services.

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Appendix 1 – PSM Diagnostic tests

The importance of the propensity score matching is two-fold: first to estimate ATT and second to obtain matched treated and non-treated observations as inputs for analysis of the impact of the income shocks on health and nutrition variables. The probit analysis of the impact of the crisis-produced income shocks on households is depicted in Table A1. The table reveals the relative importance of factors such as: size of the household, age of the household head and asset index, of being affected by an income shock. A similar table is produced with the sample restricted to the lowest quintile. The results that are obtained when the probit model is estimated on a restricted sample (poor only) are presented in Table A2.

Table A1. Estimation of propensity score for the entire sample

Variables	Estimates
Household size	0.042* (0.024)
Male head of household	0.158** (0.072)
Asset index	0.124*** (0.032)
Employment in household	0.19** (0.089)
Education of the head of household	0.010 (0.015)
Age of the head of household	-0.008*** (.0002)
Pseudo R squared	0.0343
LR chi-square	110.79***
Number of observations	3272
Log likelihood	-1561.7596

Table A2. Estimation of propensity score on the lowest quintile only

Variables	Estimates
Household size	0.08* (0.042)
Male head of household	-0.030 (0.185)
Asset index	0.060 (0.125)
Employment in household	0.513** (0.225)
Education of the head of household	0.083** (0.027)
Age of the head of household	-0.014** (0.006)
Pseudo R squared	0.0541
LR chi-square	30.97***
Number of observations	695
Log likelihood	-270.823

Tables A3 and A4 present the balancing information for propensity scores and for each covariate after matching, for both, the entire sample as well as for the lowest quintile. Tables A5 and A6 provide evidence for additional diagnostic tests (pseudo R2 and the significance of the likelihood ratio). We use the standardized bias difference between treatment and control samples as a convenient way to quantify the bias between treatment and control samples. In all cases, we observe that the bias is very low and it reduces significantly after matching. Further, the covariates demonstrate no statistical significance after matching. The low pseudo R2 and the insignificant likelihood ratio test support the hypothesis that both groups have the same distribution of covariates after matching. These results clearly show that the matching procedure is able to balance the characteristics in the treated and the matched comparison groups. Finally, Panels 1 and 2 a large area of common support between the 'affected' and 'non-affected' households is evident.

Table A3. Balancing information for propensity scores for the entire sample

Variable	Treated	Control	%bias	t-test t	p>t
Household size	2.7278	2.7593	-2.4	-0.4	0.691
Male head of household	0.80741	0.81852	-2.6	-0.47	0.64
Pct of household members employes	0.5421	0.54702	-1.3	-0.23	0.817
Asset index	0.19683	0.1859	1.1	0.2	0.844
Education of the head of household	5.0907	5.1259	-1.8	-0.33	0.742
Age of the head of household	55.08	55.43	-2.4	-0.41	0.683

Table A4. Balancing information for propensity scores for the lowest quintile

Variable	Treated	Control	%bias	t-test t	p>t
Household size	2.3947	2.2895	8.2	0.54	0.591
Male head of household	0.78947	0.76316	6	0.39	0.699
Pct of household members employes	0.4511	0.47785	-7.5	-0.44	0.662
Asset index	-1.4697	-1.4721	0.4	0.03	0.979
Education of the head of household	4.8421	4.7368	5.4	0.36	0.72
Age of the head of household	56.184	56.75	-3.9	-0.24	0.808

Table A5. Other covariates balance indicators after matching (for the entire sample)

One to one matching	
Pseudo R2	0.001
LR chi square (p value)	2.79 (0.593)
Nearest Neighbour matching	
Pseudo R2	0.001
LR chi square (p value)	1.29 (0.863)
Kernel matching	
Pseudo R2	0.001
LR chi square (p value)	2.24 (0.692)

Table A6. Other covariates balance indicators after matching (for the lowest quintile only)

One to one matching	
Pseudo R2	0.007
LR chi square (p value)	2.27 (0.686)
Nearest Neighbour matching	
Pseudo R2	0.005
LR chi square (p value)	1.74 (0.784)
Kernel matching	
Pseudo R2	0.002
LR chi square (p value)	0.64 (0.958)

To compute the ATT, three alternative matching methods (one-to-one matching, nearest neighbour matching and kernel matching) are used and compared. All the analyses are based on implementation of common support and calliper, so that the distributions of treated and non-treated units are located in the same domain.

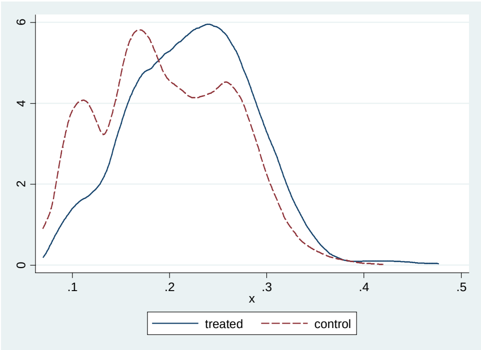
We also conduct sensitivity analysis of unobserved heterogeneity. As noted by Hujer et al. (2004), sensitivity analysis for insignificant ATT estimates is not meaningful and thus we restrict the sensitivity tests to the lowest quintile sample. Table A7 presents results of the Rosenbaum bounds sensitivity analysis. The table shows the null hypothesis of no impact of an income shock on health care expenditure is not plausible. The negative effect of an income shock is not sensitive to selection bias due to unobserved bias even if we allow households that were affected and non-affected by an income shock to differ by as much as 100 percent. Based on this result, we can conclude that the ATT estimates in Table 9 are a pure effect of the impact of the income shock.

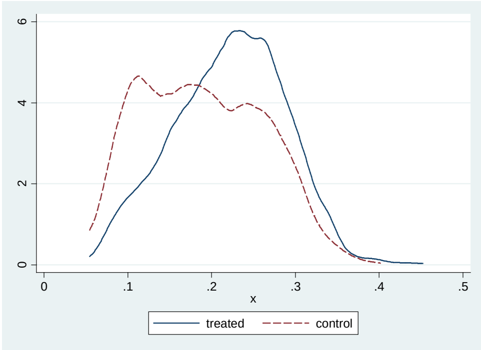
Table A7. Sensitivity analysis of unbobserved heterogeneity for health expenditure

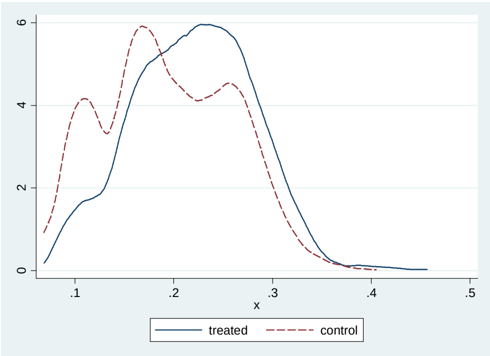
			Hodges-Lehman point estimates			
Gamma	p-value+	pvalue-	t-hat+	t-hat-	CI+	CI-
1	0	0	5.33638	5.33638	5.26003	5.40651
1.1	0	0	5.28894	5.37847	5.21834	5.45554
1.2	0	0	5.24708	5.42161	5.17574	5.4959
1.3	0	0	5.21123	5.45833	5.13966	5.53914
1.4	0	0	5.17812	5.4959	5.10726	5.56989
1.5	0	0	5.14932	5.52522	5.07783	5.598
1.6	0	0	5.11715	5.55183	5.04249	5.63387
1.7	0	0	5.09221	5.58771	5.01694	5.66192
1.8	0	0	5.06484	5.60747	4.99287	5.69026
1.9	0	0	5.03861	5.63388	4.96627	5.71148
2	0	0	5.01821	5.66106	4.94073	5.73865

Reported P-values are the Wilcoxon sign-rank test of significance under hidden bias. Results are based on stata ado routine "rbounds". Calculation is done based on Rosenbaum bounds for ATT; nearest neighbour matching with common support. The outcome variable is the log of health expenditure.

Panel 1. Area of common support between affected and non-affected families for the variables of interest, i.e. food, health and number of doctors' visits respectively (entire sample).







Panel 2. Area of common support between affected and non-affected families for the variables of interest, i.e. food, health and number of doctors' visits respectively (poor only).