IMPACT EVALUATION OF THE SOCIAL INVESTMENT FUND PROJECT IN UKRAINE

by

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Abstract

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The purpose of this study is to evaluate the impact of the Ukrainian Social Investment Fund communal services micro-projects on district level morbidity rates. Using panel data for Ukrainian districts from 2000 to 2010 with economic factors and medical infrastructure, as inputs, and treatment variable, as a measure of project impact, the effect on morbidity rate is determined. The results of difference in-difference and fixed effect estimations are similar and indicate that the morbidity rate decreased substantially in participating districts in medium and long run perspective. Furthermore, the analysis of the heterogeneity of project impact reveals important details about the estimated impact on morbidity rate. Specifically, impact on morbidity rate was larger in districts which acquired more USIF funding, represent urban areas (cities) and have higher average wage.

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GLOSSARY

WB. World Bank

SIF. Social Investment Fund

USIF. Ukrainian Social Investment Fund

Chapter 1

INTRODUCTION

> *"Success depends on knowing what works."*
>
> —Bill Gates, Co-Chair, Bill & Melinda Gates Foundation

After the collapse of the Soviet Union in 1991 Ukraine experienced a deep recession. Its impact on Ukrainian economy was tremendous with a sharp fall of GDP, increased unemployment and hyperinflation. Consequently, the individual income level decreased substantially, pushing one third of population to poverty. According to the World Bank, during the 1990s, while the poverty rates increased much, the state social assistance was ineffective in providing the sufficient support for those in need, which brought to the political agenda an issue of improving social infrastructure in Ukrainian regions (WB, 2008).

In this context, in 2001 the Government of Ukraine with the support of the World Bank established the Ukrainian Social Investment Fund (USIF). The idea of the USIF was to introduce "a demand-driven financing mechanism for community-based micro-projects to respond [to] the requests from communities for rehabilitation of the social and economic infrastructure and implementation of innovative programs to improve basic social services targeted to the most vulnerable groups of population through providing social investments in the form of grants" (USIF, 2010).

The notion of the Social Invest Fund (SIF) was not new at that time. The first SIF was created by the WB in Bolivia in 1987. In 2001 the WB operated more than 98 SIF projects in 58 countries (Rawlings et al., 2003). Today there are SIFs in Latin America, Africa, Asia and Europe. Among the transition countries, in particular, the SIFs were established in Bulgaria, Moldova, Armenia and Georgia. In all the countries mentioned the SIFs "aim to alleviate poverty by creating and upgrading social and economic infrastructure, promoting income-generating activities, and supporting the development of civil society and social capital" (Costella et al., 2010).

Today many countries are faced with the issue of reducing their public expenditures. In this respect, targeted micro-financing provides an alternative to broad state programs since it requires participating communities to share the financial responsibility in a given project. Also, it is believed to address more efficiently the needs of these communities. With an increased demand for such focused programs, there is a need for their impact evaluation. Such evaluation would provide grounds for better public governance and more efficient allocation of available resources. There have been done some evaluations of the SIFs activities in Latin America (Glaessner et al., 1994), Bolivia (Newman et al. 2002), Nicaragua (Pradhan et al, 2002), Peru (Paxson et al., 2002), Armenia (Chase, 2002), Moldova (Bezhanyan et al., 2002) and some other countries as well as one cross-country SIFs analysis by the WB (Rawlings et al., 2003). Yet, there was no impact evaluation of the SIF in Ukraine which is important in order to determine the effectiveness of the community micro-financing in institutional environment of Ukraine.

Evaluation of the SIF Project in Ukraine is based on the administrative data, which includes the districts where the micro-projects were implemented with the corresponding implementation periods and funding information. This data is complemented by data from the State Statistics Service of Ukraine on regional employment, wages, air pollution and population densities, and from Kyiv Economic Institute Data Center which contains region level health indicators (morbidity rates and number of health care institutions). Furthermore, the difference-in-difference estimation is used as a standard tool for such evaluation while propensity score matching technique augments the analysis. All in all, the analysis is focused on the district-level data which is used to evaluate the impact of the USIF micro-financing by estimating whether it achieved the original goals of the project such as poverty alleviation and community development.

It should be noted that poverty alleviation implies improving living conditions of poor people. This enhancement of living conditions implies a broad list of interconnected areas such as good nutrition, availability of clean water, vaccination, cleaner environment etc. So availability of high-quality social infrastructure (educational – schools, kindergartens, developmental – roads, water supply, sewerage, and medical – health posts) is of great importance in the respect of improving well-being of poor communities. This study is concentrated primary on the impact of USIF communal services micro-projects (related to improvement of basic social infrastructure) on health outcomes, such as morbidity rate, of participating districts. The positive result of the program upon its completion is measured by decrease in morbidity rate in targeted districts. Finally, the questions of possible heterogeneity and sustainability of project's impact is also addressed.

To sum up, the study shows the effectiveness of micro-financing projects in Ukraine. The need for such comprehensive evaluation is also explicitly stated in the WB final report on USIF (WB, 2008). Furthermore, since positive impact of the project on development of poor communities is proved, the USIF experience can be referred to as a ground for improvement of social services in Ukraine and supporting of further community-based micro-financing by both Ukrainian government and international institutions.

The thesis proceeds as following. In the next chapter there is a brief overview of the USIF Project while chapter 3 describes the existing literature on the theoretical concept of health production function and its determinants as well as the impact evaluation of the SIFs in different countries. In chapters 4 and 5 the evaluation design (methodology) and the detailed description of the data are provided. Then the major results are summarized in chapter 6. At the end of the study, the overall conclusions are given.

Chapter 2

UKRAINIAN SOCIAL INVESTMENT FUND

The Social Investment Fund Project in Ukraine operated from April 2001 to June 2008. Its preliminary budget was 50.21 million USD. Its aim was to assist Ukraine in improving "the system of social services delivery, with a specific focus on poor communities and disadvantaged groups of the population who have suffered the most from the economic and social transition and ten years of economic decline." (WB, 2001) In the light of USIF mission several specific objectives were set "to: (i) improve the living conditions of poorer and vulnerable groups of the population in targeted communities; (ii) empower communities and vulnerable groups to address local social needs; and (iii) assist the reform of social protection by creating models of targeting and service provision" (WB, 2001)

During 7 years the USIF implemented "676 communal services micro-projects […] Also, 80 social care services micro-projects were completed. […] The communal services sub-component was implemented in 78 districts[1] in 25 regions; it cost US$48.2 million (including training), and had about one million beneficiaries. The social care services sub-component was implemented in 6 regions, [and] Kyiv. It cost US$6.9 million (including training), and had about 75,000 beneficiaries" (WB, 2008).

The community-based and social care services micro-projects were implemented in the two poorest districts in each of 24 regions of Ukraine and Crimea, while

[1] Communal services sup-component was implemented in two stages with the first stage in 70 districts and the second stage in 8 districts out of the same 70.

the social care service micro-projects were also implemented in Kyiv and Sevastopol (WB, 2008). At first, the determination of USIF micro-projects participants (the poorest districts to be targeted) was done on the basis of the 4 main criteria: child mortality at the age from birth up to 1 year old per 1000 (an average for the recent 3 years); aggregate index for share of poverty risk group (adults and children with disabilities, children from large families, single retired persons) per 1000; percentage of children who go to school more than 3 kilometers away from home and do not participate in the "School Bus" program; and share of communities which do not have medical care institutions (MLSP, 2009). But then in 2007 the project expanded its communal services operation in 28 additional districts due to the hardship of fulfillment project co-financing requirement by the 50 poorest districts.

Overall, the implementation of the communal services micro-projects was done in several waves: (1) in 2002 in Khmelnytsk, Kyiv and Chernigiv regions; (2) in 2003 in Vinnytsya and Sumy regions; (3) in 2005 in Chernivtsi, Zhytomyr, Dnipropetrovsk, Zaporizhzhzya, Cherkasy, Kharkiv and Poltava regions; and (4) in 2006 in the rest of regions (Lviv, Zakarpattya, Volyn', Rivne, Ternopil', Lugans'k, Donets'k, Odesa, Mykolayiv, Kherson, Kirovograd regions and Crimea). The USIF Communal Service Micro-Projects Participating Districts are presented in Figure 1, where treatment group is 1.

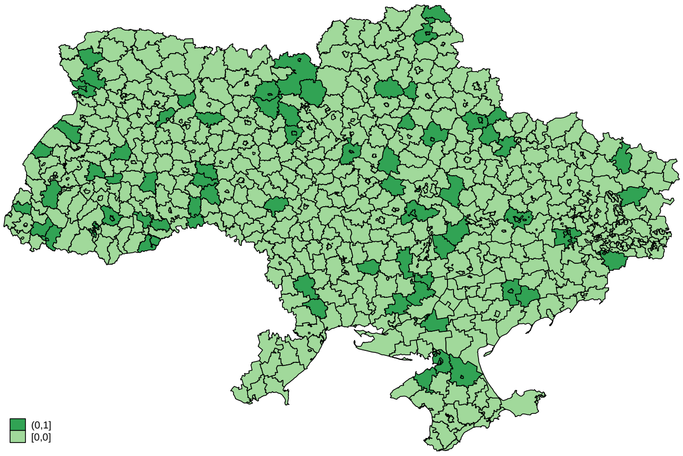

Figure 1. USIF Communal Service Micro-Projects Participating Districts
Source: Ukrainian Social Investment Fund, 2008. Author's analysis.

The communal services micro-projects included schools and kindergartens, community cultural centers, health posts, roads, water supply, environmental improvement and other spheres (see Figure 2) while the social care services micro-projects were targeted specifically at vulnerable groups (persons with disabilities, victims of human-trafficking, victims of home abuse etc.) and consisted of crisis intervention centers, early intervention centers, day care centers, community centers, day centers with labor rehabilitation, hospices, shelters, supported independent living and social support (WB, 2008).

According to the WB (2008), upon completion of the implementation of the USIF Project "six out of the seven of the 'outcome'[2] indicators… were agreed at appraisal and were met or exceeded". Among these achieved indicators were: "(1) 90% of beneficiaries expressed satisfaction with the provided services; (2) access

[2] The 'outcome' indicators were actually the 'output' indicators.

to social services, as measured by the number of micro-projects completed – 756, increased; (3) 85% of participating communities have initiated new project activities without USIF participation; (4) 487 Users' Associations were establishes; (5) 4 national and regional plans (for targeted regions) for sustainable social care services were developed; and (6) morbidity rate (case of disease per 1000) fell by 17% in beneficiary communities" (WB, 2008).

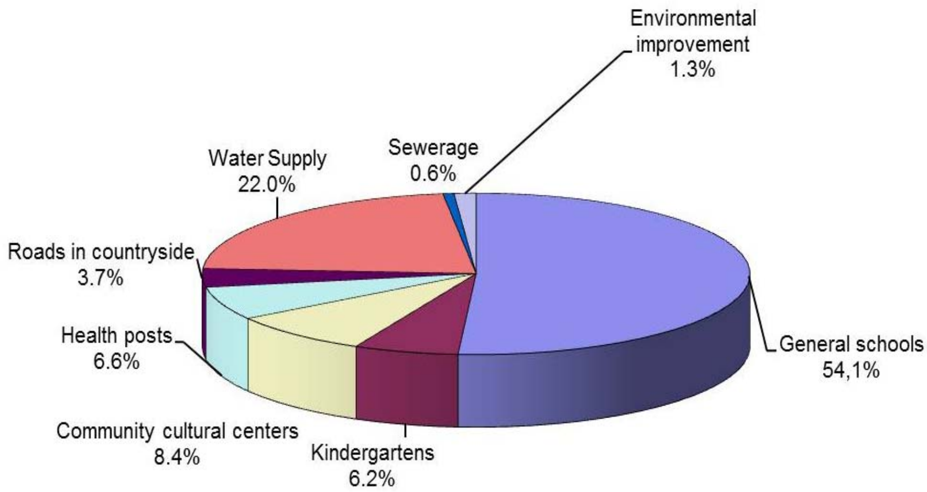

Figure 2. USIF Completed Communal Service Micro-Projects
Source: Ukrainian Social Investment Fund, 2008

It is also worth noting that the former three outcomes were confirmed by the surveys of the beneficiaries of USIF micro-projects. As for the reduction in morbidity rate the WB report state that the causality link between this outcome and USIF intervention was not proved.

Chapter 3

LITERATURE REVIEW

In the light of this study the existing literature can be split into two parts: the general theoretical research, i.e. literature on the theoretical findings devoted to the determination of inputs of the health production function, and the empirical literature about the assessment of the socio-economic effects of SIFs in different countries.

The first theoretical framework for studying the health production function was offered by Auster et al. (1969) who "was the first to examine the effectiveness of medicine adopting the economic concept of a production function" (Zweifel et al., 2009). He was also the first to list the factors entering health production function and divide them into several groups: economic factors (income per capita, years of schooling), environmental factors (urbanization, industrialization, water pollution and carbon dioxide emissions rates), consumption-related factors (alcohol and cigarette consumption per capita), medical factors (pharmaceutical outlay per person, physician density, medical auxiliary staff and the capital available to medical institutions), and organizational factors (physicians groups practice and existence of medical schools) (Zweifel et al., 2009).

Later Grossman (1972) determined the elements of individual health demand function (such as wealth, wage, education, age, family size) as well as researched further the individual health production function. Specifically, he identified health production outcomes, mortality or morbidity rates, and factors which influence the health production, such as income, alcohol and cigarettes consumption, education, nutrition, housing and recreation.

Afterwards, many authors used these models by Auster et al. and Grossman to estimate health production functions on aggregate level for different countries, where they used variables in per capita terms as inputs and life expectancy at birth or child mortality rate per 1000 as outcomes. For example, Fayissa and Gutema (2008) analyzed health production function for Sub-Saharan Africa and concluded that "an increase in income per capita, a decrease in illiteracy rate, an increase in food availability were well associated with improvement in life expectancy at birth" in the region. As for the estimation of the health production function for industrialized countries, the evidence on OECD data suggested that "there appears to be a significantly positive relation between health expenditure and health, particularly for women. […] At the same time, the results strongly suggest that environmental factors … are more important than medical inputs in explaining variations in premature mortality in industrialized countries" (Or, 2000). Lastly, the major inputs to health function in Ukraine, according to Serduk and Tymchenko (2000) (based on World Health Organization estimates), are life style (50%), genetic (20%) and environmental factors (20%), quality and availability of medical care (10%).

The impact evaluation of USIF is also grounded on the empirical literature about assessment of the socio-economic effects of SIFs in different countries. This research consists of two parts. The first set includes some general descriptive analysis, for instance, of the Moldavian SIF by Bezhanyan and Ionascu (2002), Thailand SIF by Salim (2001), and Benin SIF by Elder and Tovo (2002). In this group there is also a more general study "Poverty Alleviation and Social Investment Funds. The Latin American Experience" (1994) which was conducted by Glaessner et al. and summarized all the activities and outcomes (predicted and actual) of the SIFs in Bolivia, Honduras, Nicaragua, Ecuador, Guyana, Peru, El Salvador, Panama, Guatemala, and Chile. The authors conclude that in general the SIFs in Latin America were successful at achieving the objective of poverty alleviation in targeted communities. Moreover, the authors indicate that these SIFs advanced private sector activities and stimulated the dialogue between government officials and communities with respect to regional development policies in given countries.

Another set of research constitutes the empirical studies of the SIFs in different countries which were issued by the World Bank in 2002. However, this impact evaluation of social funds was focused only on several countries: Armenia (Chase, 2002), Bolivia (Newman et al. 2002), Nicaragua (Pradhan et al, 2002), and Peru (Paxson et al., 2002). Nevertheless, this kind of analysis is still very useful because it provides a good empirical background and basis for the assessment of USIF effects (in terms of poverty reduction, improvement of health and education) on local communities in Ukraine. In this group the evaluation is made based on either one of the three methods: randomization, propensity score matching or instrumental variable. The major results of these evaluation papers are summarized in Table 1.

Table 1. Impact evaluation results of the SIF Projects in selected countries.

Country	Positive Impact on Education[1]	Positive Impact on Health	Targeting Success
Armenia	Yes	Yes, Mild Effect	Yes
Bolivia	Little Effect	Yes	-
Nicaragua	Yes	Little Effect	Yes
Peru	Yes	-	Yes

Source: Chase, 2002; Newman et al., 2002; Pradhan et al, 2002; Paxson et al., 2002

From Table 1 it is clear that the SIFs had strong positive impact on education and targeting success in such countries as Armenia, Nicaragua and Peru while the Project impact on health outcomes was different for selected countries – from little or mild effect in Armenia and Nicaragua to strong positive effect in Bolivia.

It is also worth mentioning that there is a broad cross-country analysis of the SIFs by Rawlings et al. (2004) focused on case studies of Armenia, Bolivia, Honduras, Nicaragua, Peru and Zambia. As a result of their estimation, the authors found a general positive impact of these SIFs on community welfare.

Finally, Rawlings (2002) in her introduction to the WB research on the topic "Impact Evaluation of the Social Funds" highlighted the motivation for future impact evaluation of the SIFs in developing countries. She stated that since little had been done in this area of research so far, the impact evaluation of SIFs offered a number of useful techniques and results to be used in the appraisal of other public projects. Indeed, there is no analysis of social fund influence on local development in any other transition country except for Armenia. Therefore, this analysis of SIF in Ukraine will be a good filling-in of an existing gap in the literature for the transition countries.

Chapter 4

METHODOLOGY

A general impact evaluation framework suggests several types of evaluation design beginning from informal evaluation using expert judgments and peer review, and ending with a formal design consisting of randomized experiments and quasi-experiments. The major goal of the latter two is to analyze whether a particular outcome can be attributed to a program impact. Usually such analysis is based on comparison of outcomes for two groups: one is program participants (treatment group) and the other is nonparticipants (comparison group). In other words, to estimate an impact of the USIF Project on improvement of health outcome, such as morbidity rate, one may estimate a simple difference regression as the following:

$$Y_t = \beta_1 + \beta_2 * D_t + u_t, \text{ for } t=0,\ldots, T, \qquad (1)$$

where Y_t is a health indicator of interest, D_t is a dummy variable for community participation in the USIF Project at time t and u_t. is a white-noise.

However, it is important to emphasize that the above simple difference estimation assumes a random assignment of a given treatment, i.e. when the program participants are selected randomly from a population. So in case there is a random assignment, this kind of estimation works well and produces valid results. But when participants of a particular program volunteer for participation and/or are selected by a program management based on a number of criteria, an evaluator cannot rely on simple difference estimation. In this case a simple comparison of the two groups (with treatment and without it) will lead to biased estimates, i.e. while estimating a regression equation (1) basic assumption that $E(u_{it})=0$ for all i, t will be violated because $E(u_{it}|D_i)\neq 0$ when self-selection is present. Specifically:

$$Bias = E(Y_0|D=1) - E(Y_0|D=0) \tag{3}$$

Thus, in case the treated and comparison groups are placed randomly, the difference between the observed outcomes in these two groups is attributed to the effect of the USIF intervention. However, systematic difference between treated and non-treated districts due to program targeting makes the simple difference estimation (1) biased.

To resolve the above issue of non-random assignment of project participants, several approaches were developed. The most commonly used are difference-in-difference estimation with controls on observed covariates and propensity score estimation for better identification of treatment and control groups when selection procedure is present.

Heckman et al. stated, "the classical before-after estimator compares the outcomes of participants after they participate in the program with their outcomes before they participate. With the difference-in-differences estimator, common time and age trends are eliminated by subtracting the before-after change in nonparticipant outcomes from the before-after change for participant outcomes" (Heckman et al., 1998, p. 1031) Hence, to augment estimation of regression (1), one should also include a number of characteristics to the equation (1) which would control on time trend, communities' observed pre-existing conditions which also influence health outcome of interest (morbidity rate), for example, wage and unemployment rates, health care institutions density, air pollution and carbon dioxide emissions rates, urbanization and population density in Ukrainian districts before the inception of USIF Project[3]. Then the augmented difference-in-difference estimation becomes of the form:

$$Y_i = \beta_1 + \beta_2 * D_i + \beta_3 * T_i + \beta_4 * D_i * T_i + \beta_5 * X_i + u_i, \text{ for } i=1\ldots N, \quad (2)$$

where Y_i is an observed outcome for participant *i,* which depends on treatment effect D_i (time-invariant), the time trend T_i (similar across all districts), a vector of observed control characteristics X_i (wage and unemployment rates, health care institutions density, air pollution and carbon dioxide emissions rates, urbanization and population density) and a vector of unobserved factors – u_i.(white-noise)[4]. The coefficient on the interaction term (β_4) provides the estimate of the USIF Project effect on district morbidity rate (Y_i).

In order to correct for the selection bias Rosenbaum and Ruben (1983) proposed to use propensity score matching which is now a renowned technique. The essence of this method lies in construction of the group of program non-beneficiaries based on difference in means between treated and non-treated districts, i.e. the constructed control group mimics the treated group in all characteristics except for the participation in the USIF micro-projects. Formally, Rosenbaum and Ruben (1983) introduced a term "balancing score" *b(X)* which they defined as "a function of the observed covariates [*X*] such that the conditional distribution of [*X*] given [*b(X)*] is the same for treated [*D=1*] and control [*D=0*] units" and proved it to be equal to the "conditional probability of assignment to treatment one, given the covariates", i.e.

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[3] For the motivation of inclusion these specific characteristics as dependent variables in estimated difference-in-difference regression, please, refer to literature review – specifically, factors that enter health production function developed by Auster et al. (1969) and Grossman (1972).

[4] Since USIF micro-projects were implemented in treated districts during different years, treatment effect D_i is not time-invariant for all the participants in equation (2), which in this specific case looks as follows: $Y_i = \beta_1 + \beta_3 * T_i + \beta_4 * D_i * T_i + \beta_5 * X_i + u_i$, for $i=1\ldots N$.

$$p(X) = \Pr(D = 1|X) = E(D | X), \quad (4)$$

where $0 < \Pr(D=1|X) < 1$. Moreover, they showed that "if treatment assignment is strongly ignorable given X then the difference between treatment and control means at each value of a balancing score is an unbiased estimate of the treatment effect at that value, and consequently pair matching [...] can produce unbiased estimates of the average treatment effect" (Rosenbaum and Ruben, 1983, p. 42-43) So by choosing two communities, one in a treatment group and the other in a control group, which would have the same propensity score, one can regard them as "randomly assigned" because they have the same probability of submitting a successful application for participation in the USIF Project given their observed covariates such as number of health care institutions, population density, wage and unemployment rates.

Thus, using propensity score matching enables to better determine the treatment and control groups based on the probability to be a program participant. Moreover, after such identification of two groups of communities, by restricting the sample to common support region (overlap between the covariates of treated and non-treated districts) the difference-in-difference estimation (2) not only provides valid results but also allows controlling for the common trends for Ukrainian districts and, hence, such threats to the evaluation validity as the outside effect and maturation. The estimated β_4 coefficient represents the impact of the USIF Project.

As robustness check of the obtained average treatment effect of USIF communal service micro-projects on district-level morbidity rate, several approaches can be used. Firstly, after proper identification of treatment and control groups using propensity score matching one may look at the impact of the USIF Project within the treatment group and estimate the so-called average treatment on the treated effect (ATT), i.e.:

$$ATT = E[Y_1 - Y_0 \mid \Pr(X), D = 1] = E[Y_1 \mid \Pr(X), D = 1] - E[Y_0 \mid \Pr(X), D = 1], \quad (5)$$

where among the project participants (*D=1*) with their corresponding propensity scores Y_1 is the expected health outcome with the treatment and Y_0 is the expected health outcome without a treatment . The propensity scores are controlled for the vector of participants' observed pre-conditions and selection factors (Pr(*X*)). However, since ATT estimation using propensity scores does not include control factors that influence morbidity rates, it cannot precisely estimate the impact of USIF intervention.

A better way to check of the robustness of obtained results from augmented difference-in-difference estimation is to use fixed effects regression since the latter model includes district-specific heterogeneity fixed over time (for example, district-specific climate conditions, consumption-related and organizational effects) which may also affect dependent variable of interest (morbidity rate).

Finally, it is reasonable to expect different effects of USIF intervention depending on different factors, such as the time horizon of the analysis (short-run vs. long-run impact), availability of financial resources for implemented communal services micro-projects, urbanization level and availability of medical infrastructure. As a consequence, one can examine the heterogeneity of impact of the USIF Project on health outcome of interest (morbidity rate) by adding the interactions of lagged values of the treatment dummy and variables of heterogeneity under consideration in the estimation model.

Chapter 5

DATA

This study uses three sets of data: (a) the USIF Project data with the list of participating communities and used funds for different micro-projects; (b) region level data on unemployment and wage rates, air pollution, population and territory for 2000-2010 time period from the State Statistics Service of Ukraine; and (c) region level data on morbidity rates for 2000-2010 time period and number of health care institutions (first aid and obstetric centers - FAPs, and hospitals) in 2001[5] from the Region Centers of Medical Statistics obtained through Kyiv Economic Institute Data Center. The latter data is restricted and not publicly available.

The total number of districts and cities according to Classification of Objects of Administrative and Territorial Organization of Ukraine (KOATUU) is 669. When the city of Pryp'yat' is dropped and 63 towns are united with the corresponding districts[6], the total number of observations in the sample is 605. This panel data is balanced for all sample years except for the morbidity rate statistic, which misses several territories. However, since these gaps are not systematic, there is no bias.

For analytical purpose, several variables were constructed: population density and population density squared, log of wage, unemployment rate squared. Since the number of health care institutions in Ukraine is regulated according to the population density in a given region, the hospitals and FAPs density (number of

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[5] Year of inception of USIF Project

[6] Due to changes in KOATUU during the sample period 63 cities were separated from their district subordination, which resulted in missing data for these cities before the change occurred.

institutions per 100 thousand people), and their interaction was also constructed. The morbidity rate is an incidence rate, which is a ratio of total number of new cases of all diseases to 100 thousand people in a given district during a given year. The air pollution is a sum of emissions in tons from stationary and mobile sources a given district during a given year.

The descriptive statistics of the main variables in the full sample data are presented in Table 2.

Table 2. Descriptive statistics for the whole population

Variable	N	Mean	Std. Dev.	Min	Max
Territory, sq. km	605	998.52	608.59	2	4900
Population 2000, thd. persons	605	80.86	159.06	8.6	2613.1
Population 2010, thd. persons	605	75.61	160.75	7.6	2799.20
Average wage 2000, UAH	605	172.22	81.32	79.7	901
Average wage 2010, UAH	605	1807.29	474.75	1104	4191
Unemployment rate 2000, %	605	5.53	3.12	0.4	19.8
Unemployment rate 2010, %	605	3.11	1.86	0.1	10.3
Air pollution 2000, thd. tons	605	9.78	33.37	0	479.8
Air pollution 2010, thd. tons	605	11.06	34.18	0.4	448.8
FAPs 2001	605	25.16	18.03	0	90
FAPs density 2001	605	55.86	40.70	0	212.01
Hospitals 2001	605	5.15	6.37	0	97
Hospital density 2001	605	8.47	5.56	0	35.86
Funding obtained through participation in USIF communal service projects, thd. UAH	605	410.50	1378.38	0	9183.45
Morbidity rate 2000	310	55813.58	16229.72	18170	119276
Morbidity rate 2010	310	57397.97	17385.03	21347	123570

Table 2 shows that economic situation in Ukrainian regions improved between 2000 and 2010 since, on average, wage increased and unemployment rate fell. It is also notable that there was a drop in district population with the increased morbidity rate and increased volume of air pollution. Finally, it is worth mentioning that attracted financing for the participating districts in USIF micro-projects varied substantially: from average 410.5 thousand UAH to 9.1 million UAH.

Table 3 presents the descriptive statistics of the main variables for the working sample which is determined by the availability of data in region-level morbidity rates. Specifically, from Table 3 it is evident that the participants of USIF micro-projects were, on average, less populated regions with higher unemployment and lower wages, less air pollution, with more FAPs and less hospitals available. All these characteristics indicate that the selected project participants more likely to be located in the rural areas. The mean morbidity rates of the treated group are lower than the population average. Finally, the described above patterns of the evolution of all the variables is preserved in the working sample.

Table 3. Descriptive statistics for the working sample

Variable	Full Sample	Participants	Non-Participants
Territory, sq. km	993.85 (635.13)	1356.5 (757.34)	949.17 (605.13)
Population 2000, thd. persons	91.15 (200.67)	45.31 (26.51)	96.79 (211.83)
Population 2010, thd. persons	85.09 (204.46)	40.43 (26.01)	90.59 (215.90)
Average wage 2000, UAH	187.97 (80.01)	199.40 (52.29)	193.20 (81.91)
Average wage 2010, UAH	1910.40 (510.69)	1776.05 (527.05)	1926.95 (507.15)
Unemployment rate 2000, %	5.76 (3.27)	5.71 (3.76)	5.77 (3.21)
Unemployment rate 2010, %	3.07 (2.05)	3.36 (1.85)	3.04 (2.07)
Air pollution 2000, thd. tons	14.22 (43.64)	1.78 (1.14)	15.76 (46.03)
Air pollution 2010, thd. tons	15.68 (44.69)	4.06 (4.86)	17.11 (47.14)
FAPs 2001	20.79 (16.29)	27.24 (17.53)	19.99 (15.98)
FAPs density 2001	48.62 (40.05)	68.24 (39.18)	46.21 (39.55)
Hospitals 2001	4.96 (7.08)	3.79 (1.89)	5.10 (7.46)
Hospital density 2001	7.78 (4.65)	9.82 (5.09)	7.53 (4.54)
Funding obtained through participation in USIF communal service projects, thd. UAH	372.03 (1260.78)	3392.07 (2080.72)	0
Morbidity rate 2000	55813.58 (16229.72)	50230.98 (15176.69)	56501.29 (16248.16)
Morbidity rate 2010	57397.97 (17385.03)	51712.36 (20301.92)	58098.37 (16901.42)
N	310	34	276

Note: Standard errors in brackets.

Chapter 6

RESULTS

For proper identification of treatment and control groups the propensity score matching procedure was applied. Also, unemployment rate and unemployment rate squared, log of wage, population density, population density squared, hospitals and FAPs density, hospitals and FAPs density squared in 2001, as well as dummies for different parts of Ukraine (North, West, South, East and Center) were used as controls while region population served as basis for weighting observations. The results of propensity score matching estimation using nearest neighbor matching procedure are presented in Table 4.

From Table 4 it is clear that chosen control variables are statistically significant and have expected signs. Specifically, higher unemployment rate, lower average wage, smaller number of health care institutions and lower population density increases the probability of being chosen for participation in USIF Project. Moreover, from the propensity score estimation it is clear that, comparing to the districts in Northern part of Ukraine, the Western regions had higher probability to implement communal services micro-projects through USIF. It is also worth noting that, obviously, the average wage in corresponding districts was a major determinant for project participation which is consistent with the USIF selection criteria for participating districts. Furthermore, using either logit or probit method yields similar outcomes with balancing property (zero difference in the means of variable for treated and control groups) satisfied for all the variables.

Table 4. Propensity Score Matching Estimation

	Probit regression	*Logit regression*
Unemployment rate	0.0061***	0.0383***
	(0.0004)	(0.0007)
Unemployment rate squared	0.0019***	0.0019***
	(0.0000)	(0.0001)
Log of average wage	-0.6415***	-1.1120***
	(0.0016)	(0.0029)
Hospitals density	-0.0625***	-0.1059***
	(0.0002)	(0.0004)
Hospitals density squared	0.0011***	0.0020***
	(0.0176)	(0.0000)
FAPs density	-0.0150***	-0.0290***
	(0.0000)	(0.0001)
FAPs density squared	0.0000***	0.0001***
	(0.0018)	(0.0033)
Hospitals density * FAPS density	0.0006***	0.0009***
	(0.0047)	(0.0081)
Population density	-0.0012***	0.0002***
	(0.0000)	(0.0001)
Population density squared	-0.0000***	-0.0000***
	(0.0013)	(0.0024)
West	0.1442***	0.2727***
	(0.0012)	(0.0021)
Center	-0.0483***	-0.0435***
	(0.0011)	(0.0020)
South	-0.1640***	-0.2467***
	(0.0012)	(0.0022)
East	-0.4906***	-0.9589***
	(0.0014)	(0.0029)
Constant	3.1536***	5.3875***
	(0.0091)	(0.0164)
Prob > chi2	0.0000	0.0000
Pseudo R^2	0.2151	0.2145

**** $p < 0.0001$*

Note: Dependent variable is a probability to be a project participant with $Y_i=1$ if a district participates in USIF Project and $Y_i=0$ if it does not.

Finally, resulting region of common support is [0.047, 0.359] and most of the districts (462) fall in this region. The distribution of the propensity scores is given in Figure 3, where participants in USIF communal service projects are 1 and non-participants are 0.

Thus, propensity score estimation confirms that there existed a clear selection procedure for participation in USIF Project micro-financing.

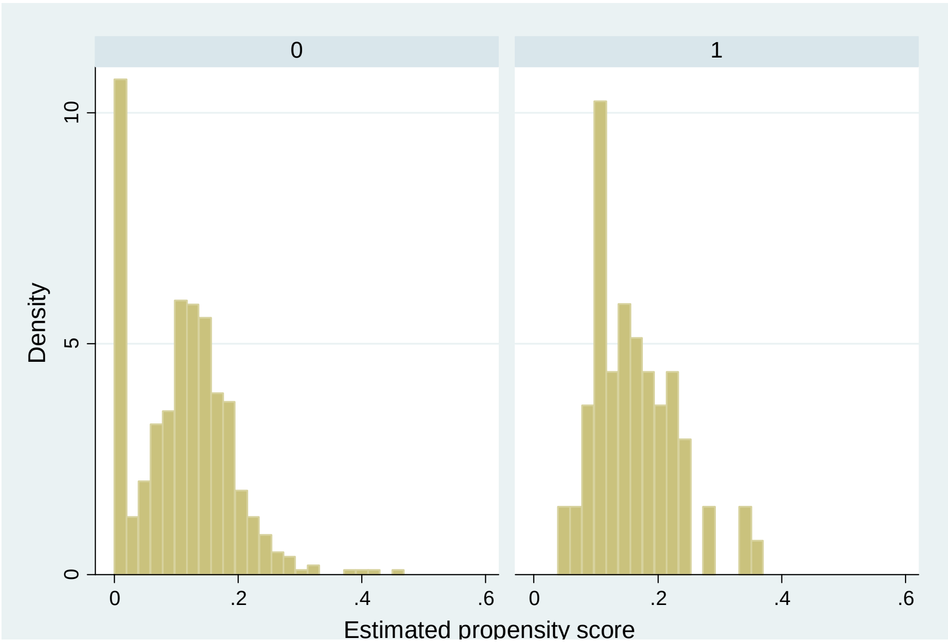

Figure 3. Distribution of Estimated Propensity Scores

After estimating the probability to be a participant of USIF Project based on a number of covariates and identification of treatment and control groups using the propensity score matching procedure, the difference-in-difference estimation for

USIF impact evaluation is applied. Table 5 shows the impact of USIF communal services projects on morbidity rate in participating districts for two samples: unrestricted and restricted to districts in common support region from propensity score estimation. The treatment variable equals to 1 if given districted participated in USIF Project communal services micro-financing in a given year. Since different regions became project participants in different year, this treatment variable is actually and interaction with specific year dummy and is an average treatment effect across districts. Also, to evaluate the impact of the USIF on district level morbidity rate several specifications were used: (1) equation without control variables; (2) equation with control variables; and (3) equation with control and lagged treatment variables.

As can be seen from Table 5, for all the specifications being a participant of USIF Project decreases the morbidity rate. Moreover, the magnitude of this fall in morbidity rate varies substantially for the two samples. The sample, restricted to common support region, reveals smaller impact on morbidity rate than unrestricted sample, which can be explained by the presence of bias in the latter one. However, this immediate effect is not statistically different from zero for almost all the specifications. This may result from the fact that the USIF communal services micro-projects were mostly concerned about the infrastructure, and so their impact on health might not be noticed in the short run. To look at the longer time horizon, the lagged values of the treatment dummy were included in the estimation. The final number of lags included is 4 because the last participants joined the project in 2006 and so the impact on morbidity can be evaluated only up to 4-year span.

Table 5. Impact of USIF Project on Morbidity Rate using Difference-in-Difference Estimation

	Unrestricted Sample		Restricted Sample		
	(1)	(2)	(1)	(2)	(3)
Treatment	-4533.96*	-2001.03	-63.40	-474.71	-711.81
	(2716.97)	(2624.20)	(2723.72)	(2435.41)	(2436.83)
1^{st} lag of Treatment	-	-	-	-	-2161.19
					(2258.90)
2^{nd} lag of Treatment	-	-	-	-	-4203.54*
					(2528.3)
3^{rd} lag of Treatment	-	-	-	-	-4791.67*
					(2580.92)
4^{th} lag of Treatment	-	-	-	-	-5190.57**
					(2442.63)
Controls	-	Yes	-	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	55813.58***	3482.75	51170.19***	-5490.52	-5976.91
	(921.92)	(9003.75)	(978.35)	(14719.08)	(14682.67)
R2	0.0045	0.0838	0.0049	0.1447	0.1490
Obs	3410	3410	2332	2332	2332

Note: Robust standard errors in brackets
** p<0.1, ** p<0.05, *** p<0.01*

From the last column in Table 5 it is clear that the participation in USIF Project decreases district-level morbidity rate and this impact is more significant with time. While instantaneous effect is such that it decreases morbidity rate but is not statistically significant, the impact in 2 years after the start of project implementation is much greater and statistically significant. In 4 years after the micro-projects inception morbidity rate on average falls by about 5191 new cases per every 10 thousand people which, if compared to the mean in 2010, constitutes approximately 10% decline (for more details see Appendix A).

To check the robustness of the latter results fixed effect estimation was applied for the sample restricted to common support region. Table 6 presents the results of this estimation. Again, participation in USIF Project reduces, on average, the district- level morbidity rate and this effect becomes statistically significant in 2 year after the project inception and also increases in magnitude with time (for more details on FE estimation see Appendix A).

Table 6. Impact of USIF Project on Morbidity Rate using Fixed Effect Estimation

Treatment	-38.10
	(1406.50)
1st lag of Treatment	-1248.08
	(1409.22)
2nd lag of Treatment	-3055.25**
	(1408.78)
3rd lag of Treatment	-3602.51***
	(1412.96)
4th lag of Treatment	-4248.25***
	(1410.18)
Controls	Yes
Year dummies	Yes
Constant	37736.13***
	(9583.68)
R2:	
• within	0.0557
• between	0.0074
• overall	0.0074
Obs	3410

Note: Robust standard errors in brackets
$*p<0.1$, $**p<0.05$, $***p<0.01$

Another way to check the robustness of obtained results is to look at the impact of USIF micro-projects within the participant group and to estimate ATT effect after propensity score procedure. But since ATT estimation does not include control factors that influence morbidity rates, it cannot precisely estimate the impact of USIF intervention and produces statistically insignificant results though indicating that the participation in USIF micro-projects indeed decreases morbidity rate (for more details on ATT estimation see Appendix A)

Finally, the analysis of heterogeneity of the USIF Project on morbidity rate was performed. Specifically, it was focused on determining: (a) impact of available financial resources; (b) possible difference in program outcomes for urban and rural areas; (c) possible difference in program outcomes for regions with higher average income; (d) possible difference in program outcomes for regions with better medical infrastructure. To estimate such differences in health outcomes, the above-mentioned factors were included in the estimation as an interaction with the treatment variable. Furthermore, to see possible long-run impact of the USIF Project lagged values of the interaction terms were also included in regressions. The results of the analysis are presented in Table 7 (for more details see Appendix B).

From Table 7 it is seen that the impact of USIF Project was indeed heterogeneous. The greatest effect was in the urban areas, i.e. cities. Moreover, the more financing district obtained through participation in USIF micro-projects the larger was the impact on morbidity rate. This effect indicates that the amount of financial resources available to project participants did matter, especially in the longer time perspective. Also, districts with higher average wage had better health outcomes through participation in USIF communal services micro-projects and this relation was also not contemporaneous. Lastly, availability of denser health infrastructure did not seem to have an effect on better outcomes for district morbidity rate as a result of project participation.

Table 7. Heterogeneity of Impact of USIF Project on Morbidity Rate

	Heterogeneity Factors			
	Project Funds *Treatment	Urban Areas *Treatment	Wage *Treatment	Hospital Density *Treatment
Immediate Impact	-113.74	-3228.78	-1321.74	0.29
	(312.35)	(6557.79)	(5662.85)	(0.46)
1^{st} lag	-312.72	-5259.08***	-353.61	-0.02
	(285.66)	(1079.26)	(358.29)	(0.34)
2^{nd} lag	-553.84*	-11156.14***	-690.46*	-0.19
	(326.25)	(2848.78)	(401.93)	(0.40)
3^{rd} lag	-620.51*	-8458.77***	-771.54*	-0.23
	(335.15)	(2003.63)	(411.97)	(0.43)
4^{th} lag	-668.22**	-9237.01***	-837.10**	-0.18
	(310.76)	(1296.72)	(392.54)	(0.40)
Controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-5739.55	-4646.96	-6241.21	-5453.04
	(14674.79)	(14738.68)	(14684)	(14718.73)
R2	0.1492	0.1464	0.1490	0.1451
Obs	2332	2332	2332	2332

Note: Dependent variable – morbidity rate.
Robust standard errors in brackets
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Chapter 7

CONCLUSION

The study presents impact evaluation of SIF Project in Ukraine. Due to data availability, the analysis is focused on health outcomes, morbidity rates in particular. Using panel data for Ukrainian districts from 2000 to 2010 with control variables, as inputs, and treatment variable, as a measure of project impact, the effect on morbidity rate is determined. Control variables are chosen based on theoretical background about the factors, which determine health production function, and include economic factors (wage and unemployment rate), ecological factors (air pollution) and medical (health care institutions density) factors.

The results are similar for both difference-in-difference and fixed effect estimations and indicate that district-level morbidity rate decreased as a results of participation in USIF micro-financing. Moreover, the project impact was not contemporaneous but rather increasing in magnitude and significance with time, especially in medium and long run perspective – after 2 years from the start of project implementation. In 4 years after the inception of project implementation morbidity rate is estimated to decline in targeted districts by approximately 10% comparing to 2010 average.

The analysis of the heterogeneity of project impact reveals important details about the estimated impact on morbidity rate. Specifically, impact on morbidity rate is larger in districts which acquired more USIF funding, represent urban areas (cities) and have higher average wage.

To summarize, the results suggest that when community shares a part of financial responsibility in a project, it addresses its particular need efficiently. Since positive impact of the project on health outcomes of poor communities is proved[7], the USIF experience can be referred to as a ground for improvement of social services in Ukraine and supporting of further community-based micro-financing by both Ukrainian government and international institutions.

[7] It is worth noting that similar analysis was also performed on district-level infant mortality rates. The estimation showed that participation in USIF Project decreased district-level infant mortality but this effect is not statistically significant.

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APPENDIX A: OLS, FE, ATT estimation of the impact of USIF Project on morbidity rate

Table A1. OLS estimates. Dependent variable: morbidity rate.

	Unrestricted Sample		Restricted Sample		
	(1)	(2)	(1)	(2)	(3)
Treatment	-4533.96* (2716.97)	-2001.03 (2624.20)	-63.40 (2723.72)	-474.71 (2435.41)	-711.81 (2436.83)
1st lag of Treatment	-	-	-	-	-2161.19 (2258.90)
2nd lag of Treatment	-	-	-	-	-4203.54* (2528.3)
3rd lag of Treatment	-	-	-	-	-4791.67* (2580.92)
4th lag of Treatment	-	-	-	-	-5190.57** (2442.63)
Unemployment	-	-1122.03*** (311.79)	-	-987.39*** (372.54)	-1026.47*** (373.41)
Unemployment sq.	-	63.49*** (21.31)	-	43.80* (25.03)	45.43* (25.08)
Log(wage)	-	12369.93*** (1426.05)	-	5379.91*** (1744.09)	5474.03*** (1760.39)
Hospital density demeaned	-	-0.1259* (0.07)	-	-6.92*** (1.82)	-6.82*** (1.78)
FAPs density	-	0.01 (0.01)	-	0.06*** (0.01)	0.06*** (0.01)
Urban areas dummy	-	-9778.44*** (3387.85)	-	-44087.21*** (6519.83)	-44355.52*** (6511.60)
Pollution density demeaned	-	45174.99** (21163.87)	-	-659012.7*** (220118.1)	-656850.1*** (220041.2)
Pollution density demeaned sq.	-	-441.06*** (93.21)	-	-2799201*** (897549.7)	-2781855*** (896759.2)
Pollution density*Hospital density demeaned	-	0.11 (0.18)	-	-40.97*** (10.97)	-40.41*** (10.74)
Pollution density demeaned * Urban areas dummy	-	-41049.8* (21132.7)	-	-176944.7*** (40347.4)	-178289.5*** (40285.81)
Year dummy	Yes	Yes	Yes	Yes	Yes
Constant	55813.58*** (921.92)	3482.75 (9003.75)	51170.2*** (978.35)	-5490.52 (14719.08)	-5976.91 (14682.67)
R2	0.0045	0.0838	0.0049	0.1447	0.1490
Obs	3410	3410	2332	2332	2332

Note: Robust standard errors in brackets
** p<0.1, ** p<0.05, *** p<0.01*

Table A2. FE estimates. Dependent variable: morbidity rate.

Treatment	-38.10 (1406.50)
1st lag of Treatment	-1248.08 (1409.22)
2nd lag of Treatment	-3055.25** (1408.78)
3rd lag of Treatment	-3602.51*** (1412.96)
4th lag of Treatment	-4248.25*** (1410.18)
Unemployment	-280.08 (240.94)
Unemployment sq.	-10.97 (15.10)
Log(wage)	-1393.39 (1301.82)
Hospital density demeaned	-2.53*** (0.47)
FAPs density	0.64*** (0.07)
Pollution density demeaned	40425.47 (54931.21)
Pollution density demeaned sq.	57.88 (103.64)
Pollution density*Hospital density demeaned	-0.24 (0.38)
Pollution density demeaned * Urban areas dummy	-42528.59 (54991.36)
Year dummy	Yes
Constant	37736.13*** (9583.68)
R2:	
• within	0.0557
• between	0.0074
• overall	0.0074
F(24, 3076)	7.56
Prob > F	0.0000
Obs	3410

Note: Robust standard errors in brackets

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

F test that all u_i=0: F(309, 3076)=37.02 Prob > F = 0.000

Table A3. ATT estimates. Dependent variable: morbidity rate.

	N treated	N controls	ATT	Std. Dev.	t-stat
Nearest Neighbor Matching method					
2007	34	33	-3236.31	4083.15	-0.793
2008	34	33	-5436.87	4212.59	-1.291
2009	34	33	-3128.97	4391.82	-0.712
2010	34	33	-3252.89	4469.30	-0.728
Kernel Matching method					
2007	34	178	-2011.22	2857.60	-0.704
2008	34	178	-2555.15	2845.49	-0.898
2009	34	178	-1349.93	3670.33	-0.368
2010	34	178	-1763.74	3380.62	-0.522
Radius Matching method					
2007	34	178	-1806.20	3119.85	-0.579
2008	34	178	-2234.53	3347.79	-0.667
2009	34	178	-1041.04	3589.49	-0.290
2010	34	178	-1507.01	3698.91	-0.407

APPENDIX B: Estimation of heterogeneity of impact of USIF Project on morbidity rate

Table B1. OLS estimates. Dependent variable: morbidity rate.

Treatment * Project Funding	-113.74
	(312.35)
1st lag of Treatment * Project Funding	-312.72
	(285.66)
2nd lag of Treatment * Project Funding	-553.84*
	(326.25)
3rd lag of Treatment * Project Funding	-620.51*
	(335.15)
4th lag of Treatment * Project Funding	-668.22**
	(310.76)
Unemployment	-1029.75***
	(373.05)
Unemployment sq.	45.54*
	(25.06)
Log(wage)	5405.78***
	(1754.98)
Hospital density demeaned	-6.82***
	(1.78)
FAPs density	0.06***
	(0.01)
Urban areas dummy	-44445.04***
	(6515.00)
Pollution density demeaned	-659807.6***
	(220010.6)
Pollution density demeaned sq.	-2795782***
	(896417.4)
Pollution density*Hospital density demeaned	-41.00***
	(10.73)
Pollution density demeaned * Urban areas dummy	-179008.6***
	(40303.42)
Year dummy	Yes
Constant	-5739.55
	(14674.79)
R2	0.1492
Obs	2332

Note: Robust standard errors in brackets
** p<0.1, ** p<0.05, *** p<0.01*

Table B2. OLS estimates. Dependent variable: morbidity rate.

Treatment * Wage	*-1321.74*
	(5662.85)
1st lag of Treatment * Wage	-353.61
	(358.29)
2nd lag of Treatment * Wage	-690.46*
	(401.93)
3rd lag of Treatment * Wage	-771.54*
	(411.97)
4th lag of Treatment * Wage	-837.10**
	(392.54)
Unemployment	-1015.35***
	(373.52)
Unemployment sq.	44.86*
	(25.09)
Log(wage)	5496.54***
	(1760.94)
Hospital density demeaned	-6.79***
	(1.78)
FAPs density	0.06***
	(0.01)
Urban areas dummy	-44345.96***
	(6513.69)
Pollution density demeaned	-659861.6***
	(220103.5)
Pollution density demeaned sq.	-2795952***
	(897271.2)
Pollution density*Hospital density demeaned	-40.24***
	(10.74)
Pollution density demeaned * Urban areas dummy	-178185.8***
	(40296.15)
Year dummy	Yes
Constant	-6241.21
	(14684)
R2	0.1490
Obs	2332

Note: Robust standard errors in brackets

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

Table B3. OLS estimates. Dependent variable: morbidity rate.

Treatment * Urban area dummy	-3228.78
	(6557.79)
1st lag of Treatment * Urban area dummy	-5259.08***
	(1079.26)
2nd lag of Treatment * Urban area dummy	-11156.14***
	(2848.78)
3rd lag of Treatment * Urban area dummy	-8458.77***
	(2003.63)
4th lag of Treatment * Urban area dummy	-9237.01***
	(1296.72)
Unemployment	-1039.13***
	(373.67)
Unemployment sq.	46.87*
	(25.11)
Log(wage)	5271.49***
	(1746.38)
Hospital density demeaned	-6.92***
	(1.82)
FAPs density	0.06***
	(0.01)
Urban areas dummy	-44734.65***
	(6537.06)
Pollution density demeaned	-655274***
	(220133.1)
Pollution density demeaned sq.	-2783137***
	(897353.3)
Pollution density*Hospital density demeaned	-40.95***
	(10.97)
Pollution density demeaned * Urban areas dummy	-183271.1***
	(40567.15)
Year dummy	Yes
Constant	-4646.96
	(14738.68)
R2	0.1464
Obs	2332

Note: Robust standard errors in brackets

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

Table B4. OLS estimates. Dependent variable: morbidity rate.

Treatment * Hospital Density	*0.29*
	(0.46)
1st lag of Treatment * Hospital Density	-0.02
	(0.34)
2nd lag of Treatment * Hospital Density	-0.19
	(0.40)
3rd lag of Treatment * Hospital Density	-0.23
	(0.43)
4th lag of Treatment * Hospital Density	-0.18
	(0.40)
Unemployment	-986.20***
	(373.14)
Unemployment sq.	43.69*
	(25.07)
Log(wage)	5379.98***
	(1744.03)
Hospital density demeaned	-6.88***
	(1.80)
FAPs density	0.06***
	(0.01)
Urban areas dummy	-44092.9***
	(6525.44)
Pollution density demeaned	-658993.4***
	(220049.4)
Pollution density demeaned sq.	-2800439***
	(896213.9)
Pollution density*Hospital density demeaned	-40.80***
	(10.85)
Pollution density demeaned * Urban areas dummy	-176951.4***
	(40390.79)
Year dummy	Yes
Constant	-5453.04
	(14718.73)
R2	0.1451
Obs	2332

Note: Robust standard errors in brackets
** p<0.1, ** p<0.05, *** p<0.01*