Pesticide Use and Health Outcomes:

Evidence from Agricultural Water Pollution in China

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Abstract:

This paper provides the first quasi-experimental evidence that pesticides adversely affect health outcomes through drinking water by linking provincial pesticide usage reports from several Chinese statistical yearbooks (1998-2011) with the Chinese Longitudinal Healthy Longevity Survey (1998-2011). First, we follow a difference-in-difference-in-differences (DDD) framework to compare health outcomes between people who drink surface water and ground water in regions with high and low intensity of rice pesticide use before and after 2004, when China shifted from taxing agriculture to subsidizing agricultural programs. Second, we measure the downstream effect of pesticide use from upstream provinces. Our results indicate that a 10% increase in rice pesticide use unfavorably alters the index of dependence (ADL) by 2.51% and 0.33% for local and downstream residents (65 and older), respectively. This is equivalent to 168.8 and 55.89 million dollars in medical costs and offspring's human capital losses, respectively (in total, 1.92% of rice production profits). Our results are robust to a variety of robustness checks and falsification tests.

Agricultural non-point source pollution has been a growing concern in developing countries due to the extensive use of synthetic organic chemicals. China, in particular, has experienced the fastest increase in pesticide usage rates and now applies between 1.5 to 4 times more pesticides than the world average (Li et al. 2014 and Zhang et al. 2015). This level of pesticide use is a major source of pollutants found in the air, waters, soil and farm products and these chemicals have been shown to cause both acute and chronic illnesses (Huang et al. 2005; Hu et al. 2015; Qiao et al. 2012). Concerns about human health sequelae of pesticides likely contributed to China's prioritization of environmental protection in recent policy statements as well as the start of supply-side reform in the farm sector (No.1 Central Document 2016; Reuters 2016).

The objective of this paper is to quantify the impact of pesticide use on the health outcomes attributable to agricultural water pollution. Extant research documents strong evidence of the connection between contaminated surface water and various types of diseases (Ebenstein 2012; Wang et al. 2008; Wu et al. 1999). These studies mainly address water pollution from industrial activities. However, according to the China Pollution Source Census (2010), agriculture is now a bigger non-point source of water contamination in China than factory effluent. Systematic analysis of this agricultural water pollution and its possible health consequences is lacking. To investigate this question, we link provincial data from several Chinese statistical yearbooks (1998-2011) with the Chinese Longitudinal Healthy Longevity Survey (1998-2011). One advantage of using Chinese data for this investigation is that population mobility was extremely low due to government regulations and, therefore, the survey respondents' residence at the time of observation in the data allow for

identification of their long-term water pollution exposure (Chen et al. 2013; Ebenstein 2012).

First, we follow a difference-in-difference-in-differences (DDD) framework to compare health outcomes between people who drink surface water versus ground water (ground water suffers much less from pesticide contamination) in regions with high versus low intensity of rice pesticide use before and after 2004, when China shifted from taxing agricultural outputs to subsidizing agriculture. Individual fixed effects are also implemented to account for potential confounding factors. The parallel trend assumption is indirectly tested via graphical analysis to establish whether high and low pesticide application regions differ in health outcomes before 2004. We also gauge the stability of the regression results by adding or deleting a comprehensive set of time-varying individual, household and regional characteristics.

We find several statistically significant and economically relevant linkages between pesticide use and human health. For example, a 10% (3.2 yuan/mu) increase in rice pesticide use unfavorably alters the index of dependence in Activities of Daily Living (Katz et al. 1963) by 2.51% (0.17 units) for residents 65 years or older. This is consistent with the extant epidemiological and economic literature that pesticide exposure adversely affects the peripheral nervous system (Ding and Bao 2014; Li et al 2014; Hu et al. 2015; Starks et al. 2012) and, therefore, can decrease the independence of older adults via degradation of this key system. Further, there is evidence that Fipronil and Imidacloprid, which both feature insect neurotoxins, are the two most widely detected pesticides in surface water during rice production (China Pollution Source Census, 2010). In addition, our significant results are mainly driven by populations in rural areas where millions of residents rely on surface water

for their drinking water supply. This suggests an unintentional policy side effect: the pesticides, promoted to increase farmers' income and welfare via enhanced agricultural productivity, are also degrading the physical independence of older adults exposed to the surface water that captures pesticide residues.

We conduct several robustness checks to help assess the validity of our results. For example, a potential concern is that, because regions with more pesticide water pollution may also have more pesticide pollution in air, soil and food, our results may be driven by pesticide pollution via these other pathways. We rule out this possibility by running analogous DDD regressions with respect to corn and wheat, which do not feature flooding as a cultural practice and, thus, should feature less water pollution. Our estimation would also be potentially problematic if people in regions with more pesticide use are more likely to change drinking water sources after 2004. We address this concern by testing whether the rates of relying upon surface water for drinking sources differ before and after 2004 in regions with more and less pesticide use. Our results are robust to a variety of robustness checks and falsification tests.

Second, we measure the downstream effect of pesticide use from upstream provinces. We follow a difference-in-difference (DD) approach to compare health outcomes between people in regions with high and low rice pesticide use in upstream provinces before and after 2004. We find that a 10% (52 million yuan) increase in upstream rice pesticide use increase ADL score of downstream aging populations by 0.33% (0.023 units). Parallel trends tests and robustness checks are conducted to help validate our results. As another robust check, we run analogous DD regressions using downstream pesticide use to predict the health

conditions in upstream provinces. We do not find this effect is significant, suggesting our results are not driven by some unobserved factors arising from geographical proximity. In addition, we also provide some suggestive evidence that land-based pollutants constitute a threat to coastal and marine ecosystems as well as to the health of coastal inhabitants (Fu et al. 2003; Guo et al. 2008; Xian et al. 2008).

Finally, we calculate the medical and human capital losses due to agricultural pesticides by exploiting the relationship between health outcomes and medical costs and offspring's weekly caring hours. Our results indicate that each additional unit increase in ADL increases medical costs and offspring's weekly caring hours by 139 yuan (20.9 dollars) and 6.55 hours, which is equivalent to approximately 46 yuan (6.9 dollars). In combination with previous information, we are able to calculate that a 10% increase in rice pesticide use increases medical costs and human capital losses of local populations by 764.48 and 252.99 million yuan, respectively (or 114.67 and 37.95 million dollars). Further, a 10% increase in upstream rice pesticide use increases downstream medical costs and human capital losses by 360.88 and 119.6 million yuan, respectively (or 54.13 and 17.94 million dollars). In sum, a 10% increase in rice pesticide use increases monetary losses by 1.5 billion yuan (224.69 million dollars), which is equivalent to 1.92% of national annual rice production profits.

Our work makes several contributions. This paper is broadly related to a body of research in economics on water pollution and health outcomes (Ebenstein 2012; Wang et al. 2008; Wu et al. 1999). It adds to the existing literature by providing the first quasi-experimental evidence of the impact of water pollution attributable to agricultural non-point pollution in China. It also speaks to the literature that identifies transboundary

water pollution spillover (Cai, Chen and Gong 2015; Helland and Whitford 2003; Kahn, Li and Zhao 2015). Although the results presented here narrowly focus on the water channel by which agricultural chemicals has led to deterioration in health outcomes in China, this issue has salience in other developing countries that face similar challenges.

Another distinguishing facet is its emphasis on non-occupational pesticide exposure. This is necessary because only a small proportion of the population is likely to receive a pesticide dose via direct exposure that is high enough to cause acute symptoms; but many more may be at risk of developing chronic effects because of exposure to contaminated water, air and soil, and due to ingestion of residues from farm products. Previous economic literature, which estimates the effect of direct exposure or only deals with "seriously poisoned" samples (Hu et al. 2015; Macharia, Mithöfer and Waibel 2013; Qiao et al. 2012), may underestimate the broader deleterious effects of pesticide use. Besides, our findings point to the aging populations, which is one of the most vulnerable groups, and the adverse impact from pesticide exposure will likely to increase as the share of China's population that is 65 or older grows.

A third feature that distinguishes this work from existing research is its reliance on more comprehensive data. Existing work employs much more restricted data sets with respect to health outcome information, length of time, sampling area and sample size (Huang et al. 2000; Qiao et al. 2012) and therefore our work provides a broader scope and greater statistical power compared to previous work. In comparison with the extant research, we are able to examine a wide range of diverse health outcomes and the span of the data allows us to consider illnesses that may take years to manifest. In terms of economic cost, besides

medical costs, we are also able to estimate human capital losses suffered by the caretakers of those affected, which are not addressed in previous literature. Our findings can be useful designing policies aimed at sustainable development.

A fourth distinguishing aspect of this work is the identification strategies. A central methodological concern is that the independent variable of interest, pesticide use, is not randomly assigned. Most existing studies use cross-sectional data sets (Huang et al. 2000; Qiao et al. 2012), which are subject to potential bias in ways that are not obvious a priori. By contrast, our identification strategy first employs individual fixed effects, so that estimates of the impact of pesticide use can be purged of the influence of unobserved time-invariant characteristics. More importantly, our identification strategies take advantage of a DDD model, which supports the view that the association between pesticide use and health outcomes is a causal relationship rather than simply a correlation

The remainder of this paper is organized as follows. The next two sections describe institutional background and the data. The next section examines the impact of pesticide use on local populations. This is followed by a section exploring downstream effect of pesticide use. Both sections include model specification, regression results and robustness checks. The final section concludes.

Institutional Background

Pesticide Use in China

Food security and self-reliance remain top priorities in China. In order to feed 19% of the world's population with 7% of the world's arable land, China promotes many measures to boost crop yields, including the extensive use of pesticides. The use of pesticides in China

has increased sharply, from 0.76 million tons in 1991 to 1.8 million tons in 2011, amounting to an average annual growth rate of 4.9%. Pesticide use per hectare is roughly 1.5 to 4 times larger than the world average (Li et al. 2014 and Zhang et al. 2015).
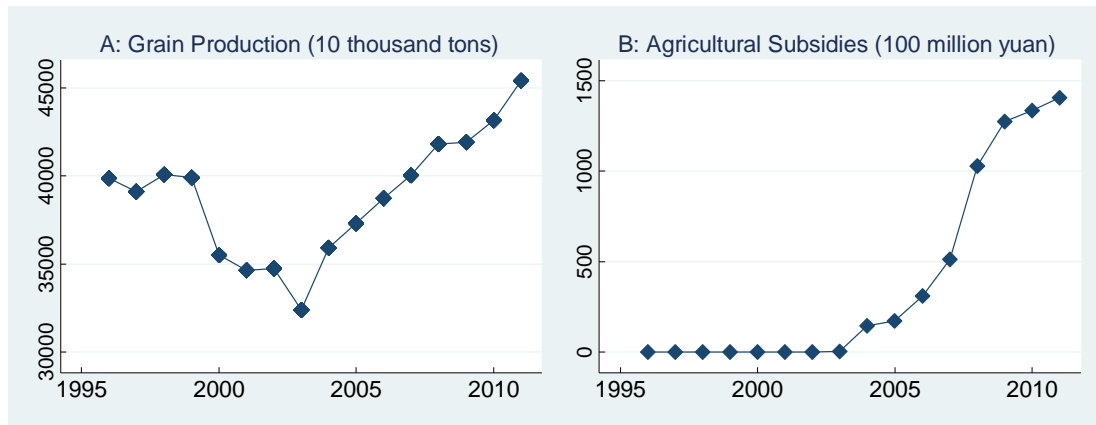

Figure 1. Annual Chinese Grain Production and Agricultural Subsidies

The most recent discrete change in pesticide use comes in 2004 when China shifted from taxing agriculture to subsidizing agricultural programs (See Gale et al. 2013 for detailed discussions of China's agricultural support policies). One main driver of this policy change is concern about maintaining food security and self-reliance. As Figure 1A shows, grain production had been stagnant from 1996 to 1999 and then decreased sharply from 1999 through 2003. Rising off-farm wages increased the opportunity cost of farm labor, weakening incentives to engage in agricultural production. This raised great concern about food security. In 2004, authorities began to eliminate an agricultural tax on farmers and introduced three subsidies targeted at grain producers: a direct payment, a subsidy for improved seed varieties, and a partial rebate for farm machinery purchases. In 2004-06, several other support programs were introduced such as a general-input subsidy, price floors for wheat and rice, reform of the grain marketing system and transfer payments to grain counties. Since then, expenditures on the initial set of programs have grown rapidly (Figure

1B). This set of supporting programs has bolstered farmer' production incentives (Chen, Fan and Gao 2010; Chen, Wu and Wang 2010; Zhou, Zhao and Zhang 2009) and crop production increased continuously since 2004, which has been accompanied with greater pesticide use. As Figure 2 shows, annul pesticide use rates for the three main crops (rice, wheat and corn) increased sharply after 2004.
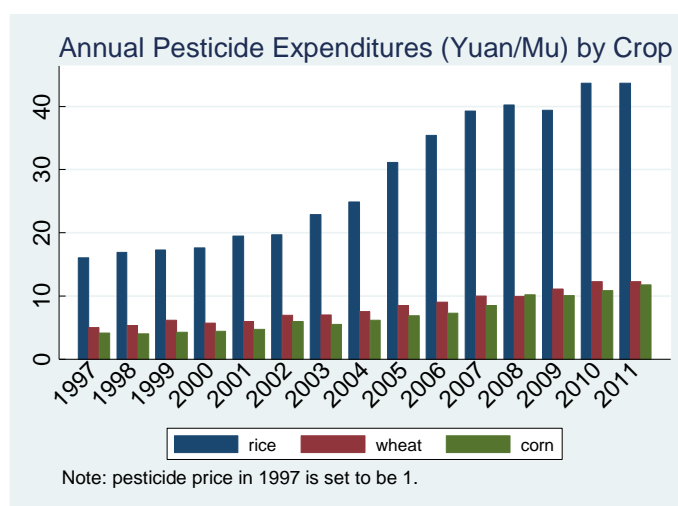
Figure 2. Annual Pesticide Expenditures (Yuan/Mu) by Crop

As for the types of pesticide, organochlorine (OC) pesticides such as DDT were widely used for agricultural pest control between the 1950s and 1980s. This extensive use of OCs caused more than 45,000 poisoning cases each year during the 1980s and 1990s and the number was believed to be higher before the 1980s although statistical records are lacking (Qiao et al. 2012). In the early 1980s, the Chinese Government banned the use of OCs and some organophosphates (OPs) in crop production because of their persistence in the environment and their toxic properties for humans and wildlife. Consequently, organophosphates (OPs) and pyrethroids (PYRs) have become attractive alternatives because of their relatively lower toxicity and persistence in the environment. However, in recent years, scientists have found that even pesticides categorized as less and least toxic can cause

critical chronic diseases that are not easy to diagnose and that some of these pesticides are even fatal to humans with persistent exposure (Pingali et al., 1997; Qiao et al. 2012; Wang et al. 2012). The detection of OPs in Arctic ice contradicts initial claims that OPs are readily degraded by the environment (Macdonald et al. 2000; Zhang et al. 2002).

Rural Drinking Water

The safety of drinking water in rural areas also has received policy attention in China. In the 1980s, the Chinese government started the rural drinking water treatment program, and spent significant resources to improve the quality of drinking water in rural China. However, the rural drinking water program is far from being complete. Even in 2010 there were still 298 million rural Chinese without safe drinking water service (Yu et al. 2015).

For many decades, river pollution was mainly due to industrial activities. However, according to the China Pollution Source Census (2010), agriculture is now a bigger source of water contamination in China than factory effluent. In terms of pesticide pollution, numerous studies document that various types of pesticide, including OCs, OPs and PYRs, are detected in rivers, lakes, estuaries and coastal oceans (Guo et al. 2008; Xian et al. 2008; Zhang, Jiang and Qu 2011). Pesticide runoff to ground water is less frequently documented and the severity differs greatly depending on environmental factors such as soil type, rainfall amount and the level of ground water (Sun, Wang and Jin 2009).

The China Pollution Source Census (2010) conducted pesticide runoff experiments for both surface and ground water in 372 sites across China for a one year cycle from 2007 to 2008. For the treatment groups, they follow the local farmers' practices of pesticide use. That is, they use the same types and amounts of pesticides with identical spraying methods and

timing. For the control groups, they only use pesticides categorized as low toxicity and high degradability. They calculated the runoff coefficients as the differences of runoff percentage between treatment and control groups. Many types of pesticides, including Fipronil, Imidacloprid, Dichlorvos and Butachlor, are detected in both surface and ground water. The runoff coefficients are much higher in the surface water than in ground water. For example, the average Fipronil runoff coefficient in the surface water was 0.15 while none was detected in ground water. The Fipronil runoff coefficients are especially high in the southern plains for single and double cropping rice (0.60 and 0.51 respectively).

Data and Summary Statistics

To conduct the analysis, we link provincial data from several Chinese statistical yearbooks (1998-2011) with the Chinese Longitudinal Healthy Longevity Survey (1998-2011). The pesticide expenditures per mu by different crops come from Agricultural Cost and Benefit Yearbook (1998-2011) and other regional variables come from the China Statistical Yearbook (1998-2011) and the China Environmental Statistical Yearbook (1998-2011).

The individual health data come from Chinese Longitudinal Healthy Longevity Survey (CLHLS). CLHLS was collected by the Center for Healthy Aging and Development Studies at Peking University and co-sponsored by the US National Institute on Aging. This survey was conducted in a randomly selected half of the counties and cities in 22 provinces (out of 31 total provinces), covering 85% of the total population in China. The CLHLS has six waves to date (1998, 2000, 2002, 2005, 2008, and 2011). It surveyed only the oldest old (aged 80 years and older) before 2002, but since 2002, the cohort aged 65–79 has also been included in the project. The survey combines an in-home interview and a basic physical

examination. Extensive information was collected on demographic characteristics, family and household characteristics, lifestyles, diet, psychological characteristics, health, disability, socioeconomic conditions, and so on. (See Zeng et al., 2015 for a detailed description of the sampling design and data quality assessment). We only use data after 1998 because the question asking whether drinking water is boiled or not starts in 2000; we include only those who drink boiled water to eliminate possible health linkages to waterborne bacteria.

Health Outcomes

We use multiple indicators for the health status of the elderly that are feasibly linked to pesticide exposure in the extant medical and toxicology literature, including the index of Activities of Daily Living (ADL), cognitive ability, measured hypertension, self-reported overall health condition.

The survey questions about ADL are based on international standards and were adapted to the Chinese culture and social context after carefully conducted pilot study tests (Zeng et al., 2002). Specifically, participants were asked if they needed any assistance with the following six activities: bathing, dressing, eating, toileting, continence and getting out of bed and into a chair, according to Katz's ADL index (Katz et al., 1963). Choices for each item are "able to do without help," "need some help," and "need full help," with scores from 1 to 3, respectively. The final score of ADL is the sum of all 6 items and ranges from 6 to 18, with higher scores indicating more difficulty.

Cognitive impairment is measured by the Mini-Mental State Examination (MMSE), which covers the following aspects of cognitive functioning: orientation, registration, duplication and design, calculation, recall, naming, and language (Folstein et al. 1975). The

MMSE score in this sample ranges from 0 to 30, with higher scores suggesting more impairment. Hypertension is defined as a blood pressure more than 140/90 mm Hg and is diagnosed by physicians. Self-reported health is assessed by a question: "In general, would you say your health is 1) very good, 2) good, 3) so so, 4) bad, or 5) very bad?"

Individual and Household Variables

Individual and household variables include information on socio-economic characteristics, health behaviors and dietary pattern. Socio-economic characteristics include age, gender, years of schooling, number of people living together and income from sons and daughters. Health behaviors measure whether the respondents smoke, drink and exercise now (Yes or No). Dietary patterns measure the frequency with which respondents eat meat, fish, fruit, fresh vegetable and salt-preserved vegetable. Answers for each item are "rarely or never," "occasionally," and "almost every day," with scores from 1 to 3, respectively.

The questionnaire also asks respondents the source of their drinking water. The answers include drinking water sources from a well; a river or lake; a spring; a pond or pool; and tap water. We construct a binary variable *water* which equals one if respondents drink surface water, i.e. water from a river or lake or a pond or pool, and equals zero otherwise.

Provincial Variables

Provincial variables include pesticide use, upstream pesticide use and other control variables. Pesticide use is measured by pesticide expenditure per mu and upstream pesticide use is measured by total pesticide expenditure. Other provincial variables include per capita measures of industrial sulfur dioxide emission (SO_2), industrial chemical oxygen of demand (COD), GDP and the number of hospital. SO_2 and COD per capita control for pollution from

industrial activities. GDP per capita measures general economy and wealth conditions. The number of hospitals per capita controls for the level of medical service. Per capita measures are used because they are relative indicators. All provincial variables are the average of the last three years, which is adopted because the health data points we observe are once every three years.

Attrition is potentially worrisome if it is correlated with the independent variable of interest. Sample selectivity could then lead to biased estimates. As it turns out, however, there is no evidence that attrition is correlated with the variables of interest. We run analogous DDD regressions where the dependent variable is the number of times this individual is sampled or whether this person has been sampled more than once. In no regression (Appendix 8) is the coefficient on the three-way interaction term significantly different from zero, which suggests the respondents lost to attrition are random with respect to our triple difference design.

Table 1. Variable Description and Summary Statistics

Variable	Description	Obs.	Mean	Std. Dev.
Household Variables				
Age	Age in years	35228	86.17	11.22
Education	Years of schooling	35121	2.17	3.51
Male	Male=1; Female=0	35228	0.45	0.50
Live_with	Number of people living together	35228	2.96	1.99
Income_sd	Annual income from son and daughter (Yuan)	28446	1538.39	2307.83
Care_time	Offspring's weekly caring hours	8187	30.29	45.01
Health Behaviors				
Smoke	Currently smoke (Yes=1; No=0)	35228	0.19	0.39
Drink	Currently drink (Yes=1; No=0)	35228	0.20	0.40
Exercise	Currently exercise (Yes=1; No=0)	35228	0.32	0.46
Dietary Pattern				
Staple	Daily staple foods consumed (gram)	35228	2.98	2.55

Variable	Description	Obs.	Mean	Std. Dev.
Meat	The frequency of meat consumption	35228	2.19	0.68
Fish	The frequency of fish consumption	35228	1.88	0.63
Fruit	The frequency of fruit consumption	35228	1.87	0.59
Vegetable	The frequency of vegetable consumption	35228	2.55	0.56
Salt_vege	The frequency of salt-preserved vegetable consumption	35228	1.81	0.77
Water	Drinking water source (Surface water=1; Ground water=0)	35228	0.01	0.12

Provincial Variables

Variable	Description	Obs.	Mean	Std. Dev.
Rpest	Rice pesticide intensity (Yuan/Mu/Year)	35228	31.86	18.84
Cpest	Corn pesticide intensity (Yuan/Mu/Year)	26756	7.59	3.25
Wpest	Wheat pesticide intensity (Yuan/Mu/Year)	18977	10.30	4.81
Tpest	Total pesticide use (Tons/Year)	41871	72679.2	40057.05
Tpest1	Total pesticide intensity (Tons/Mu/Year)	41871	0.00079	0.00037
UpRpest	Upstream rice pesticide expenditure (Million Yuan/Year)	25153	520.46	522.93
UpTpest	Upstream total pesticide use (Million Tons/Year)	32013	0.0532	0.0401
SO_2	Provincial industrial sulfur dioxide emission (10000 Tons/10000 persons/Year)	35228	0.0144	0.0039
COD	Provincial industrial COD discharge (10000 Tons/10000 persons /Year)	35228	0.0052	0.0032
GDP	Provincial Gross Domestic Product (100 million Yuan/10000 persons /Year)	35228	0.6669	0.2476
Hospnum	Number of hospital per province (10000 persons)	35228	2.9893	1.9015

Health Indicators

Variable	Description	Obs.	Mean	Std. Dev.
ADL	Activities of Daily Living score (lower=better)	35228	6.99	2.33
C_ability	Cognitive ability, MMSE score (lower=better)	35223	22.49	8.94
Hyp	Health worker diagnosis of hypertension (Yes=1; No=0)	34534	0.49	0.49
Self_health	Self-reported health condition (lower=better)	32696	2.53	0.93
Medcost	Medical cost (Yuan)	20433	1378.69	2719.93

Notes: (1) The annual income from son and daughter, *income_sd*, was not collected in the first two waves. The annual medical costs, *medcost*, and offspring's weekly caring hours, *care_time*, were not collected in the first three waves. (2) All individual and household level variables are from CLHLS and they represent their situations in the survey year. All provincial variables are from statistics yearbooks and they are the average of the last three years. This average is adopted because the health data points we observe are once every three years. (3) In the dietary panel, the answers for each consumption frequency are "rarely or never," "occasionally," and "almost every day," with scores from 1 to 3, respectively. The answers for types of drinking water source are one for surface water and zero for ground water.

The Effect of Pesticide Use on Local Populations

Model Specification

This section investigates the health impact of pesticide use on local populations. The DDD model is specified as:

$$y_{it} = \alpha + \beta_1 Rpest_{pt} * water_{it} * y04_{it} + \beta_2 Rpest_{pt} * water_{it} + \beta_3 water_{it} * y04_{it} + \beta_4 Rpest_{pt} * y04_{it}$$
$$+ \beta_5 Rpest_{pt} + \beta_6 water_{it} + \beta_7 y04_{it} + \gamma' X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (1)$$

where *i, p* and *t* indicate individual, province and year. y_{it} is measured health outcomes including ADL, cognitive ability, measured hypertension and self-reported overall health condition. *Rpest* measures the intensity of rice pesticide use (yuan/mu).[1] *water* equals one if the survey respondent drinks surface water and zero otherwise. *y04* equals one starting in 2004 and zero otherwise. *X* is a vector of control variables including individual, household and provincial characteristics. *u* is a fixed effect unique to individual *i*, and *λ* is a time effect common to all individuals in year *t*. α is the intercept and ε_i is an error term. We take two approaches in the estimation of the standard errors to avoid potential biases from error correlation across time and space and we report the most conservative ones. First, we allow for an arbitrary covariance structure within provinces over time by computing standard errors clustered at the province level[2] (Bertrand, Duflo and Mullainathan 2004). Second, we compute standard errors clustered at both individual and province-year levels (Cameron, Gelbach and Miller 2011).

The coefficient of interest is β_1, the impact of pesticide use on health outcomes. Without randomization of pesticide use, a major concern is that provinces that use more pesticide

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[1] As a robustness check of different intensity measures of pesticide use, we also use total quantity per mu (tons/mu) as our main variable of interest. The results are reported in appendix 9. We cannot estimate the effect of pesticide quantities per mu by different crops because the quantity data is crop aggregated.

[2] Cluster bootstrap methods are also implemented at the province level to reaffirm our results.

could be different from provinces that use less pesticide and that these differences may be correlated with health outcomes. For example, provinces that are stronger in agriculture and use more pesticide may be poorer. In this case, the correlation between pesticide use and health would be confounded with the wealth effect. For another example, individuals living in regions with more pesticide pollution may themselves begin in different health conditions so that any observed relationship between pesticide use and health outcomes may simply reflect the influence of unobserved initial health conditions. These types of confounding factors vary across provinces and individuals but are fixed over time. A common method of controlling for time-invariant unobserved heterogeneity is to use fixed effects.[3]

A remaining threat is confounding factors that vary over time. For example, richer provinces may have a rapidly increasing GDP or individuals in better health conditions may face more slowly growing health risks. Our solution is to use difference-in-difference-in-differences model where the key identification assumption is that the time trends in the regions with more and less pesticide use are the same in the pre-policy periods. If the time trends are the same in the pre-policy periods, then it is likely that they would have been the same in the post-policy periods if the regions with more pesticide use had used less pesticide.

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[3] Several other concerns can also be addressed by individual fixed effects. For example, the areas where rice pesticide use increased rapidly may be the same places with high historic use of DDT, and what we identify may be a long term lag effect of DDT use rather than the shorter run influence of modern pesticides. This is not the case because the accumulated health effects will be differenced out by individual fixed effects. As evidence, Figure 3 plots the residuals from a regression of ADL on individual fixed effects (detail explanations are on the next page). DDT was widely used in 1970s and banned in 1983. If our significant coefficients are driven by a long term lag effect of DDT, which means this effect is not differenced out by individual fixed effects, this lag effect is likely to manifest before 2005. It is less likely that the lag DDT effect from 1970s suddenly starts to manifest in 2005 as is shown in Figure 3. Further, our differences before and after 2004 in the DDD model can serve as another practice that eliminates this lag DDT effect as well as other accumulated health effects.

Notes: The plots are residuals from regressing ADL on individual fixed effects.
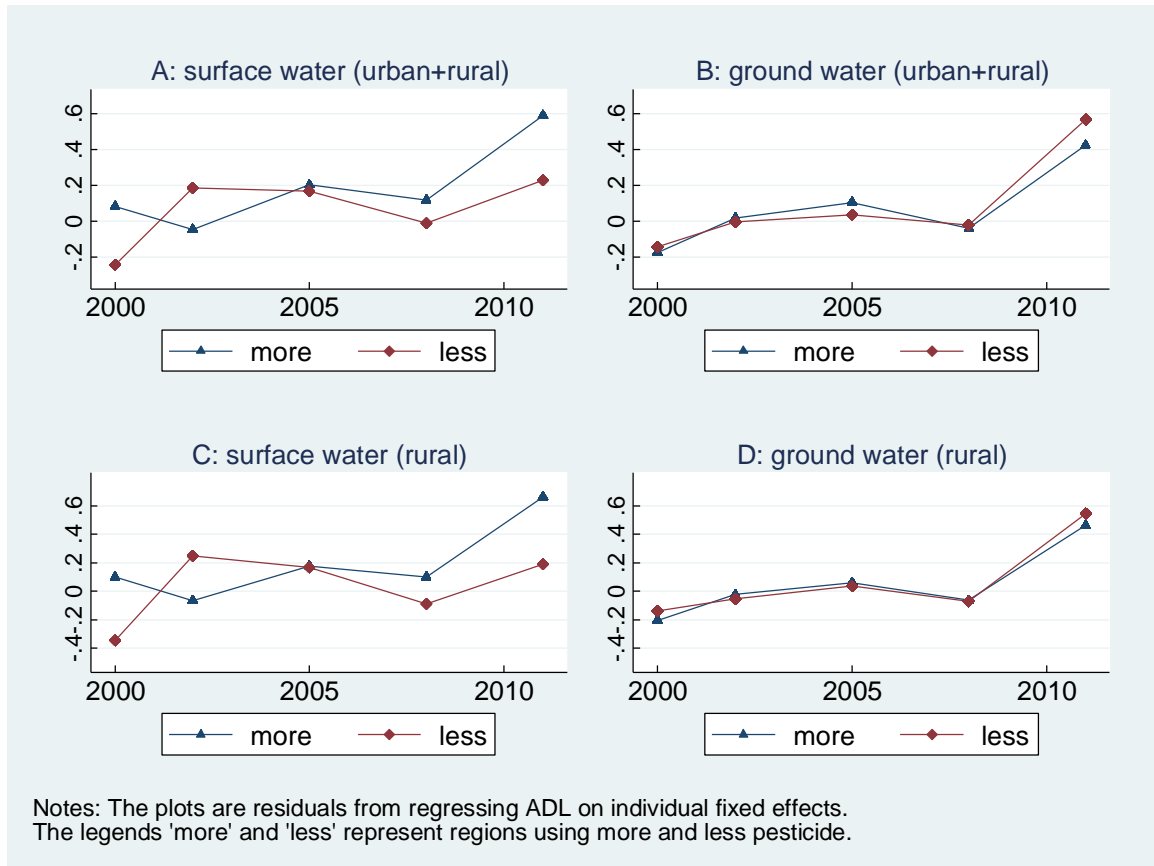The legends 'more' and 'less' represent regions using more and less pesticide.

Figure 3. ADL Trends by Drinking Water Source for Rural and Urban Respondents.

While this parallel trend assumption cannot be tested comprehensively, graphical analysis and partial tests are possible. First, we present some initial graph evidence on the validity of our quasi-experimental design. Figure 3A and Figure 3B represent samples that drink surface water and ground water respectively. Pesticide use is a continuous variable but, for the purpose of this graph, we dichotomize pesticide use by its mean. The blue lines and red lines depict the evolution of the ADL in regions with more and less pesticide use respectively. For those who drink surface water, the ADL levels have some fluctuations between regions with more and less pesticide use before 2004. However, after 2004 the ADL levels in the regions using more pesticide increase faster than those using less pesticide. As we show in Figure 4, this timing is commensurate with the timing of agricultural policy

changes.[4] Before 2004 pesticide use is relatively close between regions with more and less pesticide use, whereas the big difference occurred after 2004. By contrast, for those who drink ground water (Figure 3B), the ADL levels increase at similar rate in regions with more and less pesticide use. Our regression results are anticipated in Figure 3. These graphs serve as initial evidence that pesticide use causally affects the ADL levels through drinking water.
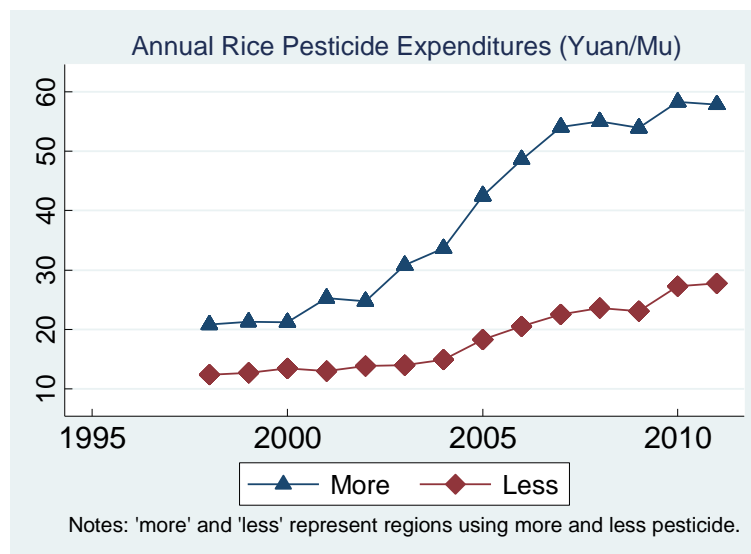

Figure 4. Annual Rice Pesticide Expenditures (Yuan/Mu).

Formally, we test that the pre-policy time trends for the regions with more and less pesticide use are not different by estimating a slightly modified version of equation (1). We use only the observations before 2005 and we modify equation (1) by excluding the policy dummy variable and including separate year dummies. In this model, we cannot statistically reject the hypothesis that the pre-policy year dummies are the same for regions using more and less pesticide at conventional levels of statistical significance (Appendix 2). This implies that the ADL levels in both groups had identical time trends in the pre-policy period and validates our DDD identification strategy.

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[4] As is also shown in Figure 1, this timing is commensurate with the rebound of grain production in 2004.

Further, a potential violation of parallel trends would be if people in regions with more and less pesticide use are systemically different in control variables from individual, household and regional levels, and health outcomes would have varied according to these control variables regardless of pesticide use. For example, rural-urban migration owing to industrialization and urbanization may increase pesticide use because of rural labor shortages; this may also worsen health conditions for those 65 and older as a result of less attendance and help. In this case, adding or deleting the number of people living together and industrial pollution are likely to change the coefficients if this migration effect is not differenced out by the DDD estimator. Therefore, examining whether coefficient estimates on the three-way interaction term change when the individual, household and regional characteristics are excluded in the regression can shed light on whether changes in outcome variables related to these characteristics are correlated with the three-way interaction term, constituting another partial test of the parallel trend assumption.

Results

This subsection reports the impact of pesticide use on health outcomes. The panel (a) in Table 2 presents coefficient from estimating equation (1) when the outcome variable is ADL. A one yuan per mu increase in expenditures on rice pesticides increases the index of ADL by 0.055 units for residents 65 and above. That is, a 10% (3.2 yuan/mu) increase in rice pesticide use increases the ADL score by 2.51% (0.17 units). The second model in panel (a) presents results without the inclusion of any other right-hand-side variables. Exclusion of the control variables makes little difference to the coefficients. These results are consistent with the extant epidemiological and economic literature that pesticide exposure adversely affects

the peripheral nervous system (Ding and Bao 2014; Li et al 2014; Hu et al. 2015; Starks et al. 2012) and, therefore, can increase the dependence of older adults via degradation of this key system. Further, there is evidence that Fipronil and Imidacloprid, which both feature insect neurotoxins, are the two most widely detected pesticides in surface water during rice production (China Pollution Source Census, 2010).

In addition, we find that this effect is mainly driven by populations in rural areas where millions of rural residents rely on surface water for their drinking supply. A one yuan per mu increase in expenditures on rice pesticides increases the index of ADL by 0.068 units (model 3). That is, a 10% (3.2 yuan/mu) increase in rice pesticide use increases the ADL score by 2.97% (0.21 units) for rural residents 65 and above. Exclusion of the control variables makes little difference to the coefficient (model 4). As Figures 3C and 3D show, we also find similar patterns as in Figures 3A and 3B. Our results suggest an unintentional policy side effect that mitigates the policy objectives of increasing farmers' income and welfare.

Table 2. Regression Results of Pesticide Use on Local Populations

VARIABLES	(1) DDD	(2) DDD	(3) DDD	(4) DDD
(a) ADL				
Rpest*water*y04	0.055**	0.065**	0.068**	0.080***
	(0.034)	(0.023)	(0.019)	(0.008)
(b) Hypertension				
Rpest*water*y04	0.020**	0.021**	0.015	0.017
	(0.049)	(0.027)	(0.197)	(0.129)
Observations	35,228	35,228	28,158	28,158
Control Variables	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes

Notes: (1) Robust p-value in parentheses *** p<0.01, ** p<0.05, * p<0.1; (2) Complete regression results are in the Appendix 1.

Note that the increase in the ADL score need not be pathological. Another possible explanation for our results is that pesticide exposure causes illnesses with clinical symptoms that increase ADL. However, in our study this hypothesis finds less support because we find no symptomatic diseases, except hypertension, are directly linked to pesticide exposure when we run DDD models with the self-reported diseases as dependent variables.[5] This insignificance may come from the inaccuracy of self-reported diseases. It may also come from our narrow focus on the drinking water pathway that pesticides have effects. It may also due to our limited focus on the non-occupational population, whereas the literature that identifies various acute and chronic diseases resulting from pesticide use usually focus on occupationally exposed samples.

In terms of hypertension, we find a one yuan per mu increase in expenditures on rice pesticides also increases measured hypertension by 0.02 percentage points. This is possible because pesticide exposure has been shown to cause various impairments in neurological, liver and kidney systems, but the epidemiological literature on the direct causal relationship between hypertension and pesticide exposure is not conclusive (Goncharov et al. 2011; Henríquez-Hernández et al. 2014). Broadly speaking, these results suggest that the health impact of pesticide use is underestimated because subclinical neuroelectrophysiological changes such as degradation of sensation and muscle strength, if not accompanied with clinical symptoms, will not be attributed to pesticide exposure (Ding and Bao 2014; Hu et al. 2015; Pingali et al. 1997).

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[5] Besides cognitive ability, measured hypertension and self-reported health condition, we also test other self-reported diseases. Self-reported diseases include cardiovascular diseases, gastrointestinal diseases, respiratory diseases, cancer and central neurological diseases. The information is measured by a survey question whether the respondent suffers from each of these diseases. Choices for each item are "Yes" and "No". Self-reported diseases are less accurate, which is the reason we do not use these as our main dependent variables.

Robustness

We conduct several robustness checks to help assess the validity of our results. A potential concern is that, because regions with more pesticide water pollution may also have more pesticide pollution in air, soil and food, our results may be driven by pesticide pollution via these other pathways. To rule out this possibility, we run analogous DDD regressions with respect to corn and wheat, which do not feature flooding as a cultural practice and, thus, should have less water pollution. If it is rice pesticides that affect health outcomes through surface water, our results should not be driven by production technologies with less water pollution. The correlations between health outcomes and pesticide use from corn and wheat production are clearly insignificant (Appendix 3). Additionally, in previous analyses, we exclude the samples in urban areas where treated tap water is provided. If it is through surface water that pesticides affect health outcomes, our results should not be driven by urban residents who do not drink untreated surface water. We find that our significant results are not driven by urban samples.

Our estimation would also be potentially problematic if people in regions with more pesticide use are more likely to change drinking water sources after 2004. To address this concern, we test whether reliance upon surface water for drinking sources differ before and after 2004 in regions with more and less pesticide use. That is, we run a difference-in-difference regression with the type of drinking water as the dependent variable and the interaction of pesticide use and year 2004 as the variable of interest. We also allow the effect of pesticide use on the type of drinking water to change each year by adding separate year dummies. All relevant coefficients are clearly insignificant, suggesting regions

with more and less pesticide exposure do not differ with respect to reliance on drinking surface water before and after 2004 (Appendix 4). These results can also be anticipated from Figure 5 where the rates of drinking surface water are largely parallel for regions using more and less pesticides before and after 2004.
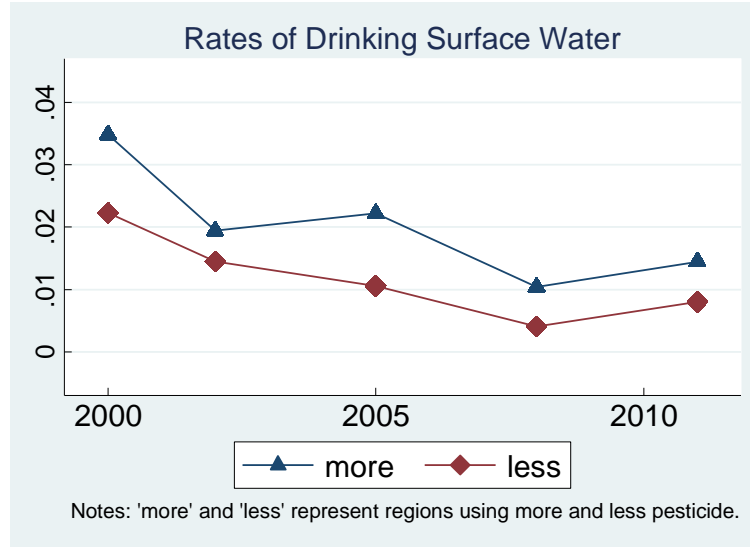

Figure 5: Rates of Drinking Surface Water

The Effect of Pesticide Use on Downstream Populations

This section investigates the impact of upstream pesticide use on the health outcomes of downstream populations. Upstream pesticide use, compared with local pesticide use, is more exogenous but spatial correlation may exist due to geographical proximity and connected economic activities. To address this concern, we adopt a difference-in-difference model[6] specified as:

$$y_{it} = \alpha + \beta_1 UpRpest_{pt} * y04_{it} + \beta_2 UpRpest_{pt} + \beta_3 y04_{it} + \beta_4 Tpest_{pt}$$
$$+ \gamma' X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (2)$$

where i, p and t represent individual, province and year. y_{it} is measured health outcomes including ADL, cognitive ability, measured hypertension and self-reported health condition.

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[6] A DDD approach similar to that used in the last section is not feasible in this section because rural farmers will not drink water from upstream provinces because of the direction of water flow.

UpRpes is rice pesticide expenditure from upstream provinces.[7] Upstream provinces are defined based on the main river systems as is shown in Figure 6. Smaller rivers and tributaries are not considered because pesticide use only has variations at the provincial level. Rice pesticide expenditure, instead of pesticide expenditure per mu, is used here because both pesticide use intensity and sown areas determine the runoff to the downstream provinces. *Tpest* represents total pesticide use (tons) in local provinces and it controls for pesticide pollution from their own provinces. *y04* takes value one starting from 2004 and zero otherwise. *X* is a vector of control variables including individual, household characteristics and provincial characteristics. *u* is the individual fixed effect and λ is year fixed effect. α is the intercept and ε_i is an error term. The standard errors are computed as in last section and we report the most conservative ones.

Water systems in China
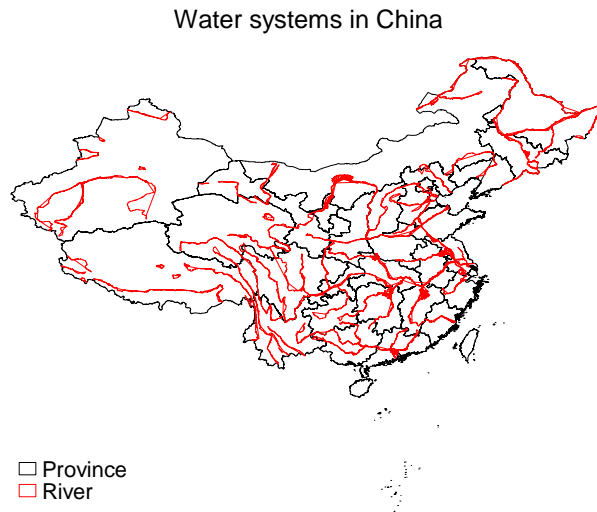

☐ Province
☐ River

Figure 6. Water Systems in China

A key identification assumption is that the outcomes have a common trend with respect to upstream regions using more and less pesticides before 2004. Similar tests as in the last

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[7] As a robustness check of different measures of pesticide use, we also use upstream total quantity (tons) as our main variable of interest and, as a falsification test, we also use downstream total quantity (tons) to predict the health conditions in upstream provinces. The results are reported in appendix 10. We cannot estimate the effect of pesticide quantities by different crops because the quantity data is crop aggregated.

section are conducted to indirectly test this assumption. Figure 7 depicts the evolution of the ADL in regions with more and less upstream pesticide use respectively. The blue and red lines have little fluctuation before 2004 and then separate after 2004. Using only observations before 2005, we cannot statistically reject the hypothesis that the pre-policy year dummies are the same for upstream regions using more and less pesticides at conventional levels of statistical significance (Appendix 6). This implies that the ADL levels in both groups had identical time trends in the pre-policy period and helps validate our DD identification strategy.
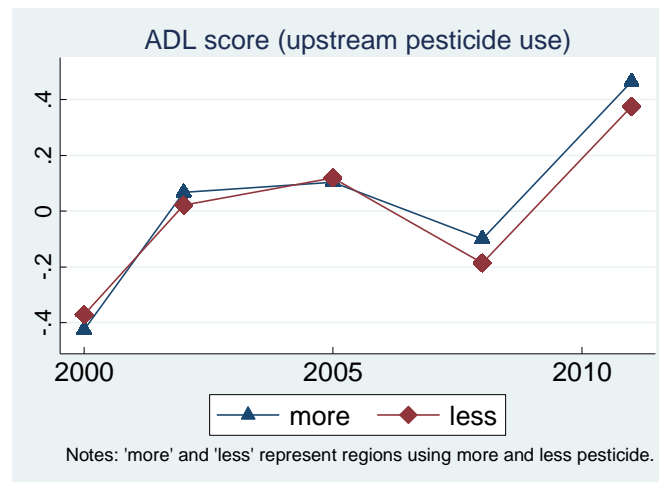

Figure 7. ADL Trends by Regions Using More and Less Pesticide.

In equation (2), we only find significant impacts when the dependent variable is ADL. A one yuan increase in upstream rice expenditure increase ADL level of downstream populations by 4.5e-10 units (Table 3). That is, a 10% (52 million yuan) increase in upstream rice pesticide use increases ADL levels of downstream aging populations by 0.33% (0.023 units).[8] Our results reveal few changes after exclusion of the control variables. This effect may come from various economic activities in connection with the use of the river water but

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[8] Please note that this effect is almost insignificant so the interpretation needs cation.

requires further information to identify the specific channels. We rule out the possible channels that feature the rural and urban differences such as direct pesticide exposure because we do not find that the effect differs between rural and urban samples.

As a falsification test, we run analogous DD regressions with the interaction of downstream rice pesticide expenditure and year 2004 as the variable of interest. If our results are driven by some omitted unobserved factors due to the geographical proximity and connected economic activities, we should expect that downstream rice pesticide expenditures also predict the health conditions in upstream provinces. However, the correlations between upstream health outcomes and downstream rice pesticide use are clearly insignificant (Models 3 and 4 in Table 3).
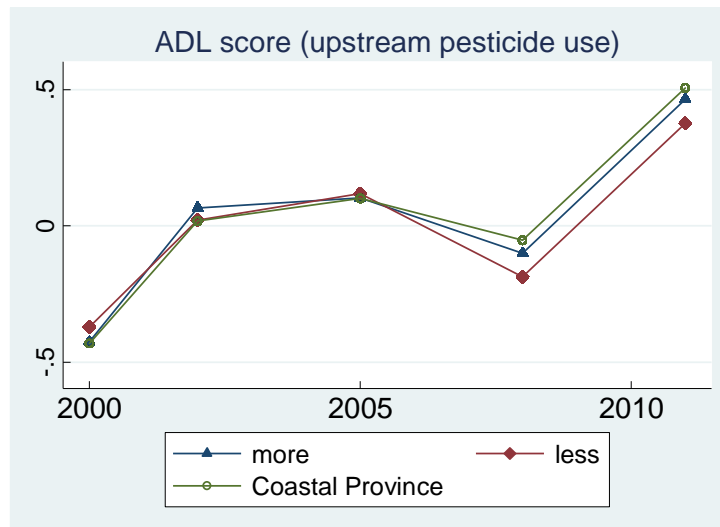

Figure 8. ADL Trends by Regions Using More and Less Pesticide and Coastal Provinces.

We also allow for heterogeneous effects of upstream pesticide use if the samples are in the coastal provinces. Coastal provinces are highlighted because they are the furthest downstream of all areas and many types of organophosphorus and organochlorine pesticides have been detected in various estuaries in China (Guan et al. 2009; Li and Daler 2004; Zhang et al. 2002). We modify Figure 6 by computing a separated ADL level for coastal

provinces. In Figure 7, compared with blue and red lines, the green line which represents coastal provinces has a higher level of ADL after 2004 which may suggest that land-based pollutants constitute a threat to coastal and marine ecosystems as well as to the health of coastal inhabitants (Fu et al. 2003; Guo et al. 2008; Xian et al. 2008). However, we formally do not find this difference is significant using regression analyses ($p = 0.745$).

Table 3: Regression Results of Pesticide Use on Downstream Populations

VARIABLES	(1) DD	(2) DD	(3) DD	(4) DD
UpRpest*y04	0.00045*	0.00039*		
	(0.09949)	(0.05933)		
DownRpest*y04			-0.00027	-0.00008
			(0.88040)	(0.83778)
Observations	26,469	26,661	22,311	22,446
R-squared	0.70833	0.69168	0.67571	0.65592
Control Variables	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes

Notes: (1) Robust p-value in parentheses *** p<0.01, ** p<0.05, * p<0.1. (2) Complete regressions results are in appendix 5. (3) Model 3 and 4 uses the downstream rice pesticide use to predict the health conditions in upstream provinces.

Monetary Losses

In this section, we further explore these results by translating estimated effects into expected monetary losses. We do this by exploiting the relationship between ADL and medical costs and offspring's weekly caring hours. As Figure 9 shows, the medical costs and offspring's weekly caring hours increase with the ADL score. Formally, we specify the model as:

$$y_{it} = \alpha + \beta_1 \text{ADL}_{it} + \gamma' X_{it} + \lambda_t + \mu_i + \varepsilon_{it}$$

where y_{it} represents medical costs and offspring's weekly caring hours. Other variables are as defined as before and the most conservative standard errors are reported.
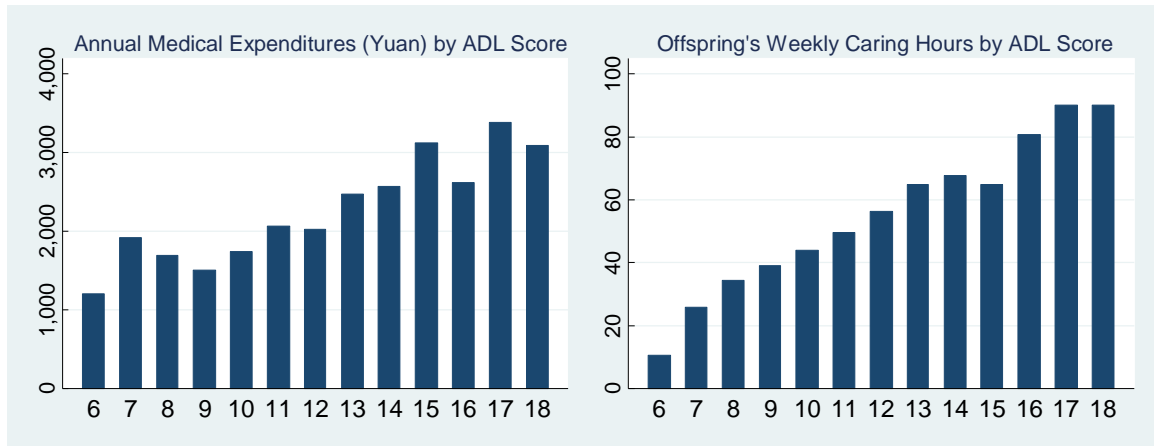
Figure 9. Annual Medical Expenditures and Offspring's Weekly Caring Hours by ADL Score

We find positive and significant effects of ADL on medical cost and offspring's weekly caring hours (Table 4) and the coefficients are little changed when adding or deleting control variables. Our estimates suggest that each additional unit increase in ADL increases medical costs and offspring's weekly caring time by 139 yuan[9] and 6.55 hours, respectively. According to China Statistical Yearbook 2012, the average annual income per capital is about 14,582 yuan, which is about 7 yuan per hour. That is, a one unit increase in ADL increases offspring's human capital losses by approximately 46 yuan.

Table 4: The Effect of ADL on Medical Costs and Offspring's Weekly Caring Time

	Medical Costs		Offspring's Weekly Caring Hours	
VARIABLES	(1)	(2)	(3)	(4)
ADL	138.858***	144.291***	6.170***	6.540***
	(0.000)	(0.000)	(0.004)	(0.001)
Observations	20,433	20,433	6,714	6,714
R-squared	0.647	0.645	0.887	0.885
Control Variables	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes

Notes: (1) Robust p-value in parentheses *** p<0.01, ** p<0.05, * p<0.1. (2) Complete regression results are in appendix 7.

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[9] 1 Yuan = 0.15 US Dollar

In combination with previous information, China's aging population ratio (118.9 million/1.34 billion) and 298 million people without safe drinking water service, we are able to calculate that a one yuan per mu increase in expenditures on rice pesticides increases medical costs and human capital losses of local populations by 238.9 and 79.06 million yuan, respectively.[10] That is, a 10% increase in rice pesticide use increases medical costs and human capital losses of local populations by 764.48 and 252.99 million yuan, respectively (or 114.67 and 37.95 million dollars). And a one yuan increase in expenditures on rice pesticides in upstream provinces increases downstream medical costs and human capital losses by 6.94 and 2.3 yuan, respectively.[11] That is, a 10% increase in upstream rice pesticide use increases downstream medical costs and human capital losses by 360.88 and 119.6 million yuan, respectively (or 54.13 and 17.94 million dollars). In sum, a 10% increase in rice pesticide use increases monetary losses by 1.5 billion yuan (224.69 million dollars), which is equivalent to 1.92% of national annual rice production profits.[12] Our results still underestimate the real costs of pesticide use because of our narrow focus on the aging population and the water exposure channel.

Conclusion

This paper provides the first quasi-experimental evidence that pesticides adversely affect health outcomes through drinking water by linking provincial data from several Chinese

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[10] Medical costs of local populations are computed by 0.065*139*(298*118.9/1340) and human capital costs of local populations are computed by 0.065*46*(298*118.9/1340). These calculations only account for those 65 and older who do not have safe water access.

[11] Medical costs of downstream populations are computed by (4.2e-10)*139*118.9 and human capital costs of downstream populations are computed by (4.2e-10)*46*118.9. These calculations use populations 65 and older and the pesticide exposures are not limited to drinking water channel.

[12] The average rice production profits per mu from 2000 to 2011 were 194.84 yuan and the data was from Agricultural Cost and Benefit Yearbook. The average sown area of rice from 2000 to 2011 was 3.996e+08 mu and the data was from China Statistics Yearbook. The average rice production profits were 194.84*3.996e+08=7.786e+10 yuan.

statistical yearbooks (1998-2011) with the Chinese Longitudinal Healthy Longevity Survey (1998-2011). We find significant impacts of pesticide use on the index of dependence in Activities of Daily Living (ADL) and translate the estimated effects into medical and offspring's human capital losses.

First, a difference-in-difference-in-differences framework shows that a 10% (3.2 yuan/mu) increase in rice pesticide use unfavorably alters the index of dependence in Activities of Daily Living (Katz Index of ADL) by 2.51% (0.17 units) for residents 65 and above. One possible explanation that is consistent with the extant epidemiological and economic literature is that pesticide exposure adversely affects the peripheral nervous system and, therefore, increases the dependence of old people. This effect is mainly driven by populations in rural areas where millions of residents rely on surface water for their drinking supply. This suggests an unintentional policy side effect: the subsidized pesticides meant to increase farmers' income and welfare via enhanced agricultural productivity are also degrading the physical independence of older adults exposed to the surface water that captures pesticide residues.

Second, we follow a difference-in-difference approach and we find that a 10% (52 million yuan) increase in upstream rice pesticide use increases ADL scores of downstream aging populations by 0.33% (0.023 units). We also provide some suggestive evidence that land-based pollutants constitute a threat to coastal and marine ecosystems as well as to the health of coastal inhabitants although we formally cannot detect the significant effects in our regression analysis. Finally, we translate these estimated effects into expected monetary losses by exploiting the relationship between ADL and medical costs and offspring's weekly

caring hours. Our results indicate that each additional unit increase in ADL increases medical costs and offspring's human capital losses by 139 yuan (20.9 dollars) and 46 yuan (6.9 dollars).

In combination with previous information, we are able to calculate that a 10% (3.2 yuan/mu) increase in rice pesticide use increases medical costs and human capital losses of local populations by 764.48 and 252.99 million yuan, respectively (or 114.67 and 37.95 million dollars). And a 10% (52 million yuan) increase in upstream rice pesticide use increases downstream medical costs and human capital losses by 360.88 and 119.6 million yuan, respectively (or 54.13 and 17.94 million dollars). In sum, a 10% increase in rice pesticide use increases monetary losses by 1.5 billion yuan (224.69 million dollars), which is equivalent to 1.92% of national annual rice production profits.

Our findings can be used to shed light on the agricultural and environmental policy designs. For example, the estimated monetary losses due to pesticide usage can be used as a guide to choosing subsidization levels for crop insurance and for funding farmers' pesticide training programs given that previous studies show that risk aversion surrounding farm production outcomes and the lack of pesticide knowledge contribute to overuse of pesticides (Chen, Huang and Qiao 2013; Liu and Huang 2013). These issues have salience in other developing countries that face similar challenges to sustainable development, particularly where countries seek greater food sovereignty. Although we provide evidence that pesticides affect health outcomes through a drinking water channel, other channels deserve future research.

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