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Abstract

In this paper, I provide a new empirical evidence that natural environment can shape individual risk preferences. By combining historical data on climate variation and contemporary survey questions on risk aversion, I find that risk aversion is significantly different for people who live in areas that have suffered high frequency of natural disaster. In particular, individuals highly affected by climate volatility show a long term risk aversion.

JEL classification: D03, Q54, O53
Keywords: Risk aversion, Climate variation, Vietnam

1. Introduction

Preferences play an important role in economics. Recent works in experimental economics have examined to what degree risk aversion lead to negative impacts on economic performance. They found that risk aversion has been inversely linked with economic outcome such as investment in physical and human capital and wage growth (Levhari and Weiss, 1974; Shaw, 1996).

However, economists have usually assumed that such preferences are fixed by individual characteristics (Stigler and Becker, 1977). In other words, while the circumstances in which the decision makers live could affect their choices, the underlying preferences could not be affected by those circumstances (Cassar, Healy and Kessler, 2011). Recent studies from behaviour economics and psychology, however, suggest that individual experiences can affect preferences such as risk and patience (Malmendier and Nagel, 2011).

Understanding the extent to which risk attitudes are innate or shaped by environment is important for making policy. A few number of studies have looked at living environment influences on shaping preferences and risk attitudes (van den Berg, Fort and Burger, 2009; Cameron and Shah, 2010; Cassar, Healy and Kessler, 2011)[1]. All of these studies using field experiments to measure the short-term impact of natural disaster on risk preferences of village farmers. However, it is difficult to know whether those effects come from one-time shock of natural disasters or from background of risks. If rural households used to be staying for a long time in regions with frequent natural disasters, the risk attitudes are likely to come from recalling the past memory rather than recent events. Therefore, we may not disentangle the short term present impacts from long term past experience.

This paper supplements current studies by implementing an empirical examination of long term effects of living environment in shaping subsequent economic development and individual behaviours. By combining contemporary individual-level survey data on risk aversion with historical data on climate variation, I ask whether the living environment can

[1] Other papers have investigated the impact of natural disasters on outcomes such as household welfare (Thomas et al, 2010), macroeconomic output (Noy, 2009), income and financial flows (Yang, 2008a), migration decisions (Halliday, 2006; Paxson and Rouse, 2008; Yang, 2008b), fertility and education investments (Baez et al., 2010; Finlay, 2009; Portner, 2006; Yamauchi et al., 2009), and mental health (Frankenberg et al., 2008).

shape risk attitudes of rural village people within Vietnam. My hypothesis is people who heavily exposed to hazardous environment with frequency of typhoons, storm and floods tend to more risk averse. Particularly, I would like to show that village peasants have different preferences responding to different aspects of the historical climate variation. Based on cumulative prospect and expected utility theories, the empirical results confirm that rural households suffering more natural disaster show significantly higher levels of risk aversion. These effects are also consistent with other evidence that observations of risky environments where events have turned out badly can lead to greater risk aversion (Malmendier and Nagel, 2011). Moreover, the results indicate that risk averse perception may have evolved over time in this environment and continue to persist to this day.

The remainder of the paper is structured as follows. I start with a detailed description of the context in Section 2. Section 3 illustrates the conceptual framework. Section 4 describes data on main variables and the way to calculate risk aversion coefficients. Section 5 presents reduced form model and estimation results. Section 6 concludes.

2. Characteristics of climate variation and natural disasters in Vietnam

Vietnam is one of the world's most exposed countries to multiple natural disasters, including tropical cyclones (typhoons), tornados, landslides and droughts (World Bank, 2010). Storms and tropical depressions often occur from June to November but mainly in September and October. It often occurs in central and northern parts of Vietnam but once appeared in Southern part. There is an average of four to six typhoons annually although in some years there are none and in others considerably more (Viet Nam MWR et al., 1994). According to Viet Nam MWR and UNDP (1992), some 62 percent of the population and 44 percent of the country are frequency affected by typhoons, with 250 persons killed annually. The worst typhoons in last century are reported to have occurred in 1904, killing and injuring 5,000 people; and in 1985, leaving 900 dead (VNCIDNDR, 1994).

The occurrence of typhoons is highly seasonal, typically affecting the north of the country between June and September, the centre from August to October and the south between October and December. However, typhoons are predominantly concentrated on the centre and north of the country, particularly the central provinces between Thanh Hoa to Quang Nam. The south experiences fewer typhoons, about once every five years (Benson, 1997).

Storms and tropical depressions result in heavy rain and flood after that. It is estimated 59 percent of its total land area and 71 percent of its population that are vulnerable to cyclones and floods (World Bank, 2005). Flooding occurs almost every year, particularly in the central provinces, as frequent typhoons typically coincide with the monsoon whilst the country's terrain, which includes steep high mountains and narrow low plains, implies a potentially high risk of flash flooding (Benson, 1997).

The two main delta regions also experience annual flooding. Major floods of the Red River are reported to have occurred in about 100 years between 977 and 1990 - equivalent to one every 10 years. Heavy rainfall combined with poor drainage facilities can also cause urban flooding. Pho and Tuan (1994), who define floods as events where discharges are three or more times the annual mean level, estimate that Viet Nam experiences some 3 to 8 floods every year. The flood season is typically earlier in the north than the south of the country, with flooding most probable in July and August in the Red River Delta and in late September or early October in the Mekong Delta. Since 1900, severe floods inundating of over 300,000 hectares of land have occurred in 1913, 1915 and 1945, 1971 and 1986 (ESCAP, 1990; ADB, 1994).

3. Conceptual framework

The existing theories are inconclusive about the effects of natural environment on risk behaviour. Climate variation and natural disaster could affect individual through many mechanisms. One possible channel would be through a large negative shock in wealth or income, then changing individual preferences (Cassar, Healy and Kessler, 2011; Cameron and Shah, 2010). Thomas et al (2010) in recent study show that natural disaster has profound effect on living condition of people. By combining repeated cross sectional national living standard measurement surveys (2002, 2004, and 2006) from Vietnam with proxy of natural disasters, they show that the immediate losses from floods and hurricanes can be substantial, with riverine floods causing losses of up to 23 percent and hurricanes reducing by up to 52 percent consumption among households close to large urban centres.

A second channel would involve an increase in the perceived likelihood that other negative events would occur. Cameron and Shah (2010) provide experimental and survey estimates that support the idea that people living in villages that have been exposed to earthquakes or floods in the past exhibit more risk aversion than others whose villages did not experience such events. They find that individuals update and increase the probability that another flood will occur in the next year because individuals perceive that they are now facing a greater risk, so they are less inclined to take risks.

A third channel, from the psychology literature, psychologists have shown that hazard experience makes people more worried and fearful, and that worry leads to more risk-averse choices (Cassar, Healy and Kessler, 2011). Empirical study by Li et al. (2009) found supporting results in case Chinese people affected by an unprecedented snowstorm and a major earthquake. Particularly, their results, based on data collected one month after the power outages and two months after the earthquake, suggest that people tend to give more weight to low probabilities after a disaster, preferring a sure loss but a probable gain. They also found that participants tend to buy both insurance and lotteries after those events.

However, psychological evidence suggests that people's preferences undergo some form of adaption: if the level of risk is high, people may not be particularly concerned about the addition of a small independent risk (Dolan and Kahneman, 2008; Kahneman and Tversky, 1979). For example, fishermen constantly make risky decisions and constantly face a trade-off between limiting fishing efforts today and receiving higher profits in the long run. Repeated exposure to such an environment is likely to build up a high level of reference for risk and patience which makes the agents more willing to make risky and patient choices (Nguyen, 2011).

4. Data description and risk aversion parameters

Risk aversion

Data for this research is taken from the fourth round of the Vietnam Access to Resources Household Survey (VARHS), starting from 2002. The survey was conducted by Institute of Labour Science and Social Affairs of the Ministry of Labour, Invalids and Social Affairs under the technical support from Department of Economics at the University of Copenhagen. It was carried out in the rural areas of twelve provinces in Vietnam: (i) four (ex-Ha Tay, Nghe An, Khanh Hoa and Lam Dong) supported by Danida under the Business Sector

Programme Support (BSPS); (ii) five (Dac Lac, Dac Nong, Lao Cai, Dien Bien and Lai Chau) supported under the Agriculture and Rural Development Sector Programme Support (ARDSPS); and (iii) three (Phu Tho, Quang Nam and Long An), which were all initially surveyed in 2002 and are now covered by the BSPS.

The special feature of this survey is the locations of these 12 provinces characterize a comprehensive climate condition throughout the country with Ha Tay in Red River Delta; Lao Cai and Phu Tho in Northeast; Lai Chau and Dien Bien in Northwest; Nghe An in North Central Coast; Quang Nam and Khanh Hoa in South Central Coast; Dac Lac, Dac Nong and Lam Dong in Central Highland; and Long An in Mekong River Delta.

The survey consists of interviews of more than 3,000 households. Of which, the VARHS10 resurvey all rural households in 12 provinces that were interviewed for the 2004 Vietnam Household Living Standards Survey (VHLSS). This amounts to 1,314 such households for whom information is available in 2010. For these households weights are available to construct statistics using the VARHS data that are representative of rural households in the 12 provinces surveyed in each year. The rest includes 820 rural households that are resurveyed from the 2002 VHLSS in Ha Tay, Phu Tho, Quang Nam and Long An provinces and 945 additional households from the five provinces covered by the ARD-SPS program, namely Lao Cai, Dien Bien, Lai Chau, Dak Lak and Dak Nong. In this study, I use the reduced sample of 1,314 rural households for whom weights are available.

To measure risk aversion of rural households, the survey uses several questions. First, it asks a question that adapts a simple unpaid lottery experiment. In this experiment, individuals were to ask to decide for each of six lotteries whether they want to accept or reject it. In each lottery the winning money is fixed at 6,000 VND and only the losing price is varied (between 2, 000 VND and 7, 000 VND). The advantage of this unpaid experiment over the real money payments is the second may result in incentive effects and may not reveal the true risk preferences of rural households[2].

[2] Some previous studies, such as Rabin (2000), Rabin and Thaler (2001), Schmidt and Zank (2005), Wakker (2005), Köbberling and Wakker (2005) suggested that this lottery may measures loss aversion rather than risk aversion. Rabin (2000), for instance, argues that risk aversion cannot reasonably explain choice behavior in small-stake risky prospects like this case loss aversion in such small-stakes lotteries would imply absurd degrees of risk aversion in high-stake gambles.

The exact words of this experiment are: “You are given the opportunity of playing a game where you have a 50:50 chance of winning or losing (for example, a coin is tossed so that you have an equal chance of it turning up either heads or tails). In each case choose whether you would accept or reject the option of playing:

Lottery	Accept	Reject
a. You have a 50% chance of losing 2,000 VND and a 50% chance of winning 6,000 VND	O	O
b. You have a 50% chance of losing 3,000 VND and a 50% chance of winning 6,000 VND	O	O
c. You have a 50% chance of losing 4,000 VND and a 50% chance of winning 6,000 VND	O	O
d. You have a 50% chance of losing 5,000 VND and a 50% chance of winning 6,000 VND	O	O
e. You have a 50% chance of losing 6,000 VND and a 50% chance of winning 6,000 VND	O	O
f. You have a 50% chance of losing 7,000 VND and a 50% chance of winning 6,000 VND	O	O

The survey also uses another question concerning hypothetical risk to estimate the coefficient of absolute (and relative) risk aversion. The following question is asked: “Consider an imaginary situation where you are given the chance of entering a state-run lottery where only 10 people can enter and 1 person will win the prize. How much would you be willing to pay for a 1 in 10 chance of winning a prize of 2,000,000 VND?”. The answer to this question is a reservation price above which the household rejects the lottery.

Calculating parameters of risk aversion

For the first question, risk aversion in the risky choice task can be identified by applying cumulative prospect theory (Tversky and Kahneman, 1992). A decision maker will be indifferent between accepting and rejecting the lottery if $w^{+}(0.5)v(G) = w^{-}(0.5)\lambda^{risk}\ v(L)$, where L denotes the loss in a given lottery and G the gain; $v(x)$ is the utility of the outcome $x \in \{G, L\}$, λ^{risk} represents the coefficient of risk aversion in the choice task; and $w^{+}(0.5)$ and $w^{-}(0.5)$ denote the probability weights for the chance of gaining G or losing L, respectively.

If I assume that the same weighting function is used for gains and losses, $w^{+} = w^{-}$, the ratio $v(G)/v(L) = \lambda^{risk}$ will define an individual's implied risk aversion in the lottery choice task. I assume that $v(x)$ is linearity ($v(x) = x$) for small amounts, which gives us a simple measure of risk aversion: $\lambda^{risk} = G/L$. I will relax some of these assumptions later.

In my lottery choice task $\lambda^{risk} = w^{+}(0.5)/w^{-}(0.5)(v(G)/v(L))$. I only consider monotonic acceptance decisions (99 percent of respondents exhibit monotonicity). Table 1 records the results of four different assumptions on probability weights and diminishing sensitivities for gains and losses. The rationale of these four models is to vary assumptions on probability weighting and diminishing sensitivities to see their differential impact of climate variation on implied levels of risk aversion. The benchmark case (model (1)) is that both probability weighting and diminishing sensitivity are set to be equal to one. Model (2) assumes that differential probability weighting for gains and losses is unimportant (that is, $w^{+}(0.5)/w^{-}(0.5) = 1$) but allows for diminishing sensitivities for gains and losses. Model (3) assumes diminishing sensitivity is unimportant but allows for differences in probability weights for gains and losses. I follow Gächter et al (2010) to take the estimates of Abdellaoui (2000) who reports that $w^{+}(0.5) = 0.394$ and $w^{-}(0.5) = 0.456$ for the median individual, which is one of the largest differences between $w^{+}(0.5)$ and $w^{-}(0.5)$ found in the literature (implying $w^{+}(0.5)/w^{-}(0.5) = 0.86$). It therefore provides an upper bound for the importance of differential probability weightings of gains and losses for the median individual in our context. Model (4) assumes that both probability weighting and diminishing sensitivities matter.

The results from the experiment shows that most households are risk averse, as expected given the high levels of poverty and the particularly unpredictable feature of agriculture According to Table 1, 1.86 percent accepted all lotteries with a non-negative expected value and only rejected lottery f, which has a negative expected value. Hence, according to the benchmark model (1) their implied $\lambda^{risk} = 1$. Only 0.81 percent of our respondents also accepted lottery #6, which has a negative expected value, that is, in model (1) their $\lambda^{risky} < 0.87$. Most participants rejected gambles with a positive expected value. A lot of respondents (68.28 percent) rejected all six lotteries; for these people $\lambda^{risky} > 3$. A variation of assumptions on probability weighting and diminishing sensitivity shows a change the values of implied λ^{risk}.

For the second question, I can rely on Pratt (1964) and Arrow (1965), who used a concave utility function U which is defined over income (or wealth), to construct formal measures of absolute risk aversion.

I assume that households are initially endowed with income of *w* and having a thrice-differentiable, state independent utility function *U*, such that $U^{'}(w) > 0$, $U^{''}(w) < 0$, and $U^{'''}(w) > 0$. The reservation price, *z*, makes the household indifferent between the risky asset and the initial income; the endowment is therefore the certainty-equivalent of the proposed investment.

Suppose that the household's behaviour can be described by the maximization of expected utility, then we have the relationship:

$$U(w) = 0.1U(w - z) + 0.9U(w - z + 2) \quad (1)$$

or equivalently,

$$10U(w) = U(w - z) + 9U(w - z + 2) \quad (2)$$

A second order of Taylor series expansion of the right-hand side of Equation 2 around an income of w gives:

$$10U(w) = U(w) - zU^{'}(w) + 0.5z^2U^{''}(w) + 9[U(w) + (2 - z)U^{'}(w) + 0.5(2 - z)^2U^{''}(w)]$$

After rearranging, we yield the Pratt-Arrow measure of absolute risk aversion as:

$$A(w) = -\frac{U^{''}(w)}{U^{'}(w)} = \frac{18 - 10z}{5z^2 + 18 - 18z}$$

Climate and Geographical Variables

A. Climate Variation

I obtain historical data on climate variability from weather stations in 46 districts from Institute of Meteorology and Hydrology. The data prolongs 35 – 60 years from 1927 to 1985 depending on each station. These stations are allocated to capture the best variation of weather within regions. For each station, I have climate data, such as precipitation and temperature, at station with latitude-longitude degree point p in district i during month m of year t .

To compute the climate variation, I first calculate average of temperature and rainfall in each station for each month (month-specific average). I take average of weather over 35-60 years to reduce the effect of extreme weather condition in specific years. After that, I obtain the standard deviation of temperature and rainfall of each station over twelve months to investigate within year weather fluctuations.

For districts without climate stations, the weather condition is assumed to be similar to other districts with the same latitude. The reason to apply this strategy is that stations are expected to gauge the significant climate variation in different regions. Therefore, climate data from one station can be used to measure neighbouring districts with similar condition.

B. Other geographical variables

Other variables may be important for my analysis. Rainfall, for example, may harm production depending on land type and plot slope. Similarly, a flood will affect only low-lying fields, whereas landslides destroy fields on or below steep or unstable slopes. General climate indicators such as average rainfall and temperature or the passage of a storm and typhoons therefore obscure differences in risk exposure among households. I therefore used household-level questionnaires to gather information on these risk exposures.

Average climate conditions

Average climatic conditions are likely to have considerable impact on agriculture and income. For example, even a region without much climate variation but low (or high) average rainfall or temperature within a year also create risks that caused by drought and flood. To account for these effects, I control for the average level of temperature and rainfall at the district level. These measures are constructed from the same dataset described above, taking their average over twelve months and over the entire period.

Elevation and Land Terrain

Land terrain and elevation can also be expected to be correlated with climate variability. For example, the presence of a mountain can lead to different climatic condition and micro-ecosystems on each side (Durante, 2009). This may decrease or strengthen the risk of negative effects of climate variation on agricultural activities. To control for the relationship between climate variability and topography, I include a plot dummy variable to measure of agricultural land terrain in regressions. The information for land terrain is withdrawn from the question to household heads on topography of household's land plot : "*In general, what is the slope of this plot? Flat, Slight Slope, Moderate Slope and Steep Slope*" The measure of land slope takes the value of 1 if plots are flat and 0 otherwise. As presented in Table 2, 35 percent of land plots are in slight to steep conditions.

Land area and quality

Land quality and growing conditions could affect the risk of crop failure and household income. To account for this aspect, I include area of land and dummy of land quality in regressions. Information on the land quality is taken from the question: "*Do you experience problems with any of following conditions on this plot? Erosion, Dry land, Low-lying land, Sedimentation, Landslide, Stone soils/clay, other or No problem*". I construct a measure of land quality that takes on the value of 1 if plot does not suffer any above problems and 0 otherwise. Only three percent of households report high quantity of land without any above problems.

C. Migration

The survey provides some useful information based on questions on how long households have lived in the commune and location that people born. I follow a strategy to take only households with head, spouse or both of them where they live are also where they were born. The argument here is the more time those people have been exposed in this environment, the more their risk attitudes adapt to this natural condition.

In Table 1, the average age of household heads who were born locally is above 50 years old. It implies that climate has long-lasting and profound effects on their living and behaviour.

5. Empirical strategies

I first investigate the relationship between climate variability and risk aversion using historical climate data. To further test the robustness of the relationship between risk aversion and historical climate variability, I extend the analysis to account for differential geographical and individual characteristic variables.

My regression model has the following general specification[3]:

$$Risk\_aversion_{i,d,p} = \alpha_p + \beta Environ\_Var_d + \mathrm{X}_{i,d}^{'}\Gamma + \mathrm{Z}_{i,d}^{'}\Phi + \gamma X_c + \varepsilon_{i,d,p}$$

where α_p indicates province fixed effects, which are included to capture provinces specific factors, such as effectiveness of local regulations and norms, that may affect risk aversion. The variable $Risk\_aversion_{i,d,p}$ denotes measures of risk aversion, which vary across households. $Environ\_Var_d$ represents the degree of variability for climate (temperature or rainfall) among districts. β is our coefficient of interest which estimates the relationship between the climate variation in a district and the individual's current level of risk aversion.

The potential effects of climate variation on this risk aversion may vary systematically across demographic groups. For example, climate variation is more likely to correlate with income and education levels, then shifting patterns of risk aversion in predictable ways. Many empirical studies indicate that higher levels of risky activities are expected to increase with wealth and income. Wealthier individuals are often found to be more likely to undertake risky activities (Rosenzweig and Binswanger, 1993; Miyata, 2003; Cohen and Einav, 2007). In addition, it is possible that wealthier households choose to stay in regions that do not

[3] Sampling weights are applied in all calculations to ensure unbiased estimates of population parameters. The weights for each household are, approximately, the inverse of the probability that the household was surveyed for the 2004 VHLSS. Because the distribution of the rainfall and temperature are highly left skewed, with a small number of observations taking on large values, I report estimates using the natural log of the climate measures

experience flooding and are more likely to choose the riskier option (Cameron and Shah, 2011).

Many other studies conclude that the willingness to take risk increases with education (e.g., Dohmen *et al.*, 2005; Donkers *et al.*, 2001; Hartog *et al.*, 2002; Miyata, 2003). However, some evidences indicate that the effect of education may be unidentified. Binswanger (1980) finds little effect of education on risk aversion at low game levels, but negative and often, but not always, significant effects at intermediate and high pay-offs. Also, the effect of education may be small. Some people are risk takers on small bets but become more risk averse on bets with larger economic consequences.

Risk-taking behavior can change as people age. In earlier studies on risk experiments, older people tend to be more risk averse than younger subjects. In a related finding, single individuals were less risk averse than married individuals, though having more children did not seem to increase loss aversion. Women, in general, are more risk averse than men (Byrnes *et al.*, 1999; Cohen and Einav, 2007; Dohmen *et al.*, 2005; Donkers *et al.*, 2001; Hartog *et al.*, 2002)

A number of studies have shown that less risk-averse agents are more likely to choose higher risk jobs for better compensation (Viscusi and Hersch, 2001). For instance, King (1974) finds that individuals from wealthier families choose riskier occupations, while Cramer et al (2002) show that less risk-averse agents are attracted to entrepreneurship, a more risky occupation.

To capture all above effects, I include information on household head, such as age, age squared/100, years of education, household income, a gender variable indicator, an indicator variable that equals one if the respondent lives in an urban location, a dummy variable for people who are ethnic minorities and occupational fixed effects into $X'_{i,d,p}$.

The vector $Z'_{i,d,p}$ consists of other geographical variables, such as average rainfall and temperature, land terrain, land quality and area of land. X_c is a variable designed to capture the share of the commune's population that is of the same ethnicity as the respondent.

In addition, many of the explanatory variables in above equation do not vary across individuals, rather at the commune level. For example, climate variation will have the similar effects for people living the same commune. Given the potential for within-group correlation of the residuals, I adjust all standard errors for potentially arbitrary correlation between households in the same commune.

Table 4 and 5 report the results using for log of rainfall variation. In baseline models, I find substantial evidence that rainfall variation is correlated with risk averse indicators. In the all cases without provincial fixed effects, the estimated coefficient for rainfall, β, is positive and statistically significant (at the 1% level), indicating that climate variability positively affecting average trust score at household level. This is consistent with the hypothesis that the climate variation affects individuals' risk attitude. However, the significant relationships disappear as I control for provincial fixed effects.

The effects of temperature variation are robust with provincial fixed effects. The estimate of β for all four models is positive and highly statistically significant and of similar magnitude. The estimates fall between 0.53 and 0.36. The interpretation is that one standard deviation increase in log of temperature variation causes an increase in risk aversion that range from 23.8 to 23.52 percent of increase in standard deviation of different risk aversion.

To control for the potential problem that climate variation may be contaminated by the effects of other geographical variables, in Table 8, I include the vector of geographic controls, which includes average temperature and rainfall, land area, land terrain and quality. When the geographical controls are included, the point estimates of the coefficients of interest increase substantially and become highly statistically significant. For the magnitude of the coefficient, holding other variables constant, one standard deviation increase in log of rainfall variation corresponds to a 0.2 increase in risk aversion (approximately 20 percent standard deviation increase in risk aversion).

I undertake a number of other robust checks. First, I separately investigate the impacts of climate variation for each gender group of population. The results are more robust to the male subsample. I find that temperature variation has higher impacts on female; however, the results are not obvious for rainfall variation. Second, I check for robustness to alternative estimation methods. Using ordered logit models produces estimates that are qualitatively identical to our baseline OLS estimates (Appendix II). The results also indicate that the estimates are stable over a range of regressions.

Table 14 and 15 repeats the same exercise but with second measure risk aversion. We see that both temperature and rainfall variation have positive effect absolute risk aversion of village members, which are also consistent with above results.

B. Potential Sources of Bias

In the above section, I deal with omitted variables by including provincial fixed effects in the climate variation equation. This does not, however, completely solve the concern of omitted variables because unobservable time varying components might be correlated with both changes in climate variables and changes in individual risk aversion in each district. One may think of specific time varying factors, such as infrastructure, affecting both risk aversion and impacts of climate volatility. By taking historical climate data that creates a lag between climate variable and contemporary outcome, this makes it less likely that unobservable time varying components could drive changes both in current measure of loss aversion and climate variation and resulting in spurious estimation.

However, another problem that may affect the estimates is selection bias. The problem happens as a non-random subgroup of village peasants select to stay in regions even with more natural risks. These groups of village peasants are likely to be more risk-averse and tend to stay at the same place where they were born even those places are not ideal for living. If these factors correlate with climate variability among district, then the estimates are also to be underestimated and the results provide lower bound estimation.

6. Conclusion

The frequency and damages created by climate variation and natural hazards have increased substantially over the past decades and will probably continue to do so in the near future, especially in developing countries. Using historical data on climate variation and from a survey on rural households in Vietnam, this paper has tested the hypothesis that individuals living in villages that have experienced a natural disaster behave in a more risk averse manner than individuals in otherwise like.

Our results strongly support the hypothesis that experiencing natural shocks in the past makes people more risk averse. Experimentally measured risk aversion was substantially higher for rural households who experienced more exposure to natural shocks. This indicates that such disasters not only have immediate effects on individual risk attitudes but also shape their long term preferences and survival strategies.

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Appendix I

Table 1. Risk behaviour from different lotteries and implied $\lambda^{risk} = \omega*(6{,}000^{\alpha}/L^{\beta})$, $\omega \equiv w^{+}(0.5)/w^{-}(0.5)$

Risk behavior (lottery choice category)	Percent	Implied Acceptable loss (thous. VND)	Implied λ^{risk} under different assumptions of probability weights and diminishing sensitivities for gains and losses (1)	(2)	(3)	(4)
Parameters:			ω=1 α=1 β=1	ω=1 α=0.95 β=0.92	ω=0.86 α=1 β=1	ω=0.86 α=0.95 β=0.92
1. Reject all lotteries	**68.28**	**< 2**	**> 3.00**	**>2.90**	**>2.49**	**>2.58**
2. Accept lottery **a**, reject lotteries **b** to **f**	**4.31**	**2**	**3.00**	**2.90**	**2.49**	**2.58**
3. Accept lotteries **a** and **b**, reject lotteries **c** to **f**	**10.61**	**3**	**2.00**	**2.00**	**1.72**	**1.72**
4. Accept lotteries **a** to **c**, reject lotteries **d** to **f**	**10.39**	**4**	**1.50**	**1.53**	**1.32**	**1.29**
5. Accept lotteries **a** to **d**, reject lotteries **e** to **f**	**3.73**	**5**	**1.20**	**1.25**	**1.07**	**1.03**
6. Accept lotteries **a** to **e**, reject lotteries **f**	**1.86**	**6**	**1.00**	**1.06**	**0.91**	**0.86**
7. Accept al lotteries	**0.81**	**≥ 7**	**≤ 0.87**	**≤0.92**	**≤0.79**	**≤0.73**
Median			**1.50**	**1.53**	**1.32**	**1.29**

Note: I follow the same strategy of Gächter et al (2010) in identifying sensitivity parameter. (1) benchmark parameters: no probability weighting, and no diminishing sensitivity. (2) no probability weighting, but diminishing sensitivity. (3) Probability weighting, but no diminishing sensitivity. (4) Probability weighting and diminishing sensitivity. Parameters on diminishing sensitivity are taken from Booij and van de Kuilen (2009); parameters on ω taken from Abdellaoui (2000).

Table 2. Bivariate correlation

	Risk 1	Risk 2	Risk 3	Risk 4	ARAC	Log Rainfall Variation	Log TempVariation
Risk 1 (ω=1; α=1; β=1)	1						
Risk 2 (ω=1; α=0.95; β=0.92)	1 *	1					
Risk 3 (ω=0.86; α=1; β=1)	1*	1*	1				
Risk 4 (ω=0.86; α=0.95; β=0.92)	1*	1*	0.99*	1			
Absolute Risk Aversion Coeff.	0.57*	0.57*	0.567*	0.57*	1		
Log Rainfall Variation	0.14*	0.14*	0.15*	0.15*	0.14*	1	
Log Temperature Variation	0.16*	0.16*	0.16*	0.16*	0.04	0.3*	1

Note: * Statistically significant at 5 percent.

Table 3. Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Risk aversion 1	915	3.39	1.09	0.87	4.1
Risk aversion 2	915	3.26	1.00	0.92	3.9
Risk aversion 3	915	2.63	0.75	0.79	3.1
Risk aversion 4	915	2.90	0.93	0.73	3.5
Absolute Risk Aversion Coefficient	921	0.34	0.73	-1.33	1.6
Log Rainfall variation (mm)	920	4.87	0.18	4.57	5.71
Log Temperature variation (oC)	920	0.62	0.49	-0.12	1.61
Average Rainfall 12 months (mm)	920	155.38	38.15	113.24	320.07
Average Temperature 12 months (oC)	920	24.33	2.08	18.31	27.36
Age of head	921	53.74	13.55	24	96
Age of head, squared/100	921	30.71	15.84	5.76	92.16
Year of schooling of head	921	8.11	3.31	0	13
Gender (Male:=1)	921	0.81	0.39	0	1
Married	921	0.85	0.36	0	1
Rural	921	0.97	0.16	0	1
Minority	921	0.22	0.41	0	1
Log Household income (mil VND)	920	4.00	0.85	0.59	7.91
Area of land (1000m2)	921	6.23	11.26	0.04	154.37
Land terrain (Flat:=1)	921	0.65	0.48	0	1
Land Quality (Good:=1)	921	0.03	0.17	0	1

Note: The summary statistics are weighted by household weight and calculated based on VARHS survey data.

Table 4. Baseline estimations. Log Rainfall variation

VARIABLES	(1) Risk aversion 1	(2) Risk aversion 2	(3) Risk aversion 3	(4) Risk aversion 4
Log Rainfall variation (100mm)	0.928***	0.847***	0.646***	0.790***
	(0.273)	(0.249)	(0.187)	(0.232)
Minority	0.109	0.0991	0.0677	0.0921
	(0.107)	(0.0979)	(0.0735)	(0.0914)
Age of head	0.0106	0.00987	0.00734	0.00904
	(0.0196)	(0.0178)	(0.0134)	(0.0166)
Age of head, square/100	-0.00258	-0.00254	-0.00199	-0.00223
	(0.0165)	(0.0151)	(0.0113)	(0.0140)
Rural	0.442*	0.403*	0.295*	0.375*
	(0.227)	(0.207)	(0.156)	(0.193)
Year of schooling of head	0.0106	0.00976	0.00778	0.00909
	(0.0128)	(0.0117)	(0.00871)	(0.0109)
Male	-0.236*	-0.215*	-0.160*	-0.200*
	(0.143)	(0.130)	(0.0965)	(0.121)
Married	-0.133	-0.120	-0.0872	-0.112
	(0.149)	(0.136)	(0.101)	(0.127)
Log Household income	-0.0371	-0.0340	-0.0287	-0.0319
	(0.0535)	(0.0487)	(0.0364)	(0.0455)
Occupational fixed effects	No	No	No	No
Provincial fixed effects	No	No	No	No
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.054	0.054	0.055	0.054

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 5. Baseline estimations. Log Rainfall variation

VARIABLES	(1) Risk aversion 1	(2) Risk aversion 2	(3) Risk aversion 3	(4) Risk aversion 4
Log Rainfall variation (100mm)	0.559	0.510	0.381	0.475
	(0.368)	(0.335)	(0.250)	(0.313)
Minority	0.123	0.111	0.0735	0.103
	(0.161)	(0.147)	(0.110)	(0.137)
Age of head	0.0124	0.0114	0.00831	0.0105
	(0.0197)	(0.0180)	(0.0135)	(0.0167)
Age of head, square/100	-0.00508	-0.00477	-0.00352	-0.00435
	(0.0164)	(0.0150)	(0.0112)	(0.0140)
Rural	0.516**	0.470**	0.348**	0.438**
	(0.229)	(0.209)	(0.157)	(0.195)
Year of schooling of head	0.0108	0.00989	0.00784	0.00922
	(0.0127)	(0.0116)	(0.00862)	(0.0108)
Male	-0.202	-0.184	-0.138	-0.172
	(0.142)	(0.129)	(0.0959)	(0.121)
Married	-0.169	-0.154	-0.113	-0.143
	(0.146)	(0.133)	(0.0988)	(0.124)
Log Household income	-0.00759	-0.00717	-0.00822	-0.00678
	(0.0522)	(0.0476)	(0.0355)	(0.0444)
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.124	0.124	0.124	0.124

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 6. Baseline estimations. Log Temperature variation

VARIABLES	(1) Risk aversion 1	(2) Risk aversion 2	(3) Risk aversion 3	(4) Risk aversion 4
Log Temperature variation (oC)	0.410***	0.374***	0.282***	0.349***
	(0.0973)	(0.0886)	(0.0661)	(0.0827)
Minority	0.143	0.130	0.0910	0.121
	(0.108)	(0.0982)	(0.0737)	(0.0916)
Age of head	0.00332	0.00325	0.00235	0.00285
	(0.0189)	(0.0172)	(0.0130)	(0.0161)
Age of head, square/100	0.00343	0.00293	0.00213	0.00287
	(0.0160)	(0.0146)	(0.0110)	(0.0136)
Rural	0.691***	0.629***	0.467***	0.587***
	(0.254)	(0.232)	(0.175)	(0.216)
Year of schooling of head	0.00727	0.00670	0.00549	0.00623
	(0.0124)	(0.0113)	(0.00843)	(0.0106)
Male	-0.203	-0.185	-0.138	-0.172
	(0.147)	(0.133)	(0.0994)	(0.124)
Married	-0.152	-0.138	-0.100	-0.129
	(0.153)	(0.139)	(0.104)	(0.130)
Household Income (mil.)	-0.0621	-0.0568	-0.0462	-0.0532
	(0.0518)	(0.0472)	(0.0353)	(0.0440)
Occupational fixed effects	No	No	No	No
Provincial fixed effects	No	No	No	No
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.065	0.065	0.065	0.065

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 7. Baseline estimations. Log Temperature variation

	(1)	(2)	(3)	(4)
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log Temperature variation (oC)	0.531***	0.483***	0.362***	0.451***
	(0.144)	(0.131)	(0.0976)	(0.122)
Minority	0.298*	0.271*	0.193*	0.252*
	(0.159)	(0.145)	(0.109)	(0.135)
Age of head	0.00381	0.00364	0.00249	0.00326
	(0.0193)	(0.0176)	(0.0132)	(0.0164)
Age of head, square/100	0.00159	0.00130	0.00102	0.00132
	(0.0160)	(0.0146)	(0.0110)	(0.0136)
Rural	0.806***	0.734***	0.546***	0.685***
	(0.254)	(0.231)	(0.174)	(0.216)
Year of schooling of head	0.0101	0.00923	0.00735	0.00861
	(0.0124)	(0.0113)	(0.00843)	(0.0106)
Male	-0.149	-0.136	-0.102	-0.127
	(0.147)	(0.133)	(0.0991)	(0.124)
Married	-0.181	-0.165	-0.121	-0.154
	(0.153)	(0.139)	(0.104)	(0.130)
Household Income (mil.)	-0.0258	-0.0238	-0.0206	-0.0223
	(0.0510)	(0.0464)	(0.0347)	(0.0433)
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.15	0.15	0.15	0.15

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 8. Climate variation and social trust. Adding geographic variables

	(1)	(2)	(3)	(4)
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log of rainfall variation	1.478**	1.352**	1.026**	1.258**
	(0.730)	(0.664)	(0.495)	(0.620)
Minority	0.159	0.144	0.100	0.134
	(0.168)	(0.153)	(0.115)	(0.143)
Age of head	0.0120	0.0111	0.00803	0.0102
	(0.0197)	(0.0180)	(0.0135)	(0.0167)
Age of head, square/100	-0.00523	-0.00491	-0.00360	-0.00447
	(0.0164)	(0.0150)	(0.0113)	(0.0140)
Rural	0.461**	0.420**	0.312**	0.391**
	(0.218)	(0.198)	(0.149)	(0.185)
Year of schooling of head	0.0119	0.0109	0.00865	0.0102
	(0.0127)	(0.0116)	(0.00866)	(0.0108)
Gender (Male:=1)	-0.192	-0.175	-0.132	-0.163
	(0.138)	(0.126)	(0.0932)	(0.117)
Married	-0.196	-0.179	-0.131	-0.166
	(0.146)	(0.133)	(0.0990)	(0.124)
Log Household income	-0.0167	-0.0156	-0.0152	-0.0146
	(0.0535)	(0.0487)	(0.0363)	(0.0454)
Average Rainfall (mm)	-0.00414	-0.00381	-0.00296	-0.00354
	(0.00406)	(0.00369)	(0.00275)	(0.00345)
Average Temperature (oC)	0.0283	0.0255	0.0179	0.0240
	(0.0484)	(0.0440)	(0.0327)	(0.0411)
Area of Land (1000m2)	0.00108	0.00100	0.000798	0.000926
	(0.00301)	(0.00274)	(0.00205)	(0.00255)
Land terrain (Flat:=1)	-0.0424	-0.0386	-0.0195	-0.0352
	(0.0924)	(0.0842)	(0.0635)	(0.0786)
Land quality	0.133	0.118	0.0829	0.112
	(0.154)	(0.140)	(0.104)	(0.131)
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.14	0.14	0.14	0.14

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 9. Climate variation and social trust. Adding geographic variables

VARIABLES	(1) Risk aversion 1	(2) Risk aversion 2	(3) Risk aversion 3	(4) Risk aversion 4
Log of temperature variation	0.564***	0.514***	0.383***	0.480***
	(0.149)	(0.135)	(0.101)	(0.126)
Minority	0.268	0.243	0.174	0.227
	(0.169)	(0.154)	(0.115)	(0.144)
Age of head	0.00667	0.00625	0.00446	0.00569
	(0.0192)	(0.0176)	(0.0132)	(0.0164)
Age of head, square/100	-0.00111	-0.00117	-0.000838	-0.000978
	(0.0161)	(0.0147)	(0.0110)	(0.0137)
Rural	0.709***	0.646***	0.481***	0.603***
	(0.220)	(0.200)	(0.150)	(0.187)
Year of schooling of head	0.0119	0.0109	0.00866	0.0102
	(0.0125)	(0.0114)	(0.00850)	(0.0106)
Gender (Male:=1)	-0.160	-0.145	-0.110	-0.136
	(0.143)	(0.130)	(0.0964)	(0.121)
Married	-0.193	-0.176	-0.129	-0.164
	(0.151)	(0.138)	(0.102)	(0.128)
Log Household income	-0.0255	-0.0236	-0.0211	-0.0221
	(0.0517)	(0.0471)	(0.0351)	(0.0439)
Average Rainfall (mm)	0.00587**	0.00535**	0.00398**	0.00499**
	(0.00286)	(0.00261)	(0.00196)	(0.00243)
Average Temperature (oC)	0.128**	0.117**	0.0871**	0.109**
	(0.0496)	(0.0452)	(0.0339)	(0.0422)
Area of Land (1000m2)	0.000706	0.000657	0.000531	0.000605
	(0.00298)	(0.00271)	(0.00203)	(0.00253)
Land terrain (Flat:=1)	-0.0800	-0.0729	-0.0450	-0.0672
	(0.0918)	(0.0837)	(0.0631)	(0.0781)
Land quality	0.147	0.131	0.0929	0.123
	(0.160)	(0.146)	(0.108)	(0.136)
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	913	913	913	913
Number of commune clusters	373	373	373	373
R-squared	0.14	0.14	0.14	0.14

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 10. Climate variation and risk aversion by female

	Female			
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log rainfall variation	1.853	1.694	1.260	1.573
	(1.344)	(1.223)	(0.911)	(1.141)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	154	154	154	154
Number of commune clusters	126	126	126	126
R-squared	0.21	0.21	0.21	0.21

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 11. Climate variation and risk aversion by female

	Female			
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log temperature variation	0.0733	0.0672	0.0591	0.0633
	(0.334)	(0.304)	(0.226)	(0.283)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	154	154	154	154
Number of commune clusters	126	126	126	126
R-squared	0.2	0.2	0.2	0.2

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 12. Climate variation and risk aversion by Male

	Male			
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log rainfall variation	1.415*	1.295*	0.988*	1.205*
	(0.795)	(0.723)	(0.540)	(0.675)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	759	759	759	759
Number of commune clusters	350	350	350	350
R-squared	0.17	0.17	0.17	0.17

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 13. Climate variation and risk aversion by Male

	Male			
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
Log temperature variation	0.675***	0.615***	0.457***	0.574***
	(0.154)	(0.140)	(0.105)	(0.131)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Number of observations	759	759	759	759
Number of commune clusters	350	350	350	350
R-squared	0.17	0.17	0.17	0.17

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 14. Climate variation and absolute risk aversion

VARIABLES	Absolute risk aversion coefficient			
	Log Rainfall variation (100mm)		Log Temperature variation (oC)	
Climate variation	0.607***	0.890***	0.101	0.190
	(0.165)	(0.257)	(0.0681)	(0.116)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	No	No	No	No
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	No	Yes	No	Yes
Number of observations	919	919	919	919
Number of clusters	373	373	373	373
R-squared	0.057	0.107	0.04	0.09

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Table 15. Climate variation and absolute risk aversion

VARIABLES	Absolute risk aversion coefficient			
	Log Rainfall variation (100mm)		Log Temperature variation (oC)	
Climate variation	0.815***	1.530***	0.185**	0.237**
	(0.271)	(0.520)	(0.0724)	(0.116)
Individual controls	Yes	Yes	Yes	Yes
Geographical control	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	No	Yes	No	Yes
Number of observations	919	919	919	919
Number of clusters	373	373	373	373
R-squared	0.08	0.124	0.08	0.12

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

Appendix II

1. Risk aversion and Climate variation. Rainfall and Temperature regression

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
	Log Rainfall variation				Log temperature variation			
Climate variation	0.00803*	0.00735*	0.00556*	0.00684*	0.240***	0.218***	0.163***	0.204***
	(0.00433)	(0.00394)	(0.00293)	(0.00368)	(0.0575)	(0.0523)	(0.0391)	(0.0489)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	913	913	913	913	913	913	913	913
Number of clusters	373	373	373	373	373	373	373	373
R-squared	0.14	0.14	0.14	0.14	0.17	0.17	0.17	0.17

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.

2. Risk aversion and Climate variation. Logistic regression

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4	Risk aversion 1	Risk aversion 2	Risk aversion 3	Risk aversion 4
	Log Rainfall variation				Log temperature variation			
Climate variation	2.6*	2.6*	2.6*	2.6*	1.46***	1.46***	1.46***	1.46***
	(1.41)	(1.41)	(1.41)	(1.41)	(0.37)	(0.37)	(0.37)	(0.37)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Number of Observations	913	913	913	913	913	913	913	913
Number of clusters	373	373	373	373	373	373	373	373
Pseudo R-squared	0.07	0.07	0.07	0.07	0.09	0.09	0.09	0.09

Notes: ***, ** and * indicates significance level of 1%, 5% and 10% respectively against a two sided alternative. Clustered standard errors are in round brackets.