Air pollution and perception-based averting behaviour in the Jinchuan mining Area, China
A structural equation modeling (SEM) approach

Abstract

We present a simultaneous equations, perception-based averting behaviour model of health risks caused by air pollution, with application to the Jinchuan mining area, China. Three types of averting behaviour and two types of perceived health risk are distinguished. The estimations show that the total willingness to pay for air quality improvement is 5.6% of net annual household income. Hence, air quality improving investments would substantially decrease health risk averting cost. For the short and medium run daily disclosure of air quality and risk protection measures would be appropriate policy handles.

Keywords: Air Pollution, Environmental Knowledge, Perceived Health Risk, Structural Equation Model, Latent Variable., Willingness To Pay, China.

1. Introduction

During the last three decades, China has experienced very rapid economic growth and has become an engine of the global economy. However, its rapid growth has also resulted in serious air pollution. For example, suspended particulate matter (PM) and sulfur dioxide (SO$_2$) are far above the World Health Organization’s Air Quality Guidelines in most Chinese cities (WHO, 2005; Chan and Yao, 2008). OECD (2012) pointed out that the death rate caused by air pollution in China rose by 5% between 2005 and 2010 and that the economic cost of air pollution in China in 2010 was about US$ 1.4 trillion.
As a typical mining city, Jinchuan’s economy is dominated by mining and processing of nickel which have substantially contributed to its local economic development. Particularly, 50% of Jinchuan’s working population is employed by the nickel industries. However, these industries have also caused serious environmental issues, especially air pollution. Jinchuan is one of the ten most seriously air polluted cities in China (Wei, 2008). Suspended particles, sulfur dioxide, chlorine gas and carbon dioxide are the main health related pollutants (Wei, 2008; Huang et al., 2009).

The objective of this paper is to analyze the responses of the inhabitants of Jinchuan to the health risks related to air pollution in their region and to estimate their preference for air quality improvement. For that purpose, we apply the household production function approach introduced by Grossman (1972), particularly the health related averting behavior model.

Traditionally, the costs of averting actions and socio-economic characteristics (e.g. age and education) are taken to explain averting behaviors. However, many researchers have pointed out that socio-psychological factors, particularly knowledge and perception, are also needed for adequate modeling of averting behavior (Cottrell, 2003; Menon et al., 2008; Temme et al., 2008; Folmer, 2009; Folmer and Johansson-Stenman, 2011; Hammitt, 2013).\footnote{Pattanayak and Pfaff (2009), amongst others, showed that social and psychological factors can be included into traditional household production functions.} For example, Cottrell (2003) found that environmental attitudes explain 23.8% of the total variance in people's environmental behavior. Folmer (2009) argued that omission of systematic psychological or social factors leads to model under-specification and thus to biased estimators of all the
model coefficients, if the omitted systematic explanatory variables are correlated with an included explanatory variable and the explanatory variables are mutually correlated, which is virtually always the case in the social sciences including (environmental) economics.

This paper provides an empirical application of the traditional household production function model, particularly the averting behaviour model, extended with psychological factors. In addition to the analysis of the various types of averting behavior to reduce perceived health risk, it estimates the willingness to pay (WTP) for health risk reduction.

The paper is organized as follows. Section 2 outlines the perception-based averting behavior model (PABM). Section 3 briefly presents the methodology (structural equation model with latent variables, SEM) and Section 4 describes the survey, the data and the empirical results. Section 5 presents the conclusions and policy recommendations.

2. The conceptual perception-based averting behaviour model (PABM)

Before presenting the conceptual model, we note that an averting behavior analysis is likely to give a distorted picture of averting behaviour and biased estimators of the impacts of its determinants when it is based on expert or objective risk measures
rather than on perception of risk (amongst others Um et al., 2002; Nauges and Van Den Berg, 2009; Richardson et al. 2012). Specifically, laboratory experiments have frequently indicated that individuals tend to underestimate objective high-risk events and overestimate objective small-risk events. Consequently, their subjective, perceived risk strongly differs from objective risk (Riddel and Shaw, 2006; Shaw and Woodward, 2008). Below we develop and estimate a perception-based averting behaviour model framework. We also consider respondents’ environmental knowledge as a determinant of risk perception. The inclusion of the latter is supported by inter alia Abdalla et al. (1992) who valued the economic costs of groundwater degradation to households with the averting behaviour method in a south-eastern Pennsylvania community. The author found that households' knowledge of contamination significantly influences their risk perception and averting actions. Other studies that argue that environmental knowledge should be included in behavioral studies are Frick et al. (2004); Duerden and Witt (2010) and Lee (2010).

Below we present the definitions of the variables in the conceptual model, discuss their relationships and the expected signs of the impacts, based on a literature review and on consultations with experts on environmental problems and protection in Jinchuan. Note that since the literature on the relationship between averting behaviour and perceived health risk caused by air pollution is limited, we have expanded the scope of the literature review by also including some researches on the relationship between averting behaviour and other forms of environmental risks than air pollution. Since several of the relationships in Figure 1 are well-known or intuitively clear, we only present a brief discussion of the less familiar aspects of the conceptual model.
The conceptual PABM is summarized in Figure 1.

**FIGURE 1: Conceptual Framework of the Perception-based Averting Behaviour Model (PABM)**

*Note*: (i) Expected signs within brackets  
(ii) Variables in italics are latent variables. See note 2 for a definition

**Averting behaviour** (*AVB*)

Based on the literature review, we distinguish the following three types of observed

* Averting behaviour which are taken as indicators of the latent variable *Averting*
behaviour.²

- Improving the quality of the air inhaled; for example, by installing mechanical air filters, or growing air filtering plants at home, or wearing mask outdoors (Bresnaha et al. 1997; Richardson et al., 2012).

- Taking preventive or curing medication or food (Dickie and Gerking. 1991; Richardson et al., 2012).

- Adjusting activities, i.e. limiting, rescheduling, or otherwise changing planned outdoor leisure activities and spending more time indoors, (Bresnahan et al, 1997; Eiswerth et al., 2005).

We expect the impacts of the explanatory variables on the three types of Averting behavior to have the same signs. The unknown magnitudes, however, may differ. Therefore, we do not discuss the expected impacts of the determinants on each type separately.

² Oud and Folmer (2008) define latent variables as referring to phenomena that are supposed to exist but cannot be directly observed. However, they can be measured by indicators (observed or manifest variables).
**Perceived health risk (PHR)**

Following Menon et al. (2008), we define *Perceived health risk* as the knowledge based subjective likelihood (judgement) of the occurrence of a negative event related to the health of a person or a group of persons, over a specified spell of time. *Perceived health risk* is assumed to have a positive impact on *Averting behaviour*. Support for this hypothesis is given by *inter alia* Talberth et al. (2006) who added perceived wildfire risk to their conventional averting behaviour model and found that it had a significant impact on individuals’ aversion to catastrophic wildfire risk in the East Mountains area of New Mexico. See also Um et al. (2002); Nauges and Van Den Berg (2009); Richardson et al. (2012). *Perceived health risk* is a latent variable measured by five indicators (see Figure 2).

**Environmental knowledge (EK)**

*Environmental knowledge* is defined as an individual’s cumulative body of knowledge of the interdependency between human society and its natural environment (Berkes et al., 2000). Knowledge is generally considered a prerequisite of other psychological factors such as value and attitude (Kollumuss and Agyeman, 2002), and, especially, risk perception (Peters and Slovic, 1996). Following Kitzmüller (2009) in their analysis of the determinants of people’s pro-environmental behaviour, we assume that *Environmental knowledge* positively – though indirectly, via *Perceived health risk* - impacts on *Averting behavior*. We also assume a reverse effect: *Perceived health risk* positively impacts on one’s *Environmental knowledge*. That is, high perceived risk will induce people to collect more and better information about the risk (Osberghaus and Reif, 2010). We measure *Environmental knowledge* by means of eight items. See
Exogenous variables

Age (AGE)

In the literature review, we found substantial empirical evidence that Age impacts on Avoiding behavior, but there is uncertainty about the sign. Eisworth et al. (2005) and Atreya (2008) found positive impacts; Abrahams et al. (2000) and Talberth et al. (2006) negative effects. Given these opposing outcomes, we leave the sign of the impact of Age on Avoiding behavior an open question. Following Aminrad et al. (2011) and Al Khamees and Alamari (2009), who argued that older individuals commonly have more experience with environmental problems in their home region, we assume that Age positively influences Environmental knowledge. We expect Age to indirectly impact Perceived health risk via Environmental knowledge. We distinguish seven Age classes (see Table 1 for details).

Family size (FS)

There is empirical evidence that Family size impacts Avoiding behavior, but again, the expected impact is ambiguous. Positive and negative impacts are found by Vásquez (2014) and Talberth et al. (2006), respectively. We also include Family size in the Perceived health risk equation. The rationale is that a larger family has larger capacity to absorb risks. For instance, the larger the number of family numbers implies more options for burden sharing in the case of illness. Empirical evidence of a negative sign is provided by Ajetomobi and Binoumote (2006) and Amaefula et al., (2012). We define Family size as the number of family members who live in the same house (see Table 1).
We define *Ability* as the capacity to adequately understand problems and to act accordingly (Cropley and Dehn, 1996). *Ability* which is taken as a latent variable, can be measured via indicators such as income and education (see *inter alia* Furnham et al. (2002), Mackay (2006), and Finnie and Mueller (2008) for overviews and details). Specifically, people with higher *Ability* commonly achieve higher educational levels and earn more than individuals with lower *Ability* (Smedley and Syme, 2001). Thus, we assume that *Ability* has a positive impact on *Averting behaviour*. This assumption is supported by *inter alia* McConnell and Rosado (2000) and Abrahams et al. (2000).

We also postulate that *Ability* positively impacts on *Environmental knowledge* and *Perceived health risk*. That is, people with higher *Ability* commonly have a better understanding of environmental issues and can make better assessment of risks (Diamantopoulos et al., 2003; Khan et al., 2009; Lee et al. 2009; Ogunbode and Arnold, 2012). Education is measured as the highest degree obtained and net income by classes (see Table 1 for details).

**Proximity to the pollution source (PPS)**

We assume that the concentration of air pollutants decreases by distance from the source (smelting plant). Therefore, people who live close to the smelting plants are more susceptible to illnesses and may be more likely to take averting actions than those who live further away. This assumption is supported by Devi et al. (2010). We also hypothesize that Proximity to the pollution source negatively influences

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3 Housing allocation in Jinchuan is not based on supply and demand. Rather, it is the local government and the mining company that allot relatively cheap housing to their employees (source: private communication with local administrators). Thus, proximity to the pollution source is considered as an exogenous variable in this paper.
Perceived health risk. The reason is that respondents who live further away from the smelting plants are less exposed to air pollution than those who live nearby. This assumption is supported by inter alia Bickerstaff and Walker (2001) and Riddel and Shaw (2006). We distinguish three proximity categories: (1) SAP (serious air pollution), (2) MAP (medium air pollution) and (3) LAP (light air pollution).

Family health experience (FHE)

People who have experienced adverse health effects - from air pollution or otherwise - are likely to be more concerned about air pollution and to take more precautions to protect themselves and their family members than those who have not. Therefore, we expect that individuals who themselves or whose family members have experienced health problems tend to take averting actions. This hypothesis is supported by Khan (2012) and Dickie and Gerking (1991). We also postulate a positive impact of Family health experience on Perceived health risk. Support for this hypothesis is provided by inter alia Howell et al. (2003) and Walker (1999). We measure Family health experience by means of a dichotomous variable which takes the value 1 if the respondent, or one or more of their family members, have been hospitalized for cardiovascular or respiratory diseases, and 0 otherwise (see Table 1).

Work environment (WE)

We hypothesize an indirect impact of Work environment on Averting behaviour via Environmental knowledge and Perceived health risk. Since the Jinchuan mining company (JMC) is the source of Jinchuan's environmental issues, we expect JMC employees to have better knowledge of Jinchuan's environmental issues than non-JMC individuals. The reason is that JMC employees, especially miners and
3. Methodology (SEM)

A basic feature of the Conceptual Model depicted in Figure 1 is that there are several direct and indirect paths from socio-economic and demographic variables to Environmental knowledge, Perceived health risk and Averting behaviour. To capture the direct and indirect paths as well as the cycles in the Conceptual Model, we need simultaneous-equations models (e.g. Greene, 2003). Another feature of the Conceptual Model is that it contains both observed and latent variables within one model framework. Both features of the Conceptual Model can be handled by the class of Structural Equation Models with latent variables (SEMs) (Jöreskog and Sörbom, 1996).

A SEM is made up of three sub-models: two measurement models and the structural model (Jöreskog and Sörbom, 1996). Specifically:

\[ y = \Lambda_y \eta + \varepsilon \quad \text{with} \quad \text{cov} (\varepsilon) = \Theta_{\varepsilon} \quad (1) \]

\[ x = \Lambda_x \xi + \delta \quad \text{with} \quad \text{cov} (\delta) = \Theta_{\delta} \quad (2) \]

\[ \eta = B\eta + \Gamma \xi + \zeta \quad \text{with} \quad \text{cov} (\xi) = \Phi, \quad \text{cov} (\zeta) = \Psi \quad (3) \]
Equations (1) and (2) are the measurement models that describe the relations between the latent variables and their indicators, i.e. they present operational definitions (correspondence statements) of the latent variables. Specifically, \( y \) and \( x \) are \((p \times 1)\) and \((q \times 1)\) vectors of observed endogenous and exogenous variables, respectively, and \( \eta \) and \( \xi \) \((m \times 1)\) and \((n \times 1)\) vectors of latent endogenous and latent exogenous variables, respectively. \( \Lambda_y \) is a \((p \times m)\) matrix of loadings of \( y \) on \( \eta \); \( \Lambda_x \) a \((q \times n)\) matrix with the loadings of \( x \) on \( \xi \). \( \Theta_{\epsilon} (p \times p) \) and \( \Theta_{\delta} (q \times q) \) are covariance matrices of \( \epsilon \) and \( \delta \) which are the measurement errors of \( y \) and \( x \), respectively.

Equation (3) is the structural model which specifies the relationships between the latent variables. \( B \) is an \((m \times m)\) matrix that contains the structural relationships among the latent endogenous variables, \( \Gamma \) an \((m \times n)\) matrix of the impacts of the exogenous latent variables on the endogenous latent variables, and \( \zeta \) is a random \((p \times 1)\) vector of errors with covariance matrix \( \Psi (p \times p) \). The covariance matrix of \( \xi \) is \( \Phi (n \times n) \) \(4\). For details on identification, estimation, testing and model modification of a SEM, we refer to Jöreskog and Sörbom (1996).

The use of SEM allows a closer correspondence between theory (which is formulated in terms of theoretical constructs) and empirics (which is based on observed variables) (Oud and Folmer, 2008). It furthermore reduces attenuation bias (bias towards zero) in the structural model because the measurement errors of the explanatory variables are purged of the true latent variables in the measurement model. Finally, the use of SEM

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4 It is possible to include intercepts in the measurement models and in the structural model. However, below we standardize the variables. Note also that directly observed variables can be included in the structural model by specifying an identity relationship between a latent variable and its indicator in its measurement model and fixing the measurement error at zero.
reduces multi-collinarity because strongly correlated observed variables are linked to a smaller number of (usually one) latent variable(s) in the measurement model. In the structural model the latent variables are substituted for the observed variables (Folmer, 1986).

In terms of equations (1)-(3), the conceptual model (Figure 1) reads:

**Measurement models**

\[
\begin{bmatrix}
    \lambda^y_{11} & 0 & 0 \\
    \vdots & \vdots & \vdots \\
    \lambda^y_{31} & \lambda^y_{42} & 0 \\
    0 & \lambda^y_{52} & 0 \\
    \vdots & \vdots & \vdots \\
    0 & \lambda^y_{82} & \lambda^y_{93} \\
    0 & 0 & \lambda^y_{103} \\
    \vdots & \vdots & \vdots \\
    0 & 0 & \lambda^y_{163}
\end{bmatrix}
\times
\begin{bmatrix}
    \text{AVB} \\
    \text{PHR} \\
    \text{EK}
\end{bmatrix}
+
\begin{bmatrix}
    \epsilon_1 \\
    \epsilon_2 \\
    \epsilon_3 \\
    \epsilon_4 \\
    \epsilon_5 \\
    \epsilon_6 \\
    \epsilon_7 \\
    \epsilon_8 \\
    \epsilon_9 \\
    \epsilon_{10} \\
    \epsilon_{11} \\
    \epsilon_{12} \\
    \epsilon_{13} \\
    \epsilon_{14} \\
    \epsilon_{15} \\
    \epsilon_{16}
\end{bmatrix}
\times
\begin{bmatrix}
    \text{AVB} \\
    \text{PHR} \\
    \text{EK}
\end{bmatrix}
\]

\((4)\)

**The structural model**

\[
\begin{bmatrix}
    \lambda^x_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    \lambda^x_{21} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 100000 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 010000 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 001000 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 000100 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 000010 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 000001 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\times
\begin{bmatrix}
    \text{EDU} \\
    \text{FS} \\
    \text{AGE} \\
    \text{FHE} \\
    \text{MAP} \\
    \text{SAP} \\
    \text{NMS} \\
    \text{MS}
\end{bmatrix}
+
\begin{bmatrix}
    \delta_1 \\
    \delta_2 \\
    \delta_3 \\
    \delta_4 \\
    \delta_5 \\
    \delta_6 \\
    \delta_7 \\
    \delta_8 \\
    \delta_9 \\
    \delta_{10} \\
    \delta_{11} \\
    \delta_{12} \\
    \delta_{13} \\
    \delta_{14} \\
    \delta_{15} \\
    \delta_{16}
\end{bmatrix}
\times
\begin{bmatrix}
    \text{AB} \\
    \text{FS} \\
    \text{AGE} \\
    \text{FHE} \\
    \text{MAP} \\
    \text{SAP} \\
    \text{NMS} \\
    \text{MS}
\end{bmatrix}
\]

\((5)\)
4. Empirical results

4.1 Survey and data collection

The data analyzed in this paper come from a household survey that was conducted in
August 2012. A stratified random sample of 800 respondents, aged between 21 and
78, was drawn. Specifically, Jinchuan was divided into three sub-areas based on the
level of air pollution (corresponding to the distance from the smelting plant): severely
polluted, moderately polluted and lightly polluted (Wei, 2008; JEQMR, 2011). Since
the questionnaire was eight pages long, face-to-face interviews were held. The
interviewees in each area were randomly selected in proportion to its total population
size. Particularly, per hundred households, 1–2 households were randomly selected
which gave a total sample size of 800. The response rate was about 90% which is
high, but not uncommon in China (see inter alia Grant et al., 2004; Zhang et al., 2008;
Wah et al., 2012;). Interviewees were family heads, usually husbands, with ‘Hukou’,
i.e. permanent residence permit, who had lived in Jinchuan for at least ten years.

Prior to the survey, a group of college students at Gansu Non-ferrous Metallurgy
College in Jinchuan, who understood the environmental issues in Jinchuan and the
local language, were selected and trained to be interviewers. Moreover, a pilot survey
was carried out on the basis of which the questionnaire was adjusted, corrected and

\[
\begin{bmatrix}
\text{AVB} \\
\text{PHR} \\
\text{EK}
\end{bmatrix} =
\begin{bmatrix}
\beta_{12} & 0 \\
0 & \beta_{23} \\
0 & \beta_{32}
\end{bmatrix}
\begin{bmatrix}
\text{AVB} \\
\text{PHR} \\
\text{EK}
\end{bmatrix} +
\begin{bmatrix}
Y_{11}Y_{12}Y_{13}Y_{14}Y_{15}Y_{16} & 0 & 0 \\
Y_{21}Y_{22} & 0 & Y_{24}Y_{25}Y_{26} & 0 & 0 \\
Y_{31} & 0 & Y_{33} & 0 & 0 & Y_{37}Y_{38}
\end{bmatrix}
\begin{bmatrix}
\text{AB} \\
\text{FS} \\
\text{AGE} \\
\text{PHE} \\
\text{MAP} \\
\text{SAP} \\
\text{NMS} \\
\text{MS}
\end{bmatrix} +
\begin{bmatrix}
\zeta_{1} \\
\zeta_{2} \\
\zeta_{3}
\end{bmatrix}
\]
re-worded.

4.2 Descriptive statistics

Of the 800 filled out questionnaires, 41 (5.12%) were rejected because they were incomplete. There was no evidence of non-random drop out. Descriptive statistics are presented in Table 1, Figures 2 and 3.

<table>
<thead>
<tr>
<th>TABLE 1: Descriptive Statistics of Sample and Population</th>
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<td>Variables</td>
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<td>Age (AGE)</td>
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<td>Family size (FS)</td>
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<td>Family health experience (FHE)</td>
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<td><strong>Averting behaviour</strong></td>
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<td>AVBE1 (CNY per year)</td>
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<td>AVBE2 (CNY per year)</td>
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<td>AVBE3 (hours per week)</td>
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</table>

| Notes: (i) The population statistics on Family health experience and on the indicators of Averting behaviour are not available. The population distribution of Household income is not available. However, the population average is 4315 CNY per month; the sample average is . (ii) AVBE1: annual household expenditure on air filters and plants at home, or on face mask. AVBE2: annual household expenditure on special foods or medicines or seeing doctors. AVBE3: reduction of outdoor activities (hours per week) including limited, rescheduled, or otherwise postponed planned leisure time. Family size: number of family members living in the same house. Family health experience: 1 if the respondent or one or more of the family members has/have been hospitalized for cardiovascular diseases (e.g., hypertension, heart attack, chest pain, arrhythmia and myocardial infraction) or respiratory diseases (e.g., upper respiratory tract infection, bronchiits, pneumonia, asthma, and lung cancer), 0 otherwise. The differences between the sample and the population in Table 1 with respect to age,
income and education are caused by the fact that the sample is drawn from the sub-population of heads of households aged 21-78.

![Figure 2: Distribution of the Indicators of Perceived health risk](image)

**FIGURE 2:** Distribution of the Indicators of Perceived health risk

Note: PHR1: What is the average number of days per week during the past year you perceived the air in Jinchuan to be heavily polluted? PHR2: In my perception, Jinchuan’s air pollution increases the possibility of suffering from respiratory illnesses. PHR3: In my perception, Jinchuan’s air pollution increases the possibility of suffering from cardiovascular illnesses. PHR4: In my perception, Jinchuan’s air pollution increases the possibility of suffering from lung cancer. PHR5: In my perception, Jinchuan’s air pollution increases the possibility of suffering from death.

Five indicators (relating to two domains) were used to measure *Perceived health risk* caused by air pollution. For the first domain, respondents were asked to answer the question (PHR1): *what is the average number of days per week you perceived the air in Jinchuan to be heavily polluted during the past year?* Figure 2 shows that the percentages of respondents who answered ‘heavily polluted’ (4 or more days a week) and ‘lightly polluted’ (0 or 1 day a week) were 18.3% and 19.6%, respectively. The majority (62.1%) answered ‘medium polluted’ (2 or 3 days a week). Regarding the second domain, four major types of health problems were presented to the respondents. They were questioned about their perception that Jinchuan’s air pollution
increased the probability of suffering from four well-known health problems. A five-point scale was used with 1 indicating ‘strong negative perception’ and 5 ‘strong positive perception’. The results show that respiratory illnesses (95.9%) were most frequently mentioned, followed by lung cancer (83.6%), cardiovascular illnesses (75%) and death (73.1%).

We examined the respondents’ knowledge of environmental issues by means of eight indicators (Figure 3). Each indicator is measured on a five-point scale ranging from 1 (Certainly not) to 5 (Certainly). The first four indicators (EK1-EK4) test a respondent’s knowledge of Jinchuan’s general environmental issues and their causes. Figure 3 shows that over 80% of the respondents ‘certainly acknowledged’ or ‘acknowledged’ that air pollution, industrial solid waste and water pollution are environmental issues in Jinchuan. Moreover, 93.2% ‘acknowledged’ or ‘certainly
acknowledged’ that Jinchuan’s environmental problems are mainly caused by local industrial activities (EK4). The final four indicators (EK5-EK8) specify the main air pollutants. Figure 3 shows that the majority (over 55%) of the respondents either ‘certainly acknowledged’ or ‘acknowledged’ that chlorine gas, sulfur dioxide, suspended particles and carbon dioxide are the main pollutants.

### 4.3 The estimated SEM

Before going into detail, we note that the SEM estimates are standardized or beta coefficients that give the standard deviation change in a dependent variable due to a standard deviation change of an explanatory variable. Standardized coefficients are directly comparable, as the scales of the explanatory variables are irrelevant.

As mentioned above, *Averting behaviour* is a latent variable measured by three indicators: AVBE1, AVBE2 and AVBE3 (see Table 1 for definitions). To obtain percentage changes of the first two indicators, we took natural logarithms of their scores. We re-labeled them as AVB1 and AVB2, respectively. As some outcomes of AVBE1 and AVBE2 are equal to zero, we increased all scores by 1. Hence, AVBi=ln (AVBEi+1), i=1, 2. Note that we also re-labeled AVBE3 as AVB3 but did not log-transform AVBE3.

As described in the previous section, several observed variables, notably the indicators of *Perceived health risk* and *Environmental knowledge*, are ordinal or dichotomous. Moreover, the indicators of *Environmental knowledge* are highly skewed and non-normally distributed (See Figure 3) Therefore, WLS based on the

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5 Additional output including the variance-covariance matrices of the measurement models and the matrix of modification indices is available upon request from the first author.
matrix of polychoric correlations, was employed to estimate model (4)-(6).\textsuperscript{6}

As a first step, we estimated the full Conceptual Model presented in Section 2 and in equations (4)-(6), denoted Initial Model. In the estimated initial averting behaviour measurement models (Appendix A.1), the reliability of AVB3 was very low (0.01). Following Bollen (1989), we took this as an indication that ABV1 and ABV2 on the one hand, and ABV3 on the other, measure different dimensions of *Averting behaviour*.\textsuperscript{7} In addition to the reliabilities, there are substantive arguments for this interpretation. Specifically, whereas AVB1 and AVB2 relate to expenditures (on masks, purifying equipment or plants or food or medicine), AVB3 measures activities. Therefore, we split the latent variable *Averting behaviour* into an expenditure latent variable (*Expenditure* for short) measured by the indicators AVB1 and AVB2, and an activities reduction latent variable (*Reduction*) measured by AVB3.

The reliability of PHR1 was also very low (0.02) (Appendix A.1) indicating that it also measured a different dimension than the other indicators. Therefore, we split the latent variable *Perceived health risk* into perceived health risk caused by the intensity of exposure (*Exposure*), measured by PHR1, and perceived health risk caused by the hazardousness of pollutants (*Hazardousness*), measured by PHR2-5. Note that this split is supported by Sjöberg et al. (2004) and Egondi et al. (2013).

Another outcome of the estimated Initial Model was that several explanatory variables of *Expenditure* and *Reduction* were highly insignificant. We deleted the variables with insignificant coefficients in a stepwise procedure starting with the one with the largest

\textsuperscript{6} Note that latent variables are unobservable and thus have no measurement scale. To render the model identified and to make the parameters interpretable, we assigned measurement scales to the latent variables by fixing their variances (at 1). See Jöreskog and Sörbom (1996) for details.

\textsuperscript{7} Note that the reliability of AVB2 is a border case.
p-value (stepwise backward elimination). This gave the Final Model. (For illustrative purposes, we include also some of the insignificant variables in the Final Model (see Table 4).) Below we discuss the latter.

The goodness-of-fit indices indicate that the Final Model has satisfactory fit which all meet their cut off values given in brackets. $\chi^2$/DF=2.22 (3), Goodness-of-fit index =0.98 (0.90), Adjusted goodness-of-fit index=0.97 (0.90), Standardized root mean square residual=0.027(0.08), Root mean square error of approximation=0.41 (0.05)). (see Bentler and Bonnet,1980; Jöreskog and Sörbom, 1993; Byrne, 2013; Schreiber et al., 2006; Tabachnick and Fidell, 2007; Ouyang, 2009 for details).

The Final estimated measurement models are presented in Table 2. For each indicator, we present its loading, standard error and reliability ($R^2$), respectively. Table 2 indicates that the loadings of all indicators are significant at 1% or less.

### TABLE 2: Measurement Models

<table>
<thead>
<tr>
<th>Latent variables</th>
<th>Indicators</th>
<th>Coefficient</th>
<th>Standard errors</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expenditure</td>
<td>AVB1</td>
<td>0.36</td>
<td>0.12</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>AVB2</td>
<td>0.28</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>Reduction</td>
<td>AVB3</td>
<td>1.00</td>
<td>0.02</td>
<td>1.00</td>
</tr>
<tr>
<td>Exposure</td>
<td>PHR1</td>
<td>1.00</td>
<td>0.02</td>
<td>1.00</td>
</tr>
<tr>
<td>Hazardousness</td>
<td>PHR2</td>
<td>0.6</td>
<td>0.03</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>PHR3</td>
<td>0.52</td>
<td>0.03</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>PHR4</td>
<td>0.62</td>
<td>0.03</td>
<td>0.38</td>
</tr>
</tbody>
</table>
The structural model is presented in Table 3. It shows that Exposure positively and significantly induces Reduction.\(^8\) That is, the more days a week an individual perceives the air to be heavily polluted, the more this person restricts outdoor activities. The impact of Exposure on Expenditure on the other hand, was highly insignificant and deleted from the Initial Model. Apparently, Expenditure is not seen as a cure for Exposure. The intuition is that Exposure relates to outdoor air quality and Expenditure to purification of indoor air quality (via filtering equipment and plants at home)\(^9\) and to the consequences of exposure (via medication, food and medical consultation) but not to Exposure itself. Moreover, the effects of medication and food materialize over time whereas Exposure is instantaneous. Reduction on the other hand, is adequate with respect to Exposure because it immediately reduces the cause of the perceived risk, and because of ease of application. The structural model furthermore shows that Hazardousness positively impacts Expenditure whereas its impact on Reduction was highly insignificant and thus was deleted from the Initial Model. The intuition is that food and medicines mitigate the impacts of hazardous

---

8 The R squares of Reduction and Exposure are low. Note that low R-squares are quite common in cross section analyses in the social science. Although a low R square indicates that many other factors than the ones included in the model impact on the dependent variable, it does not necessarily mean poor estimation of the ceteris paribus relationships between the dependent variable and the explanatory variables (Wooldridge, 2012). That is, if the zero conditional mean assumption is met, then the estimator of the impacts of the explanatory variables on the dependent variable are unbiased.

9 An exception is wearing masks. However, this type of prevention is so common that it belongs to everyone’s daily outfit.
pollutants rather than their cause.

*Environmental knowledge* positively and significantly influences both types of *Perceived health risk*. The reverse effect, however, was highly insignificant and not included in the Final Model. A possible explanation for the latter is that the suffocating and pungent odor deriving from the main air pollutants of Jinchuan, particularly sulfur dioxide and chlorine gas, is sufficient evidence of the health risks that one runs. The persistence of the odor renders further knowledge acquisition redundant.

### TABLE 3: Structural Equation Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Expenditure</th>
<th>Reduction</th>
<th>Exposure</th>
<th>Hazardousness</th>
<th>EK</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Expenditure Reduction</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exposure</td>
<td>0.20***</td>
<td>(0.06)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hazardousness</td>
<td>0.15</td>
<td>(0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Environmental knowledge (EK)</td>
<td></td>
<td></td>
<td>0.13***</td>
<td>0.69***</td>
<td></td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.09)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ability (AB)</td>
<td>0.69***</td>
<td>(0.49)</td>
<td>0.03</td>
<td>0.05</td>
<td>0.10*</td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.04)</td>
<td></td>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Age (AGE)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.09***</td>
</tr>
<tr>
<td>(0.03)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family size (FS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.08***</td>
</tr>
<tr>
<td>(0.03)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family health experience (FHE)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.05</td>
</tr>
<tr>
<td>(0.03)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium air pollution (MAP)</td>
<td></td>
<td></td>
<td></td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>(0.03)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>Serious air pollution (SAP)</td>
<td></td>
<td></td>
<td></td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>(0.03)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>JMC employment not miner or smelter worker (NMS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
<tr>
<td>(0.05)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JMC miners and smelter workers (MS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.17***</td>
</tr>
<tr>
<td>(0.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.57</td>
<td>0.04</td>
<td>0.05</td>
<td>0.51</td>
<td>0.17</td>
</tr>
</tbody>
</table>

*Note: Standard errors in parenthesis. *, ** and ***: 10%, 5% and 1%, respectively.*
In line with the conceptual model, *Ability* substantially, positively and significantly influences *Expenditure* whereas its impact on *Reduction* is positive, though marginally significant. This difference in outcome is due to the fact that the purchase of purification equipment, special food or medicine requires financial outlays whereas restricting outdoor leisure activities does not have financial implications. Moreover, *Expenditure* requires knowledge of the healing effects of medicines and food. The positive impact of *Ability* on *Environmental knowledge* and *Hazardousness* supports the hypothesis that individuals with more *Ability* can acquire better understanding of the nature of environmental issues and make a better judgment of the health risk caused by the main air pollutants in the Jinchuan area.

Apart from *Environmental knowledge* and *Ability*, Family size, significantly impacts *Hazardousness*, as hypothesized. This result indicates that there is dampening of risk perception in larger families. Proximity to the pollution source measured by the dummies SAP and MAP positively influence *Exposure* and *Hazardousness*, as hypothesized, although the impact on *Hazardousness* is marginally significant. *Hazardousness* is also positively and significantly, though marginally, influenced by Family health experience indicating that a family’s health experience tends to raise awareness of and increase concerns about the health risks correlated with air pollution.

The positive effect of *Age* on *Environmental knowledge* suggests that older individuals—who in virtually all cases have spent most of their lives in Jinchuan—have better knowledge of Jinchuan’s environmental issues. *Environmental knowledge* is also positively and significantly associated with Work environment, as measured by
the dummies NMS and MS. Apparently, the workplace, particularly the mine and smelter, where knowledge of the production processes and their impacts are concentrated, provides employees opportunities to collect knowledge of Jinchuan's environmental issues.
### TABLE 4: Total and Indirect Effects

<table>
<thead>
<tr>
<th>Variables</th>
<th>Total effects</th>
<th>Indirect effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expenditure</td>
<td>Reduction</td>
</tr>
<tr>
<td><strong>Expenditure Reduction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Exposure</strong></td>
<td>0.20***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td><strong>Hazardousness</strong></td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td></td>
</tr>
<tr>
<td><strong>Environmental knowledge (EK)</strong></td>
<td>0.10</td>
<td>0.03**</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.02)</td>
</tr>
<tr>
<td><strong>Ability (AB)</strong></td>
<td>0.74***</td>
<td>0.05*</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Age (AGE)</strong></td>
<td>0.01</td>
<td>0.002*</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>Family size (FS)</strong></td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td><strong>Family health experience (FHE)</strong></td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td><strong>Medium air pollution (MAP)</strong></td>
<td>0.01</td>
<td>0.02**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>Serious air pollution (SAP)</strong></td>
<td>0.01</td>
<td>0.04**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>JMC employment not miner or smelter worker (NMS)</strong></td>
<td>0.01</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.002)</td>
</tr>
<tr>
<td><strong>Miners and smelter workers of JMC (MS)</strong></td>
<td>0.02</td>
<td>0.005*</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis. *, ** and *** : 10%, 5% and 1%
Table 4 presents the standardized indirect and total effects of all variables (endogenous and exogenous) on all endogenous variables. (An indirect effect is the effect of an endogenous or exogenous variable on an endogenous variable through intervening endogenous variables (Jöreskog and Sörbom, 1996). The total effect is the sum of the direct and indirect effects). Table 4 indicates that *Ability* has the largest positive total effect (0.74) on *Expenditure* followed by *Hazardousness*, although the latter impact is marginally significant. The total effects of the other variables on *Expenditure* are insignificant.

*Exposure* is the most important determinant of *Reduction* with a total effect of 0.20. Next is *Ability* (0.05). Although they have no direct effects on it, *Environmental knowledge*, *Age*, *Proximity* to the pollution source and *Work environment* also positively and significantly influence *Reduction*. *Environmental knowledge*, *Ability*, and *Proximity* to the pollution source are the most important determinants of *Exposure*. *Age* and *Work environment* also significantly and positively impact on *Exposure*, but their total effects are small.

The most important determinant of *Hazardousness* is *Environmental knowledge* with a total effect of 0.69. Next is *Ability* (0.35). *Age* and *Work environment* indirectly and significantly influence *Hazardousness* via *Environmental knowledge*. Serious (SAP) and medium (MAP) polluted areas also positively influence *Hazardousness* with total effects of 0.06 and 0.05, respectively, although they are marginally significant. *Family size* and *Family health experience* impact *Hazardousness* with total effects of -0.08 and 0.05, respectively, although Family health experience is marginally significant.
*Ability* is the most important determinant of *Environmental knowledge* with a total effect of 0.36. Employees of the mining company but not miners or smelter workers (NMS) and miners and smelters (MS) have better *Environmental knowledge* than individuals not affiliated with the mining company with total effects of 0.08 and 0.17, respectively. The total effect of NMS, however, is insignificant. The total effect of age is 0.09.

**TABLE 5: Total Effects of Exposure and Hazardousness on AVB1-AVB3 (standardized coefficients)**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Annual household expenditure on air filters, houseplants at home and masks. (AVB1)</th>
<th>Annual Households expenditure on special foods and medicines, and seeing doctors (AVB2)</th>
<th>Reduction of outdoor activities (hours per week) (AVB3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure</td>
<td>0.20***</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td><strong>HAZARDOUNESS</strong></td>
<td>0.05*</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis. *, ** and ***: 10%, 5% and 1%

We now turn to the calculation of the WTP for improved air quality measured by *Averting behaviour* costs induced by reduced *Perceived health risk* measured by the indicators of *Exposure* and *Hazardousness*. As a first step, we present in Table 5 the total effects of the latent variables *Exposure* and *Hazardousness* on the observed indicators AVB1-AVB3. As shown in Table 5, an increase of *Exposure* by 1 standard deviation, i.e. 2.02 days a week of severe air pollution, reduces outdoor activities by a fifth of a standard deviation of AVB3 (1.508 hours per week). For one day a week this implies a reduction of 0.75 hour (45 minutes) per week or 7 minutes per day. If we value this at the average hourly wage rate in Jinchuan (26.01 CNY per hour in 2011), we arrive at a loss of 19.51 CNY per week (26.01*0.75). Put differently, the

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10 Source: Jinchuan Statistical Yearbook (2011)
WTP for the reduction of one day a week of severely polluted air is 19.51 CNY per week per individual. For the average household of 2.95 persons this amounts to 57.6 CNY per household.

For the calculations of the impacts of the ordinal indicators PHR2-PHR5 of *Hazardousness* on expenditures on filters or plants or masks (AVB1) and special foods or medicines or seeing a doctor (AVB2), we need to transform them to the underlying unobservable continuous variables and to transform the standardized coefficients to the corresponding un-standardized coefficients. The various steps are summarized in Appendix B and the results are presented in Table 6. The table shows that the WTP for averting the common impairments of cardiovascular (PHR3) and respiratory (PHR2) illnesses are larger than those for the more rare impairment of lung cancer (PHR4) and death (PHR5). This applies to both purifying equipment or plants, and curative or preventative food or medicine. These results are in line with Bresnahan et al. (1997) who pointed out that people prefer to take more actions against common health problems than against less familiar impairments. Note that the WTP in terms of filters, masks or plants is systematically larger than that for curative or preventive food or medicine.

Table 6 and the mean values of annual expenditures on air filters (AVB1), foods or medicines (AVB2) (Table 1) indicate that a one level increase of all four indicators of *Hazardousness* will result in an increase of annual expenditure on AVB1 and AVB2 by 40 CNY\(^{11}\) (0.07% of average household income). This outcome is substantially larger than Gupta’s (2008) finding that the WTP in Kanpur, India for the reduction of air

\[^{11}\] 40 CNY = (177.59+1)*(2.91%+3.48%+2.14%+2.86%)+(344.83+1)*(1.61%+1.67%+1.03%+1.46%).
Note: 177.59 and 344.83 are mean values of AVBE1 and AVBE2, respectively. See Table 1

28
pollution to a safe level was 0.04%.

The total average WTP for improved air quality as derived from all three indicators of *Averting behaviour* (AVBE1-AVBE3) amounts to 5.6%\(^2\) of average yearly net household income (54000 CNY). This outcome is substantially larger than obtained by Murthy et al. (2003), who found that households in Delhi and Kolkata, India, are willing to pay 0.13% and 0.21% of their average household income, respectively, to reduce the level of suspended particulate matter (PM) to a safe level. Note, however, that the latter study is substantially smaller in scope in terms of pollutants considered and types of averting behavior analyzed.

To appreciate the WTP outcome for Jinchuan, it should be also noted that Jinchuan is located in a peripheral, poor region of China with average net household income of 51780 CNY per year which is far below the national annual average of 68000 CNY, Under these conditions, 5.6% is an indication that the inhabitants of Jinchuan are very concerned about the health risks caused by air pollution.

\[
12 \quad 5.6 = \frac{57.6 \text{ (CNY per week)} \times 52 \text{ weeks} + 40 \text{ (CNY per year)}}{54000 \text{ (CNY per year)}}
\]

Note: 52 weeks in a year, 54000 CNY is the average net annual household income in the sample

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**TABLE 6:** The Impacts of PHR2-PHR5 on AVB1- AVB2 (Percentage Changes) (Un-standardized Coefficients)
### 5. Summary and Conclusions

Based on a cross-sectional data set of 759 households in the Jinchuan mining area, China, we measured and analyzed perception of health risk correlated with air pollution and its impact on averting behaviour. By means of structural equation modeling with latent variables (SEM), particularly the measurement models, we identified two related, though different, dimensions of each concept. For averting behaviour the two dimensions are (i) expenditures on air purifying filters and plants, medicine or curative food, and (ii) restriction of outdoor activities. For risk perception, the dimensions are intensity of exposure and hazardousness of the pollutants, respectively. Distinguishing and modeling each of the two dimensions of both variables is needed for comprehensive understanding of the impacts of perception-based risk on averting behaviour.

We found that better perception of risk commonly drives people to take more action to mitigate the negative health effects. In addition, ability, measured by income and education, and environmental knowledge are important determinants.
The average household total WTP for improved air quality as derived from averting behaviour expenses amounts to 5.6% of average annual net household income. It follows that air quality improving investments by the mining company would substantially decrease health risk averting cost. Since such investments can only be implemented in the medium or long run, short run policy handles, such as daily disclosure of air quality to assist residents to take the right kind and level of risk reducing actions would be appropriate. For instance, information on local air quality conditions could be broadcasted, possibly in combination with the weather forecast. Suggestions about protective measures - for example, spending more time indoors - could be also made.

This study needs extension in several ways. First, the latent variables averting behaviour, perceived risk and environmental knowledge need further conceptualizing and defining. In this paper, we identified two different dimensions of the first two concepts. It is important to investigate if there are additional dimensions. Secondly, the set of test items needs re-testing, and, possibly, revision and expansion. Finally, this paper relates to a specific mining area in China. It important to understand the universality of the concepts analyzed here and their applicability in other geographical settings, notably developing and newly industrialized countries.

Appendix A: The estimated Initial model\textsuperscript{13}

<table>
<thead>
<tr>
<th>TABLE B.1: Initial Measurement Models</th>
<th>latent variables</th>
<th>Indicators</th>
<th>Coefficient</th>
<th>Standard errors</th>
<th>$R^2$</th>
</tr>
</thead>
</table>

\textsuperscript{13} The goodness-of-fit indices indicate that the Initial Model also has satisfactory fit since they all meet their cut off values given above: ($\chi^2/DF=2.41$ (3), Goodness-of-fit index =0.98 (0.90), Adjusted goodness-of-fit index=0.97 (0.90), Standardized root mean square residual=0.029(0.08), Root mean square error of approximation=0.43(0.05)).
<table>
<thead>
<tr>
<th>Variables</th>
<th>AVB</th>
<th>PHR</th>
<th>EK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averting behaviour (AVB)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived health risk (PHR)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Environmental knowledge (EK)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ability (AB)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (AGE)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family size (FS)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family health experience (FHE)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium air pollution (MAP)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Serious air pollution (SAP)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JMC employment not miner or smelter worker (NMS)</td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
<tr>
<td>Miners and smelter workers of JMC (MS)</td>
<td></td>
<td></td>
<td>0.15</td>
</tr>
<tr>
<td>R²</td>
<td>0.51</td>
<td>0.37</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis. *, ** and ***: 10%, 5% and 1%, respectively.

**TABLE B.2: Initial Structural Equation Model**

Appendix B: Calculation of the impacts of the ordinal indicators of
Hazardousness on the indicators of Expenditure

1. Calculate for each category of the ordinal variable its proportion of scores.
2. The ordinal variable is considered a measurement of an underlying unobserved continuous variable that is (usually) assumed to follow a normal distribution.

The categories of the ordinal variable are taken to correspond to intervals of the continuous variable. The endpoints of the intervals are the threshold values of the continuous variable which can be obtained by PRELIS 2, a subroutine of LISREL 8 (Jöreskog and Sörbom, 1996).

3. For each endpoint determine its cumulative probability based on the normal distribution underlying the ordinal variable. The mean and standard deviation of the normal distribution are given by PRELIS 2.
4. From the cumulative probability of the endpoints, calculate the probability of each category under the normal distribution as the difference between the cumulative probability of the upper and lower endpoint.
5. Calculate the midpoint for each interval as the normal distribution quintile corresponding to the lower endpoint cumulative distribution +0.5 times the probability of the corresponding category calculated under 4.
6. Calculate the distance between successive midpoints.
7. Calculate the unstandardized structural and measurement coefficients. The unstandardized coefficient \( \beta_1 \) of, say \( X_1 \) on \( Y \), is \( \beta_1' = \beta_1 \frac{S_y}{S_{X_1}} \) where

\[ S_y \quad \text{and} \quad S_{X_1} \] are standard deviations of \( Y \) and of \( X_1 \), respectively, and \( \beta_1 \) is the standardized coefficient.
8. The effect of a shift between successive categories is obtained by multiplying the unstandardized coefficients with the distance between their midpoints.

The expected effect of a shift effect between successive categories is obtained as the
weighted average of the one shift effects, i.e. each shift effect is multiplied by its proportion of scores, divided by the sum of the proportions.