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Causal Analysis in Happiness Research

Nattavudh Powdthavee
Institute of Education, University of London, London, UK
Corresponding author: n.powdthavee@ioe.ac.uk

Abstract

There are some misunderstandings in the way we interpret estimated coefficients in happiness equation regressions, especially when the words "effect", "cause", or "impact" are used to describe a relationship between self-rated happiness and some personal characteristics which may or may not be causal. This paper describes the potential damages in the way we interpret estimated coefficients on some of the observable characteristics in happiness equations as having causal impacts on well-being, and reviews a number of methods used to make effective causal inferences about what determine our happiness in the economic literature.

Keywords: Happiness, Well-being, Causal Inferences, Review

1. Introduction

The rapid growth in the number of published articles on happiness over the recent years is quite astonishing: over 460 journal articles were published between 1960 and 2006. Of those, over 170 were published in the last three years alone (for the same impression, see Clark *et al.,* 2006). Much of the work in this area, which is empirical in nature, relied on using either one-time or repeated cross-section datasets to find the determinants of subjective well-being, whether it is 'happiness', 'life satisfaction', 'perceived quality of life', or 'mental well-being' (see, for example, Blanchflower & Oswald, 2004; Di Tella *et al.,* 2003; Frey & Stutzer, 2000; Powdthavee, 2005).

It is known that cross-sectional studies have the ability to reveal important correlations between measures of subjective well-being and different socio-economic factors or life circumstances. Yet there is no persuasive reason to believe that all observed relationships obtained from cross-sectional regressions are causal. The correlation between X and Y can either mean that i) X causes Y, ii) Y causes X, or iii) X and Y are not related but both are correlated with an unobserved Z, leading to a spurious correlation between X and Y.

Whilst the majority of papers that used cross-sectional datasets are very cautious with the interpretations of their estimated coefficients, some go so far to treat everything they see as a clear-cut, cause-and-effect when, in reality, no causality of any kind has been fully established. For instance, it would not be very difficult to find a paper on the internet today that use the words 'effect', 'cause', or 'impact' to interpret the estimated coefficients on many of the personal socio-economic statuses (e.g. marriage, education, income, unemployment) in a cross-sectional happiness regression equation. Such treatment of the estimated coefficients can be potentially damaging if, say, policy makers were to take them as causal effects on well-being and design a public policy around what economists would call 'spurious correlations'.

In this paper, I will go through different analytical methods that have been used to try and establish causality in the happiness literature. I will also discuss as to why we should be caring about the causality issue in happiness research.

2. Issues

Imagine a reported well-being equation of the following form:

$$W_i = X_i'\beta + \varepsilon_i, \tag{1}$$

where W denotes well-being of individual i, X is a vector of individual i's socio-economic characteristics such as income, marital status, and employment status, and the parameter ε is the model's error term. Given that there is a zero correlation between the personal characteristics, X, and the error term, ε, then we may be able to make a causal inference on the effect of X on W.

This however seems too strong an assumption. It is difficult to imagine, for example, that causality only runs from having higher incomes to higher subjective well-being. Studies in economics and psychology have found two contradicting relationships between incomes and the unobserved determinants of happiness. First, studies have shown that those who are born happy – or have personalities that keep them happy – are also more likely than others to be more productive in various ways (Frank, 1985; Graham *et al.,* 2004; Salgado, 1997). Hence, omitting personal traits will lead to a positive bias on the estimated income coefficient. On the contrary, incomes are also positively correlated with long hours spent at the office and the commuting to and from work. It also correlates positively with other things that are known to be negatively correlated with subjective well-being, namely, less time spent with loved ones and the amount of stress involved with earning high incomes. In other words, omitting these variables will generally cause the estimated income coefficient to be biased downward. As a result, the direct of bias on income in happiness regression is unknown on *a priori* ground. Worse still, the observed positive relationship between income and happiness may not even be there for us to see once we control for both the unobserved individual fixed characteristics and the omitted time-varying variables in the happiness equation regression. If that is the case, then it may even be arguable that money does not buy happiness (even though we observe a positive and statistically important relationship between happiness and income at the cross-section).

To make more sense of the issue, we can rewrite equation (1) to include unobserved fixed and time-varying characteristics as follows:

$$W_{it} = X'_{it}\beta + u_i + v_{it}, \tag{2}$$

Note that we have introduced a time variable, t, into the well-being function. The parameters u_i and v_{it} denote the unobserved heterogeneity (or individual fixed effects) and time-varying characteristics of person i, respectively. The vector of X is assumed to be completely exogenous <u>if, and only if,</u> it is not correlated with both u_i and v_{it}. It is only then can we be confident in making causal inferences about our estimated coefficients.

3. Moving towards Causal Analysis of Happiness Data

3.1 Longitudinal Data

One of the first steps in trying to establish some causality between happiness and life circumstances – even though it is not a perfect fix – is to use datasets that are longitudinal in nature (i.e. repeated observation of the same individual over time). Whilst we cannot say much about the direction of causality in a cross-sectional relationship between, say, poor health and happiness, some inferences can be made on their relationship over time. For example, we can use longitudinal data to observe the happiness of people <u>before the year of becoming ill</u> and, again, their happiness level <u>in the years afterwards.</u> We can then, in principle, examine the relationship between the changes in health status and the changes in happiness over time. This allows us to partially answer the question of whether unhappiness leads to poor health or whether poor health leads to lower happiness in the years that follow. As such, economists have used longitudinal data to investigate whether marriage makes people happy or happy people get married (Frey & Stutzer, 2006) and, comparing two years before and two years afterwards, whether people become happier by divorcing (Gardner & Oswald, 2006).

Further, longitudinal data allow us to control for unobserved heterogeneity u_i in the happiness regression in the usual way. For instance, it is possible that our personality traits such as extroversion or agreeableness that do not vary over time – or the time-invariant parameter u_i in equation (3) – may be correlated with how we rate our happiness and our physical health status (i.e. people who are born extrovert may report higher happiness on average and, at the same time, are more likely to take risks and therefore tend to run into accidents and injured themselves. In which case, the estimated coefficients on health problems will be underestimated in the happiness regression). In order to correct for such personality bias, we can use longitudinal data to estimate an individual fixed effects model (i.e. by including personal dummies or estimate within-subject model) in order to factor out u_i from simultaneously influencing both the dependent variable (e.g. happiness) and the right-hand side variables (e.g. health).

More formally, equation (2) can be rewritten longitudinally as follows:

$$\widetilde{W}_{it} = \widetilde{X}'_{it}\,\beta + \widetilde{v}_{it}, \tag{3}$$

where $\widetilde{W}_{it}$ and $\widetilde{X}'_{it}$ denotes the time-demeaned well-being and socioeconomic variables (for example, $\widetilde{W}_{it} = W_{it} - W_i$). Note that the parameter for the unobserved individual fixed effects, u_i, has now been factored out from the equation and will no longer bias the relationship between the dependent variable and the explanatory variables. However, there is still a possibility of an omitted time-varying variables bias on the estimated coefficient on the socioeconomic variables if $\widetilde{X}'_{it}$ correlates significantly with $\widetilde{v}_{it}$. For examples on papers that use longitudinal data to estimate individual fixed effects model, see Clark (2003), Powdthavee (2007), Winkelmann and Winkelmann (1998).

3.2 Instrumental Variables

A more conventional way in dealing with the endogeneity of the right-hand side variables in the happiness equation is to apply the instrumental variables (IV) method. The IV method relies on finding an appropriate shift variable – the instrumental variable – that moves the explanatory variable of interest (e.g. income, education, or unemployment) but is not correlated with self-reported well-being beyond its correlation with the endogenous regressors.

For example, we know that income is potentially endogenous in a subjective well-being equation. In order to deal with the endogeneity of income, one can try to find a variable that causes income to rise but, theoretically, does not cause well-being to rise or fall at the same time. Using the British Household Panel Survey, Oswald and Powdthavee (2007) apply two exclusion restriction variables – a dummy representing whether a payslip (or a record of income received by the individual from his or her employer) is seen by the interviewer and a continuous variable representing the lagged regional house price – to tease out the causal effect of income on well-being. So, theoretically-speaking, the information about income is likely to be more accurate if the payslip is seen. However, there is no reason to expect happiness itself to be affected by whether or not the interviewer sees the payslip. Secondly, the use of regional household price at t-1 to instrument for income depends on the assumption that high house prices eventually act to raise wages in a region. The resulting outcome is that the estimated IV coefficient on personal income is significantly larger than the one obtained using an ordinary least squares (OLS). This suggests that the bias under OLS is negative: happy people tend to work less to earn income so that, in simple correlations, where no correction for simultaneity is done, this can produce the illusion that money does not buy much happiness.

Hence, in an IV and individual fixed effects setting, we can rewrite equation (3) as:

$$\tilde{W}_{it} = \tilde{X}'_{it}\beta + \tilde{v}_{it}, \tag{4}$$
$$\tilde{X}_{it} = \tilde{Z}_{it} + \tilde{\omega}_{it},$$

where $\tilde{Z}_{it}$ denotes the time-demeaned instrumental variable that is correlated with $\tilde{X}'_{it}$ but is uncorrelated with $\tilde{W}_{it}$ beyond its correlation with $\tilde{X}'_{it}$. By estimating the $\tilde{X}'_{it}$ equation first and use the predicted value for $\tilde{X}'_{it}$ in the well-being regression, we can be sure that the predicted $\tilde{X}'_{it}$ will be free from bias from its correlation with the error term, $\tilde{v}_{it}$.

3.3 Natural Experiments

One can also use natural experiments to study the causal effect of our explanatory variables of interest. For instance, winning a lottery, which is considered to be an exogenous event that leads to an increase in income for the individual, has been used to study the causal impact of money on happiness (Gardner & Oswald, 2007). Using the German Socio-Economic Panel, Frijters *et al.,* (2004) examined whether the exogenous rise of income from the reunification leads to a rise in happiness for the East Germans. In other studies other than income, Pezzini (2005) uses changes in the abortion law throughout Europe to study the role of female's right on life satisfaction. Gruber and Mullainathan (2006) explored whether some public policies can make people happier by investigating the impact of cigarette taxes on smokers' happiness.

Alternative methods to the aforementioned include field (or laboratory) experiments, simultaneous equations modelling, and propensity-score matching methods. However, IV and natural experiments are the more popular methods amongst empirical economists in making causal inferences in happiness research.

4. Conclusion

As a former PhD student of Andrew Oswald – one of the early scholars working in the filed of the economics of happiness, I have been taught to always be cautious with my interpretations of the estimated coefficients in the happiness equations. Using the words like 'effect', 'cause', and 'impact' to describe a cross-sectional relationship between happiness and some other observed characteristics or behaviours can be very damaging if, say, policy makers were to take such results at their face values and start building policies around them. Hence, I feel that more humility is required here from all of us when trying to make any econometric inferences using only cross-section datasets on happiness.

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