OESTERREICHISCHE NATIONALBANK
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WORKING PAPER 204

Background Indicators

Burkhard Raunig

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Publisher and editor *Oesterreichische Nationalbank*
Otto-Wagner-Platz 3, 1090 Vienna, Austria
PO Box 61, 1011 Vienna, Austria
www.oenb.at
oenb.info@oenb.at
Phone (+43-1) 40420-6666
Fax (+43-1) 40420-046698

Coordinating editor Martin Summer

Design *Communications and Publications Division*

DVR 0031577

ISSN 2310-5321 (Print)
ISSN 2310-533X (Online)

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February 22, 2016

Abstract

Indicators of latent variables are usually assumed to be driven by the latent variable and some random noise. Background indicators are in contrast also systematically driven by variables outside the structural model of interest. This paper assesses instrumental variable estimates of effects of latent variables when a background indicator is substituted for the latent variable. It turns out that such estimates become inconsistent in empirically important cases. In certain cases the estimates capture causal effects of the indicator rather than effects of the latent variable. A simulation experiment that considers the effect of economic uncertainty on aggregate consumption illustrates some of the results.

Keywords: Graphical methods, indicator, instrumental variable, financial development, stock market volatility.

JEL codes: C18, C26, E21.

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Non-Technical Summary

Policy evaluations and empirical tests of economic theories often depend on the estimation of causal effects of unobserved or error ridden variables. A popular strategy to cope with such variables is to replace the unobserved variable in the structural model of interest with an effect indicator. The standard assumption in this context is that effect indicators are only systematically driven by the unobserved variable. This paper considers indicators that are in contrast to ordinary effect indicators also systematically driven by additional variables that act in the background. Such indicator may therefore be called "background" indicators. These indicators deserve attention because they may easily get confused with ordinary effect indicators. This paper studies how estimates of effects of unobserved variables are affected when a background indicator is substituted for the latent variable. Background indicators may for instance arise in empirical studies that assess the link between financial development and economic growth or in studies on the link between uncertainty and economic activity. This analysis of background indicators uses causal graphs and path-tracing rules. Causal graphs make underlying assumptions transparent and path tracing can be used to derive algebraic expressions for estimates of effects of unobserved variables. The theoretical analysis first presents some results about effect indicators through the lens of graphical methods. Then the analysis moves on to background indicators. It turns out that background indicators complicate the identification of effects of unobserved variables. Moreover, background indicators may produce misleading estimates in empirically relevant cases. A simple simulation experiment where stock market volatility is used to assess the effect of uncertainty on consumption demonstrates that estimates of negative effects of uncertainty on consumption may be too large when stock market volatility is a background indicator.

1 Introduction

Policy evaluations and empirical tests of economic theories may require the estimation of causal effects of latent or error ridden variables. A popular strategy to cope with such variables is to replace the latent variable in the structural model of interest with an effect indicator – an observable variable that is assumed to be driven by the latent variable and some random noise. The effect of the latent variable is then estimated from the resulting auxiliary model. As is well known, ordinary least squares (OLS) yields inconsistent estimates because the effect indicator becomes endogenous in the auxiliary model. Instrumental variable (IV) estimates are consistent when the auxiliary model is estimated with a proper instrument for the indicator.

The literature on latent variables focuses on effect indicators.[1] This paper considers a type of indicator that has until now been neglected. This type of indicator is in contrast to ordinary effect indicators also systematically driven by additional variables that act in the background and do not belong to the structural model of interest. Such indicator may therefore be called "background" indicators. These indicators deserve attention because they may easily get confused with ordinary effect indicators. This paper studies how estimates of effects of latent variables are affected when a background indicator is substituted for the latent variable.

Background indicators may for instance arise in empirical studies on the link between financial development and economic growth. Such studies often use some measure of bank credit relative to gross domestic product (GDP) as an indicator for the development of the banking sector of a country.[2] Credit to GDP ratios may, however, not only capture domestic financial development. International financial integration (IFI) may affect credit to GDP ratios as well, in particular in developing economies where foreign lending is important (Giannetti and Ongena, 2009). IFI may also directly affect the financial sector of a country via entry or the thread of entry of foreign banks. Thus credit to GDP ratios may be background indicators of financial development and IFI may be the background variable.

Stock market volatility could also be a background indicator. Empirical studies that estimate effects of uncertainty on economic activity often use stock market volatility to measure uncertainty.[3] Bloom (2009) finds that spikes in stock market volatility correspond to bad events such as war or terror. These bad events could simultaneously drive stock market volatility and

[1]See Wansbeek and Meijer (2001) for a recent survey of errors in variables and latent variable models.
[2]See Levine (2005) for a survey of the literature on finance and growth.
[3]Ramey and Ramey (1995), Carruth et al. (2000), Bloom (2009), Baker and Bloom (2012), Leduc and Lui (2013), among others.

economic uncertainty. Furthermore, Romer (1990) and more recently Farmer (2015) argue that high levels of stock market volatility or stock market crashes may amplify uncertainty when people view the stock market as a predictor of future economic activity. Thus, stock market volatility could be a background indicator of uncertainty that is in addition a cause rather than an effect of economic uncertainty.

This paper studies how background indicators affect the identification and estimation of effects of latent variables with the help of causal graphs and path-tracing rules (Chen and Pearl, 2014). Both tools are useful in this context. Causal graphs make underlying assumptions transparent and path tracing can be used to derive algebraic expressions for OLS and IV estimates from causal graphs when the model is assumed to be linear. Graphical methods for studying structural models are well known in other fields like statistics, computer science (Pearl, 2009), or sociology (Morgan and Winship, 2007). These methods are, however, not well known in economics.[4] The next section therefore briefly introduces graphical methods.

The theoretical analysis that follows hereafter first presents some well known results about effect indicators through the lens of graphical methods. The graphical exposition also explains what types of control variables enable or prevent identification of effects of latent variables. The later results are not discussed in standard econometrics texts. Then the analysis moves on to background indicators. It turns out that background indicators complicate the identification of effects of latent variables. Moreover, background indicators produce inconsistent estimates or estimates that capture the total rather than the direct effect of the latent variable in empirically relevant cases. The last part of the theoretical analysis demonstrates that background indicators may nevertheless be useful instruments for standard effect indicators.

A simple simulation experiment where stock market volatility is used to estimate the effect of uncertainty on consumption illustrates how background indicators affect OLS and IV estimates. The simulations show that IV methods may overestimate negative effects of uncertainty on consumption when stock market volatility is a background indicator.

2 Graphs and path tracing rules

This section introduces the graphical tools and path tracing rules that are used in the paper. Figure 1 shows five graphs. Solid nodes represent observed variables, hollow nodes represent unobserved variables, solid arrows indicate causal links, and curved dashed bi-directed arrows

[4]See Hoover (2001) for one of the rare applications of causal graphs in economics.

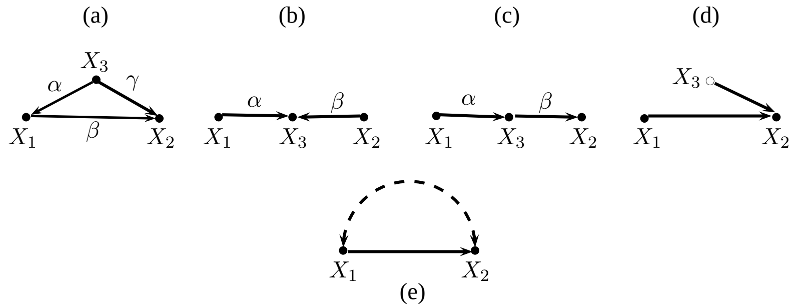

Figure 1: Confounder (a), collider (b), mediator (c), unobserved cause (d), joint unobserved causes (e).

indicate covariances that arise from unspecified causes. Hence, all variables in graphs (a), (b), and (c) are observed, X_3 is unobserved in (d), and X_1 causes X_2 in graph (e) but the variables are also correlated because of other unmodeled causes.

A *path* is a sequence of nodes connected by arrows. A path is *d-connected* if it does not traverse any collider.[5] A variable is a *collider* on a path if two arrows are pointing into it. Thus, the paths $X_1 \to X_2$ and $X_1 \leftarrow X_3 \to X_2$ in (a) are d-connected. The path $X_1 \to X_3 \leftarrow X_2$ in (b) is not d-connected because the collider X_3 blocks the path.

Two *path tracing rules* (Pearl, 2013) yield analytical expressions for covariances between variables in a graph.[6] These expressions can then be substituted into other formulas.

The *first path tracing rule* applies to standardized variables (i.e. variables that have been normalized to have zero mean and unit variance). Let $\pi_i = c_{1(i)} \cdot c_{2(i)} \cdot \ldots \cdot c_{n(i)}$ be the product of the $n(i)$ path coefficients $c_{j(i)}$ along a path i that d-connects two standardized variables A and B, say. A path coefficient can either be a structural coefficient or a covariance. The first rule states that the covariance between A and B is the sum of the products of the path coefficients along all d-connected paths between A and B, i.e. $\sigma_{AB} = \Sigma_i \pi_i$.

The *second path tracing rule* modifies the first rule and applies to non-standardized variables. The product π_i associated with a path i of non-standardized variables A and B must be multiplied by the variance $\sigma^2_{X_{j(i)}}$ of the variable $X_{j(i)}$ from which path i originates. Double arrows serve as their own origin. Thus, when A and B are non-standardized variables then $\sigma_{AB} = \Sigma_i \pi_i \sigma^2_{X_{j(i)}}$.

It is instructive to apply the path tracing rules to derive the covariance between X_1 and X_2 conditional on X_3 in graphs (a), (b), and (c) in Figure 1 because the results demonstrate

[5] The d stands for dependence.

[6] Both rules follow from covariance mathematics and date back to Wright (1921). See, Goldberger (1972), and Bollen (1989) for further details.

how conditioning on a third variable may affect the covariance between two variables. For convenience, let us assume that X_1, X_2, and X_3 are standardized normally distributed random variables.[7] Thus $\sigma^2_{X_1} = \sigma^2_{X_2} = \sigma^2_{X_3} = 1$. Equation (1) expresses the covariance between X_1 and X_2 conditional on X_3 in terms of the unconditional covariances,

$$\sigma_{X_2X_1|X_3} = \sigma_{X_1X_2} - \frac{\sigma_{X_1X_3}\sigma_{X_3X_2}}{\sigma^2_{X_3}}. \tag{1}$$

In graph (a) conditioning uncovers the true link between X_1 and X_2. Fixing X_3 blocks the path $X_1 \leftarrow X_3 \rightarrow X_2$. Path tracing yields $\sigma_{X_1X_2} = \beta + \alpha\gamma$, $\sigma_{X_1X_3} = \alpha$, and $\sigma_{X_3X_2} = \gamma$. Plugging into (1) gives $\sigma_{X_2X_1|X_3} = \beta$. In (b) the variables X_1 and X_2 are independent. Thus $\sigma_{X_1X_2} = 0$, but conditioning on the common outcome X_3 creates dependence between X_1 and X_2. Intuitively, information about one of the causes makes the other cause more or less likely given that we know the outcome. Here, $\sigma_{X_1X_3} = \alpha$, $\sigma_{X_3X_2} = \beta$, and (1) yields $\sigma_{X_2X_1|X_3} = -\alpha\beta$. In graph (c) the variable X_3 mediates the effect of X_1 on X_2. The unconditional covariance is $\sigma_{X_1X_2} = \alpha\beta$. Conditioning on X_3 breaks this link and $\sigma_{X_2X_1|X_3} = 0$.

3 Effect indicators

Consider a linear structural model

$$Y = \alpha + \beta L + \gamma X + u \tag{2}$$

where Y is caused by the latent variable L, X is a column vector of control variables, γ is a row vector of coefficients, and u is an error term. The problem is to estimate the coefficient β that measures the effect of the latent variable.

A standard solution is to find an indicator I of the latent variable

$$I = \lambda L + e \tag{3}$$

where the error e is assumed to be uncorrelated with L. Most latent variables have no natural scale. It is therefore customary to set $\lambda = 1$ such that the observable indicator and the latent variable have the same scale.

Rearranging (3) and plugging in for L in (2) yields

$$Y = \alpha + \delta I + \gamma X + \epsilon \tag{4}$$

[7]Under the normality assumption the conditional covariance between X_1 and X_2 does not change for different values of X_3. Under more general assumptions this covariance may depend on the specific value $X_3 = x_3$.

where $\delta = \beta/\lambda$ and $\epsilon = u - \delta e$.[8] It is easy to show that I is correlated with the compound error ϵ and therefore endogenous. Thus OLS is inconsistent but IV methods may provide consistent estimates.

For simplicity let us assume that the structural model (2) has only a single control variable X and that all variables are demeaned such that $\alpha = 0$. Let Z be an instrument for the latent variable L. The IV estimator for δ in the auxiliary model (4) is

$$\delta^{IV}_{Y.IX} = \frac{\sigma^2_X \sigma_{ZY} - \sigma_{ZX}\sigma_{XY}}{\sigma^2_X \sigma_{ZI} - \sigma_{ZX}\sigma_{XI}}. \tag{5}$$

When Z is uncorrelated with X (i.e. $\sigma_{ZX} = 0$) then (5) collapses to the simple IV estimator

$$\delta^{IV}_{Y.I} = \frac{\sigma_{YZ}}{\sigma_{IZ}} \tag{6}$$

that arises when model (4) is estimated without X.

Figure 2 depicts five causal graphs where I is an effect indicator of the latent variable L. Graph (a) shows a case where the error e in I and the error u in the structural model (2) are uncorrelated. This is the usual assumption made in applied work. One path connects Z and Y via L and one path runs from Z via L to I. Hence, $\sigma_{YZ} = \pi\beta\sigma^2_Z$ and $\sigma_{IZ} = \pi\lambda\sigma^2_Z$. Moreover, $\sigma_{ZX} = 0$ because the only path between Z and X is blocked by Y. Thus the simple IV estimator applies. Plugging the expressions for σ_{YZ} and σ_{IZ} into (6) yields

$$\delta^{IV}_{Y.I} = \frac{\beta}{\lambda} \tag{7}$$

and hence β by imposing $\lambda = 1$ in (3).[9]

Graph (b) relaxes the standard assumption of uncorrelated errors because the errors e and u are correlated. Furthermore, X is now a confounding variable and the latent variable L in the structural model is endogenous because of neglected other joint causes of L and Y. These complications appear to be substantial, but they have no effect because L and I are colliders. In particular, $\sigma_{ZX} = 0$. The simple IV estimator still applies and there is no need to control for the confounding variable X.

Graph (c) shows a case where X is an outcome of Z and Y. Including X in the regression would now even be harmful because the "back-door" path between Z and Y would be opened. Although Z and X are correlated Z is only a valid instrument for I without controlling for X.

[8]Note that the auxiliary model (4) is not causal. In structural relationships like (3) and (2) the equality sign must be understood in a non-symmetric sense (Pearl, 2009, p159 ff). L determines I but L is not determined by inverting (3).

[9]Throughout the paper variances are understood to be population variances to which the corresponding estimated variances eventually converge in large samples.

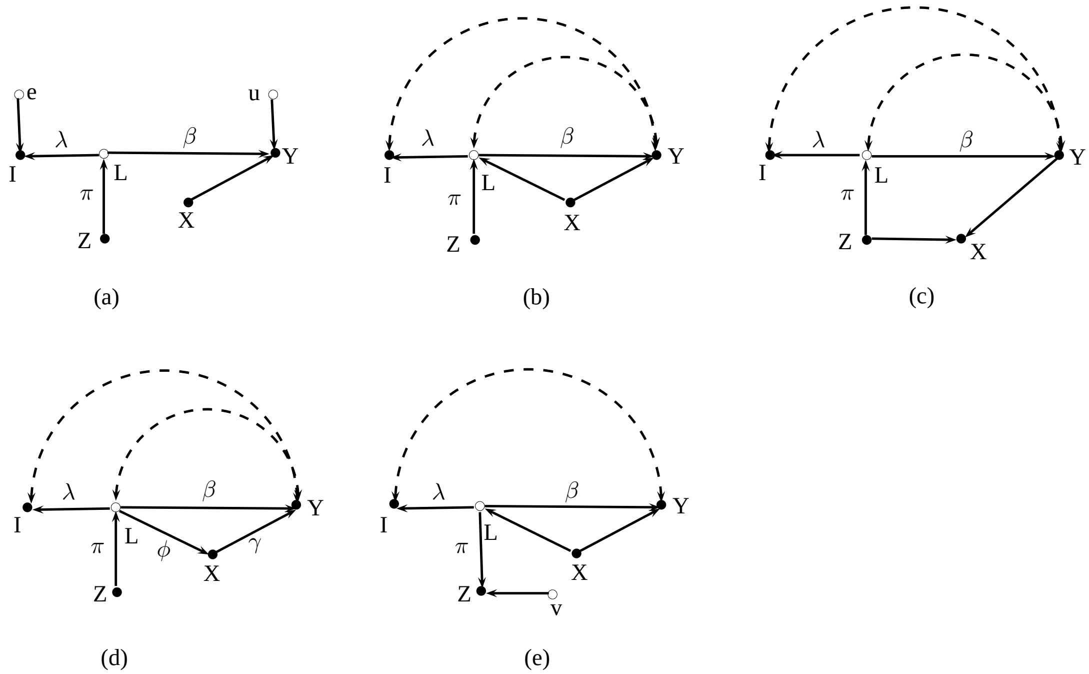

Figure 2: Effect indicators.

Path tracing verifies that the simple IV estimator (6) works but the IV estimator (refivc) that takes X into account does not.

In graph (d) the latent variable affects the dependent variable directly and also indirectly via the mediating variable X. Now the IV estimator $\delta^{IV}_{Y.IX} = \beta/\lambda$ yields the direct effect of the latent variable. The simple IV estimator yields $\delta^{IV}_{Y.I} = (\beta + \phi\gamma)/\lambda$ which is the total effect (i.e. the direct + the indirect effect) of L on Y. Hence, identification of the direct effect of the latent variable requires controlling for the mediating variable X.

In all former cases the instrument Z caused the latent variable L. Graph (e) shows a situation where the instrument Z is a second effect indicator of L. This apparently minor difference to the former cases has important consequences. First, the errors e and u may be correlated but the error v in Z must be uncorrelated with both errors. Second, the latent variable L must now be exogenous in the structural model. Third, one must control for all mediating and confounding variables. Thus, IV estimates of the effect of the latent variable that are based on two effect indicators require stronger assumptions than estimates where the instrument causes the latent variable.

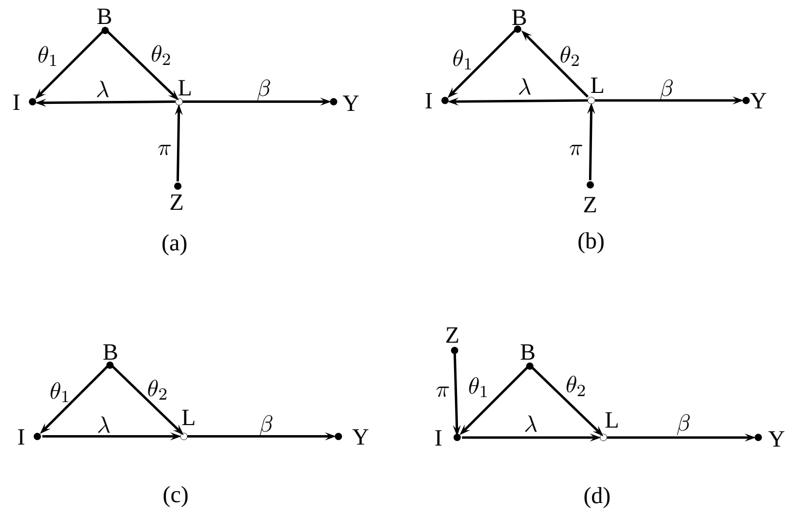

Figure 3: Background indicators.

4 Background indicators

As already explained, background indicators are in contrast to ordinary indicators also systematically affected by other variables that are not part of the original structural model. Background variables could be joint causes of the latent variable and the indicator or variables that mediate effects of the latent variable to the indicator.

Figure 3 shows four cases with background indicators. For clarity the graphs now abstract from error terms and additional control variables because these issues have already been discussed in the previous section.

Graphs (a) and (b) describe cases that may for instance arise in studies on the link between financial development and economic growth. The variables L, I, and B could be financial development, a bank credit to GDP ratio, and IFI, respectively. Y would be economic growth and Z would be an instrument for financial development.

In graph (a) the background variable B causes the latent variable and the indicator. The covariances between Z and Y and I and Z are $\sigma_{YZ} = \pi\beta\sigma_Z^2$ and $\sigma_{IZ} = \pi\lambda\sigma_Z^2$, respectively. The resulting IV estimate is therefore

$$\delta_{Y.I}^{IV} = \frac{\sigma_{YZ}}{\sigma_{IZ}} = \frac{\beta}{\lambda}. \tag{8}$$

As can be seen, this estimate is not affected by the background indicator. The usual practice of setting $\lambda = 1$ may, however, be more difficult to justify.

Graph (b) shows a situation where the latent variable affects the indicator directly and indirectly via the mediating background variable B. The covariances are now $\sigma_{YZ} = \pi\beta\sigma_Z^2$ and

$\sigma_{IZ} = \pi\lambda\sigma_Z^2 + \pi\theta_2\theta_1\sigma_Z^2$. The estimate becomes

$$\delta_{Y.I}^{IV} = \frac{\beta}{\lambda + \theta_2\theta_1}. \tag{9}$$

Thus the presence of B biases the simple IV estimate. This bias can only be removed by controlling for B as can be verified by computing the IV estimate $\delta_{Y.IB}^{IV}$ using (5). Thus, the background variable B must now be included in the regression although B does not affect the dependent variable Y.

Graphs (c) and (d) of Figure 3 show cases that could arise in studies on the link between uncertainty and economic activity. As already mentioned, background indicators may easily be confused with effect indicators. Graph (c) depicts such a case. The exogenous events captured by the background variable B simultaneously drive uncertainty L and stock market volatility I and volatility amplifies uncertainty further. Variables that just cause the latent variable do not work as instruments because such variables are uncorrelated with the indicator. Thus, one is tempted to use the exogenous variable B that is correlated with the indicator I as instrument.

Taking B mistakenly as an instrument for I yields $\sigma_{YB} = \theta_2\beta\sigma_B^2 + \theta_1\lambda\beta\sigma_B^2$ and $\sigma_{IB} = \theta_1\sigma_B^2$. The resulting IV estimate

$$\delta_{Y.I}^{IV} = \frac{\sigma_{YB}}{\sigma_{IB}} = \left(\lambda + \frac{\theta_2}{\theta_1}\right)\beta \tag{10}$$

is inconsistent. The estimate captures three distinct effects, namely the effect $\lambda\beta$ of I on Y, the effect $\theta_2\beta$ of B on Y, and the strength θ_1 of the effect of B on I. The estimate tends to the causal effect of I on Y when θ_2 is small. When θ_1 is close to zero the estimate blows up. This happens because B is then a "weak instrument".

What does OLS yield when stock market volatility causes uncertainty? Since $\sigma_{YI} = \lambda\beta\sigma_B^2 + \theta_1\theta_2\beta\sigma_B^2$ the OLS estimate

$$\delta_{Y.I}^{OLS} = \frac{\sigma_{YI}}{\sigma_I^2} = \lambda\beta + (\theta_1\theta_2\beta)\,\frac{\sigma_B^2}{\sigma_I^2} \tag{11}$$

is also biased and inconsistent because the background variable B has been omitted. The second term in (11) reflects this bias.

Regressing Y on I and B removes the omitted variable bias in (11) but the resulting estimate $\delta_{Y.IB}^{OLS} = \lambda\beta$ is the causal effect of I on Y. In this example one would therefore estimate the causal effect of stock market volatility on output rather than the effect of uncertainty.

Let us now assume that $\theta_1 = \theta_2 = \lambda = 1$ This is a situation where exogenous bad events affect the uncertainty of traders and the public to the same extent and where stock market volatility fully amplifies uncertainty. Let us further assume that the effect of uncertainty on

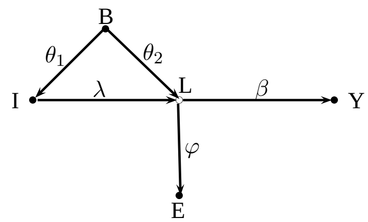

Figure 4: Background indicator as instrument.

output is negative as theory predicts.[10] The IV estimate given in (10) becomes -2β and the OLS estimate (11) is $-(\beta+r\beta)$ where r denotes the ratio of σ_B^2/σ_I^2. Both quantities overestimate the negative effect of uncertainty but OLS gets closer to β the smaller r. In contrast, a weaker link (i.e. $\theta_1 < 0$) between B and I would inflate the IV estimate further.

Graph (d) shows a case where Z is indeed a valid instrument for stock market volatility I. Even if such an instrument could be found it would not solve the problem. Path tracing yields $\sigma_{YZ} = \pi\lambda\beta\sigma_Z^2$ and $\sigma_{IZ} = \pi\sigma_Z^2$. The resulting IV estimate $\delta_{YI}^{IV} = \lambda\beta$ would only capture the causal effect of stock market volatility on output rather than the direct effect of uncertainty on output.

5 Background indicators as instruments

We have seen that background indicators complicate the identification and estimation of effects of latent variables. Identification becomes virtually impossible without an additional effect indicator for the latent variable when the background indicator causes the latent variable.

Figure 4 shows a case where a background indicator and an effect indicator E for the latent variable L are available. The graph abstracts again from error terms and control variables. All issues concerning the inclusion or exclusion of control variables discussed in sections 3 apply here as well.

The background indicator I can is now be used as an instrument for E. The IV estimate is

$$\delta_{Y.E}^{IV} = \frac{\sigma_{YI}}{\sigma_{EI}} = \frac{\beta(\lambda\sigma_I^2 + \theta_1\theta_2\sigma_B^2)}{\varphi(\lambda\sigma_I^2 + \theta_1\theta_2\sigma_B^2)} = \frac{\beta}{\varphi} \tag{12}$$

and yields β by setting $\varphi = 1$. The background indicator I is also a valid instrument when the causal link goes from L to I or when B mediates the effect of L on I. There is no need to control for the background variable, but it must be kept in mind that one must control for all

[10]See Bernanke (1983), McDonald and Siegel (1986), Dixit and Pindyck (1994), Bertola and Caballero (1994), and Abel and Eberly (1996) among others.

confounding or mediating variables that belong into the structural model when the background indicator is caused by the latent variable.

6 Simulations

The simulation experiment that follows considers the impact of uncertainty on aggregate consumption growth. As already mentioned, economic theory predicts that uncertainty about future income reduces consumption since the value of postponing consumption decisions rises with increasing uncertainty. In the simulations it is therefore assumed that higher uncertainty leads to lower aggregate consumption growth. Uncertainty itself cannot be observed. Consumption growth is therefore regressed on the logarithm of stock market volatility which is taken to be an indicator of uncertainty. The estimated coefficient on the logarithm of stock market volatility may be interpreted as an estimate of the semi-elasticity of consumption growth with respect to uncertainty.

6.1 Setup

The setup of the simulation experiment is very simple. A process

$$ln(B_t) = \omega_0 + \omega_1(ln(B_{t-1}) - \omega_0) + e_t^B \tag{13}$$

represents the flow of exogenous events that cause uncertainty. The parameter ω_0 captures the average level of this process and the parameter ω_1 determines how fast the process moves towards its average. The random variable e_t^B represents new events at time t. This variable follows a normal distribution with zero mean and variance σ_B^2 and is identically and independently distributed (iid), i.e. $e_t^B \sim$ iid N(0,σ_B^2).

B_t plus unsystematic noise $e_t^U \sim$ iid N(0, σ_U^2) creates uncertainty of the amount

$$U_t = ln(B_t) + e_t^U \tag{14}$$

at time t.

The simulations consider three different models. The first model ($m1$) corresponds to Figure (2a). Here the logarithm of stock market volatility

$$V_t = U_t + e_t^V \tag{15}$$

is an effect indicator of the usual type. The random noise e_t^V in V_t is iid N(0, σ_V^2). Note that stock market volatility $SV_t = exp(V_t)$ itself is always positive by construction.

Table 1: Parameters

equations	parameters
(13)	$\omega_0 = 2.0$, $\omega_1 = 0.90$, $\sigma^2_B = 0.2$
(14)	$\sigma^2_U = 0.1$
(15), (17)	$\sigma^2_V = 0.3$
(16), (18), (19)	$\eta_0 = 0.7$, $\eta_1 =$ -0.5, $\omega_0 = 2.0$, $\sigma^2_C = 0.3$

Consumption growth is generated as

$$C_t^{m1} = \eta_0 - \eta_1(U_t - \omega_0) + e_t^C \tag{16}$$

with $e_t^C \sim$ iid N(0, σ^2_C). Hence, people reduce consumption when uncertainty exceeds its average level of ω_0 and expand consumption when uncertainty is below average.

The second model ($m2$) corresponds to Figure (3c). Uncertainty has now two sources. Uncertainty comes directly from B_t via equation (14) and also indirectly via stock market volatility

$$V_t = ln(B_t) + e_t^V. \tag{17}$$

Consumption is now given by

$$C_t^{m2} = \eta_0 - \eta_1[(U_t - \omega_0) + (V_t - \omega_0)] + e_t^C. \tag{18}$$

The third model ($m3$) combines ($m1$) and ($m2$). People ignore lower levels of stock market volatility but get nervous when volatility is high. Thus, stock market volatility is a standard effect indicator as long as volatility remains below a critical level lc and consumption is determined by equation (16). But when volatility exceeds lc then volatility becomes a background indicator that causes uncertainty and consumption follows equation (18). Hence, in ($m3$) consumption growth is generated as

$$C_t^{m3} = (1 - d) \cdot C^{m1} + d \cdot C^{m2} \tag{19}$$

where $d = 1$ when $SV_t > lc$ and zero otherwise.

The models above are very simple and are just meant to be examples. Nevertheless, an attempt is made to obtain simulated data with reasonable statistical properties. The parameters reported in Table 1 produce series that have properties that are similar to the statistical properties of US stock market volatility and US aggregate consumption growth.

The upper part of Table 2 shows summary statistics for quarterly US consumption growth and quarterly stock market volatility for the period 1985q2 -2011q4. The lower part of Table

Table 2: Stock market volatility and consumption growth: statistics for US data and simulated data.

Variable	Obs	Mean	Std	Min	Max	AR(1)
US data 1985q2 -2011q4						
Volatility	107	9.96	5.68	4.05	40.5	0.55
Consumption growth	107	0.70	0.56	-1.31	1.88	0.41
Simulated data, 1000 repetitions						
(numbers are averages across repetitions)						
Model $m1$						
Volatility	200	8.66	4.96	1.85	32.0	0.52
Consumption growth	200	0.70	0.37	-0.33	1.72	0.30
Model $m2$						
Volatility	200	8.62	4.84	1.90	31.1	0.55
Consumption growth	200	0.70	0.55	-0.77	2.17	0.54

2 reports the same statistics averaged across 1000 simulated volatility and consumption growth series obtained with models $m1$ and $m2$.

In the simulations the starting value in (13) is always $ln(B_1) = \omega_0$. In each repetition 300 observations are first generated. Observations $t = 1, ..., 100$ are then discarded to remove possible effects of the starting value. The remaining 200 observations $t = 101, ..., 300$ are then used all in further calculations.

Most statistics for the US data and the simulated data in Table 2 are quite similar. The minimum of simulated consumption growth tends to be somewhat too high and the maximum of simulated stock market volatility tends to be somewhat too low compared to the US data. It has to be remembered, however, that the US data cover the crisis of 2007 -2009 where volatility rocketed and consumption dropped dramatically.

The experiment considers three regression of the type

$$C_t = \alpha + \beta X_t + \epsilon_t. \tag{20}$$

First, consumption growth is regressed on the true but unobservable amount of uncertainty (i.e. $X_t = U_t$). This OLS regression provides the benchmark. Next consumption growth is regressed on the logarithm of stock market volatility (i.e. $X_t = V_t$) using OLS. Finally, the same equation is estimated with two stage least squares (2SLS).

The instrument for V_t in the 2SLS regression is constructed in the spirit of Bloom (2009) and Baker and Bloom (2012). These authors identify important exogenous events such as terrorist

Table 3: Medians of estimated coefficients for simulated models.

Model	OLS, $X = U$	OLS, $X = V$	2SLS
$m1$	-0.499	-0.340	- 0.504
$m2$	-0.499	-0.836	-1.004
$m3a$	-0.500	-0.571	-0.810
$m3b$	-0.499	-0.497	-0.714

attacks and political shocks as causes of uncertainty. In the simulation experiment a dummy variable plays the role of such "important" events. The dummy variable takes on a value of one when $ln(B_t)$ exceeds the 75% percentile of its empirical distribution and is zero otherwise.

6.2 Results

Figure 5 shows empirical distributions of the estimated coefficient β in (20). The distributions are based on samples of 200 observations, generated as described above, and 1000 repetitions. Table 3 shows the medians of these distributions. Medians rather than means are reported because in finite samples the expectation of 2SLS estimates of β in (20) based on a single instrument does not exist (Kinal, 1980).

The upper left graph in Figure 5 shows the distributions for β for model $m1$. As to be expected, OLS is inconsistent and the estimates are biased towards zero when stock market volatility is substituted for uncertainty. 2SLS is consistent but the estimates are more dispersed than in the benchmark OLS regression where consumption is regressed on the true amount of uncertainty.

The results for model $m2$ where V_t is a background indicator are shown in the upper right half of Figure 5. Now OLS and 2SLS markedly overestimate the negative effect of uncertainty on consumption when V_t is used as an indicator. The median of the estimates is about -0.8 for OLS and -1 for 2SLS (see Table 3) which is in line with the theoretical results in equations (11) and (10).

The lower part of Figure 5 shows results for two versions of model $m3$. In $m3a$ stock market volatility becomes an additional determinant of uncertainty when volatility exceeds the 75% percentile. Thus, 25% of the observations are determined by model $m2$ and 75% are determined by model $m1$. As can be seen, OLS and 2SLS again overestimate the negative effect of uncertainty, but OLS tends now to be much closer to the true value of -0.5 than 2SLS.

In model $m3b$ only 10% of the observations come from $m2$. The rest comes from model $m1$. The 2SLS estimates are again to be quite far away from the true value, but the estimates of

OLS with stock market volatility and OLS with the true amount of uncertainty happen now to be very similar. More noise in V_t would move the OLS estimates based on V_t closer to zero.

Overall the simulations suggest that IV approaches may overestimate negative effects of economic uncertainty on measures of economic activity when stock market volatility is a background indicator that becomes (at least in certain periods) an additional cause of uncertainty.

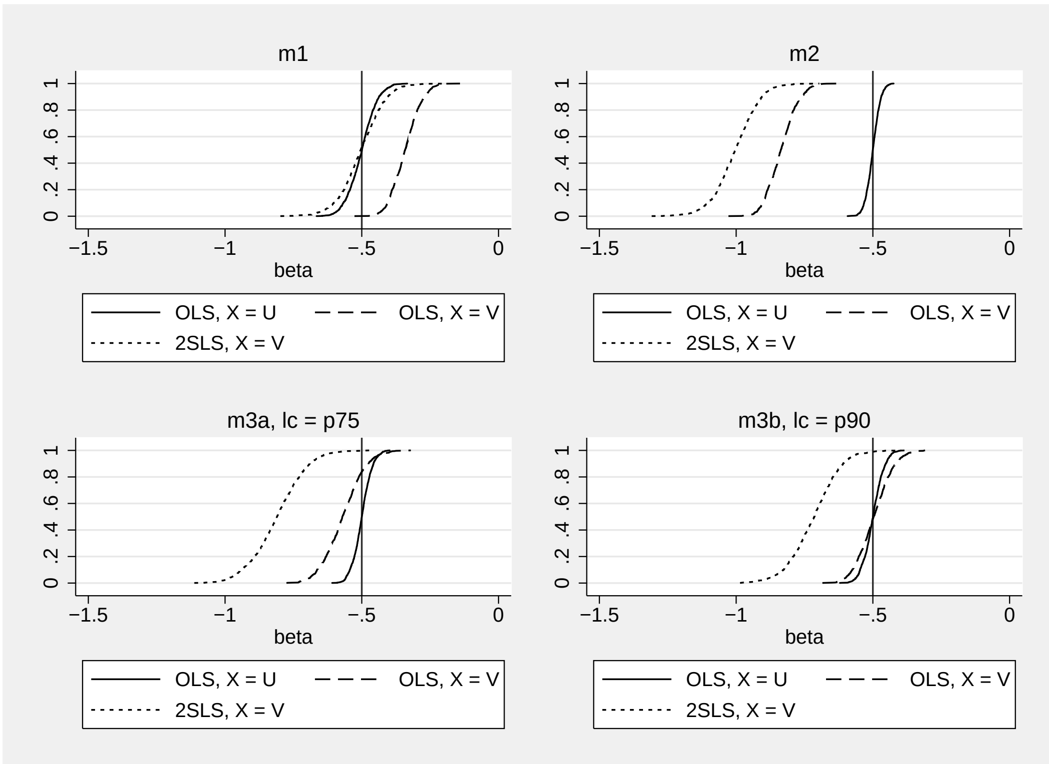

Figure 5: Simulated distributions of OLS and 2SLS estimates of the effect of uncertainty on consumption.

7 Conclusions

Background indicators of latent variables have until now been neglected although they might easily be confused with ordinary effect indicators. This paper studied simple linear models to gain a conceptual understanding of background indicators.

The analysis showed that background indicators produce inconsistent estimates of effects of latent variables in empirically relevant cases. In the simulation experiment, for instance, the estimated effects of uncertainty are too large when stock market volatility is a background indicator of uncertainty. Background indicators may be useful instruments but they should better not be substituted for latent variables. The results also suggest that the choice of indicators should, just like the credibility of instruments, be guided by theoretical considerations and careful judgment.

Future work could extend the analysis to nonlinear models. Analytical results are then of course be more difficult to obtain. Another possible extension would be to investigate the usefulness of causal search algorithms for identifying background indicators. These issues are, however, beyond the scope of this paper and left for future research.

References

Abel, A. B., Eberly, J. C., 1996. Optimal investment with costly reversibility. Review of Economic Studies 63 (4), 581–93.

Baker, S. R., Bloom, N., 2012. Does uncertainty reduce growth? Using disasters as natural experiments. unpublished manuscript.

Bernanke, B. S., 1983. Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics 98 (1), 85–106.

Bertola, G., Caballero, R. J., April 1994. Irreversibility and aggregate investment. Review of Economic Studies 61 (2), 223–46.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.

Bollen, K. A., 1989. Structural Equations with latent Variables. Wiley.

Carruth, A., Dickerson, A., Henley, A., 2000. What do we know about investment under uncertainty? Journal of Economic Surveys 14 (2), 119–53.

Chen, B., Pearl, J., 2014. Graphical tools for linear structural equation modeling. Technical report, r-432, University of California.

Dixit, A. K., Pindyck, R. S., 1994. Investment under Uncertainty. Princeton University Press.

Farmer, R. E. A., 2015. The stock market crash really did cause the great recession. Oxford Bulletin of Economics and Statistics, n/a–n/a.

Giannetti, M., Ongena, S., 2009. Financial integration and firm performance: Evidence from foreign bank entry in emerging markets. Review of Finance 13 (2), 181–223.

Goldberger, A. S., 1972. Structural equation methods in the social sciences. Econometrica 40 (6), 979–1001.

Hoover, K. D., 2001. Causality in Macroeconomics. Cambridge University Press.

Kinal, T. W., 1980. The existence of moments of k-class estimators. Econometrica 48 (1), 241–49.

Leduc, S., Lui, Z., 2013. Uncertainty shocks are aggregate demand shocks. Working Paper 2012-10, Federal Reserve Bank of San Francisco.

Levine, R., 2005. Finance and growth: Theory and evidence. In: Aghion, P., Stephen, N. D. (Eds.), Handbook of Economic Growth, Volume 1A. Elsevier B. V., pp. 885–934.

McDonald, R., Siegel, D. R., 1986. The value of waiting to invest. Quarterly Journal of Economics 101 (4), 707–727.

Morgan, S. L., Winship, C., 2007. Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge University Press.

Pearl, J., 2009. Causality: models, reasoning and inference, 2nd Edition. Cambridge University Press.

Pearl, J., 2013. Linear models: Auseful ”microscope” for causal analysis. Journal of Causal Inference 1 (1), 155–170.

Ramey, G., Ramey, V. A., 1995. Cross-country evidence on the link between volatility and growth. American Economic Review 85 (5), 1138–51.

Romer, C. D., 1990. The great crash and the onset of the great depression. The Quarterly Journal of Economics 105 (3), 597–624.

Wansbeek, T., Meijer, E., 2001. Measurement error and latent variables. In: Baltagi, Badi, H. (Ed.), A Companion to Theoretical Econometrics. Blackwell Publishing Ltd., pp. 162–179.

Wright, S., 1921. Correlation and causation. Journal of Agricultural Research 20, 557–585.

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