

independent, real valued, nondegenerate random variables with unknown distributions. The unknown constant c is real valued, finite, and nonzero.

ASSUMPTION A3: Either the median or the mean of U , V , or W is zero. The characteristic functions of U , V , and W do not vanish.

Assumption A3 is mainly used for identification of the distributions of U , V , and W , not for the identification of c . Kotlarski's Lemma requires some location normalization, as in Assumption A3. Evdokimov and White (2012) provide alternative conditions under which Kotlarski's Lemma holds even when the characteristic functions of U , V , and/or W can have zeros.

Kotlarski's Lemma assumes $c \neq 0$. We assume $c \neq 0$ because, if $c = 0$ then trivially we can only identify the distributions of W and of $V \subset U$. Moreover, we can immediately tell if $c = 0$, because in that case the distributions of X and Y will be independent.

For any random variables R and S , let $\sigma_R^2 = \text{var}[R]$ if this variance exists, and let $\sigma_{RS} = \text{cov}[R, S]$ if this covariance exists. Also let $\psi_R(t) = \ln E[\exp(itR)]$, the log characteristic function (also known as the cumulant generating function) of R , and similarly $\psi_{RS}(t_1, t_2) = \ln E[\exp(it_1R + it_2S)]$.

We begin with a tiny Lemma:

LEMMA 1: Let Assumptions A1, A2, and A3 hold. If the constant c is point identified, then the distributions of U , V , and W are all also point identified.

equations give a bound on c (it must lie between zero and the coefficient of $t_1 t_2$), but this bound is tightened below.

Lemma 1 and Theorem 1 together show how to tell if V is normal or not, and show that Kotlarski's Lemma extends to point identification with an unknown factor loading c as long as V is non-normal.

Now consider the case where V is normal. For this case, we need some more notation. For a random variable R , define R 's "largest normal factor" to be the variable \tilde{R} having the maximum variance such that $R \stackrel{D}{=} \tilde{R} \overset{C}{\bar{R}}$, where \tilde{R} and \bar{R} are independently distributed and \tilde{R} is normally distributed. Without loss of generality, assume \tilde{R} has mean zero. Call \bar{R} the non-normal factor. If no normal \tilde{R} exists, then R does not have a normal factor, and in this case we can let $\tilde{R} \stackrel{D}{=} 0$ and $\bar{R} \stackrel{D}{=} R$. If R is normal then $\tilde{R} \stackrel{D}{=} R \overset{E}{\square} \square R /$ and $\bar{R} \stackrel{D}{=} E \square R /$. See Schennach and Hu (2013) and Lewbel, Schennach, and Zhang (2020) for a similar use of normal factors. Reiersøl (1950) calls a normal factor a normal divisor.

Given a random variable R , the variance of \tilde{R} can be determined by

$$\sigma_{\tilde{R}}^2 \stackrel{D}{=} \sup \left\{ \sigma^2 \geq 0 : \sigma_R^2 \bar{t} / C t^2 \sigma^2 \text{ is a log characteristic function} \right\}$$

If $\sigma_{\tilde{R}}^2 \stackrel{D}{=} 0$ then R does not have a normal factor, otherwise, $\sigma_{\tilde{R}}^2$ given by this expression is the variance of the largest normal factor \tilde{R} . This follows immediately from the definition of a characteristic function, since a positive $\sigma_{\tilde{R}}^2$ means by construction that R equals the convolution of two independent random variables, one of which has the log characteristic function of a mean zero normal.² This means that if R has a known distribution, and hence a known characteristic function, we can determine if it has a normal factor or not, and we can point identify the distributions of \tilde{R} and \bar{R} .

THEOREM 2: Let Assumptions A1, A2, and A3 hold. Assume V is normally distributed. Then $\sigma_{\tilde{X}\tilde{Y}}^2$, $\sigma_{\tilde{X}}^2$, and $\sigma_{\tilde{Y}}^2$ are identified. If $\sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2 \stackrel{D}{=} \sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2$ then c is point identified by $c \stackrel{D}{=} \sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2 \stackrel{D}{=} \sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2$ and in this case neither W nor U have a normal factor. Otherwise, c is interval identified by $c \in \left[\sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2, \sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2 \right]$, and for each value of c in this interval, there is a corresponding, identified unique distribution for U , V , and W . This interval bound on c is sharp.

The fact that c is point identified when neither W nor U have a normal factor also appears in Reiersøl (1950). The identified sets in Theorem 2 are new, but are closely related to the Frisch (1934) bounds on mismeasured linear regressions. Taken together, Lemma 1, Theorem 1, and Theorem 2 completely characterize the identification of our model.

Proof of Theorem 2: Separating Y and X into their normal and non-normal factors, we have $Y \stackrel{D}{=} \tilde{Y} \overset{C}{\bar{Y}}$ and $X \stackrel{D}{=} \tilde{X} \overset{C}{\bar{X}}$. Similarly, Separating W and U into normal and non-normal factors, we also have $Y \stackrel{D}{=} cV \overset{C}{\bar{W}}$ and $X \stackrel{D}{=} V \overset{C}{\bar{U}}$. When V is normal, this implies $\tilde{Y} \stackrel{D}{=} cV \overset{C}{\bar{W}}$, $\bar{Y} \stackrel{D}{=} \bar{W}$, $\tilde{X} \stackrel{D}{=} V \overset{C}{\bar{U}}$ and $\bar{X} \stackrel{D}{=} \bar{U}$. This in turn means that, with V

²An explicit mathematical expression for "being a characteristic function" and hence defining $\sigma_{\tilde{R}}^2$ can be obtained from Bochner's Theorem, e.g., Theorem 4.2.2 in Lukacs (1970).

normal, \bar{X} and \bar{Y} are independent of each other and of the joint distribution of \tilde{Y} and \tilde{X} . Since the marginal distributions of \bar{Y} and \bar{X} are identified, we can identify the left side of

$$\sigma_{Y|X}^2(t_1, t_2) / \sigma_{\bar{Y}}^2(t_1) / \sigma_{\bar{X}}^2(t_2) / D = \sigma_{\tilde{Y}|\tilde{X}}^2(t_1, t_2) /$$

And therefore the joint normal distribution of the mean zero variables \tilde{Y} and \tilde{X} is identified. In particular, this means that $\sigma_{\tilde{Y}}^2$, $\sigma_{\tilde{X}}^2$, and $\sigma_{\tilde{X}\tilde{Y}}^2$ are identified.

The remaining step now borrows heavily from the Frisch (1934) bounds on mismeasured linear regression. From the identified second moments of \tilde{Y} and \tilde{X} , we have $\sigma_{\tilde{Y}}^2 = c^2 \sigma_V^2 + \sigma_W^2$, $\sigma_{\tilde{X}}^2 = \sigma_U^2 + c \sigma_V^2$, and $\sigma_{\tilde{X}\tilde{Y}}^2 = c \sigma_V^2$, which provides three equations in the four unknown constants σ_U^2 , σ_W^2 , σ_V^2 , and c . The only constraints on these parameter values are that $c \neq 0$, σ_U^2 and σ_W^2 must be non-negative (either can be zero if the corresponding normal factor doesn't exist), and σ_V^2 must be positive. These being the only constraints is what makes the corresponding bounds be sharp. The equation $\sigma_{\tilde{X}\tilde{Y}}^2 = c \sigma_V^2$ means that the sign of c equals the sign of $\sigma_{\tilde{X}\tilde{Y}}^2$ to ensure $\sigma_V^2 > 0$. Then $\sigma_U^2 = 0$ requires $\sigma_{\tilde{X}}^2 = \sigma_{\tilde{X}\tilde{Y}}^2 / c = 0$ and $\sigma_W^2 = 0$ requires $\sigma_{\tilde{Y}}^2 = c \sigma_{\tilde{X}\tilde{Y}}^2 = 0$. Therefore, either $\sigma_{\tilde{X}\tilde{Y}}^2 > 0$ and $\sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2 = c \sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2$, or $\sigma_{\tilde{X}\tilde{Y}}^2 < 0$ and $\sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2 = c \sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2$. Either way c lies in the interval between $\sigma_{\tilde{X}\tilde{Y}}^2 \sigma_{\tilde{X}}^2$ and $\sigma_{\tilde{Y}}^2 \sigma_{\tilde{X}\tilde{Y}}^2$.

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