 Journal of Business & Economic Statistics, January 1992, Vol. 10, No. 1

Editor's Note: The following article is the *JBES* 1991 Invited Lecture at the Joint Statistical Meetings, Atlanta, Georgia, August 18–22, 1991.

On the Estimation of Panel-Data Models With Serial Correlation When Instruments Are Not Strictly Exogenous

Michael P. Keane
Industrial Relations Center and Department of Economics, University of Minnesota, Minneapolis, MN 55455, and Research Department, Federal Reserve Bank of Minneapolis, MN 55480

David E. Runkle
Research Department, Federal Reserve Bank of Minneapolis, MN 55480, and Department of Finance, Carlson School of Management, University of Minnesota, Minneapolis, MN 55455

In recent years, researchers in many disciplines, including economics, accounting, finance, and marketing, have increasingly relied on panel data to model the behavior of individuals and firms. They have done so because panel data allow them to control for temporally persistent unobserved differences among individuals or firms that in many instances may bias estimates obtained from cross-sections.

Since the original work of Balestra and Nerlove (1966), panel-data econometricians have commonly assumed that the instruments used to identify model parameters are strictly exogenous with respect to the time-varying error component. For example, Hausman and Taylor (1981), Amemiya and MaCurdy (1986), and Breusch, Mizon, and Schmidt (1989) all considered models of the form

$$Y_{i,t} = X_{i,t}\beta + \eta_i + \nu_{i,t}, \qquad (1)$$

where η_i is an individual fixed or random effect (i.e., η_i is fixed or random with respect to $X_{i,t}$) for person i that is invariant over time t. In the fixed-effects case, they proposed an instrumental variable (IV) estimator for (1) that is obtained by taking deviations from individual means (to eliminate η_i from the equation) and then using the orthogonality conditions $E[(\nu_{it} - \bar{\nu}_i)X_{i,t}] = 0$. In the random-effects case, quasi-demeaning is applied to (1) to obtain the orthogonality conditions $E[(\nu_{i,t} - \gamma\bar{\nu}_i)X_{i,t}] = 0$, where $0 < \gamma < 1$. Of course, in either case the X's are not valid instruments unless $X_{i,t}$ is strictly exogenous with respect to ν_{it}; that is, $E(X_{i,t}\nu_{i,s}) = 0$ for all t and s.

There are, however, many important cases in which the regressors or other potential instruments are only predetermined with respect to the time-varying error component. [In other words, we only have $E(X_{i,t}\nu_{i,s}) = 0$ for $t \le s$.] Some examples are models with lagged dependent variables, rational-expectations models in which potential instruments are functions only of variables in the time $t - 1$ information set so that there are never *any* strictly exogenous instruments, and models with predetermined choice variables as regressors, such as hours equations that include children.

Previously, Anderson and Hsiao (1981), Bhargava and Sargan (1983), Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bover (1990), and Ahn and Schmidt (1990) considered models with individual effects and lagged dependent variables as elements of $X_{i,t}$. These authors noted that taking deviations (or quasi-deviations) from individual means in such models leads to inconsistency even if $X_{i,t}$ is strictly exogenous because $Y_{i,t-1}$ is correlated with $\bar{\nu}_i$ by construction. They proposed instead the IV estimator obtained by first-differencing (1) to eliminate the individual effect (or, in the work of Arellano and Bover, the use of deviations from means that are taken over only current and future values) and then including only $Y_{i,s}$ for $s \le t - 2$ in the instrument set.

In this article, we propose an alternative procedure for IV estimation of models with predetermined but not strictly exogenous instruments that is more generally applicable and has other important advantages over this first-differencing approach. We propose a new estimator for panel data, based on the time series work on forward filtering by Hayashi and Sims (1983), that eliminates any form of serial correlation in models with predetermined instruments yet does not cause parameter estimates to be inconsistent.

In the fixed-effects case, we propose that, following first-differencing, the estimating equation be forward filtered to eliminate any serial correlation in the time-varying error component. Instruments that were only predetermined prior to forward filtering remain valid after forward filtering, so the procedure does not require instruments to be strictly exogenous. Our forward-filtering procedure provides a potential efficiency gain over procedures that only first-difference.

In the random-effects case, the advantages of forward filtering are more important. Of course, one may obtain consistent estimates of random-effects models that do not contain lagged dependent variables by ignoring the random effects and simply applying ordinary least squares (OLS) or two-tape least squares (2SLS). Consistent but inefficient estimates of the covariance matrix of the parameters are also easy to compute. But compared to OLS or 2SLS, the forward-filtering procedure provides a potential efficiency gain because it eliminates serial correlation. Alternatively, one may first-difference to eliminate random effects, but this entails unnecessary loss of efficiency. The forward-filtering procedure provides a potential efficiency gain by eliminating serial correlation without differencing.

In the case of a lagged dependent variable, the simple procedure of ignoring the random effects and applying OLS will produce inconsistent parameter estimates. 2SLS will only produce consistent parameter estimates if instruments that are uncorrelated with the random effect are available for the lagged dependent variable. This may be difficult in practice because the y_{is} for all $s \leq t - 1$ are correlated with the random effect by construction, ruling them out as potential instruments. The lagged dependent variable model may of course be estimated by first-differencing and using lagged instruments, but, as in the fixed-effects case, application of forward filtering provides a potential efficiency gain if there is serial correlation in $\nu_{i,t}$. More important, several of the authors cited previously have noted that dynamic random-effects models can be estimated via generalized least squares (GLS) (or quasi-demeaning) procedures that preserve identification of coefficients on time-invariant regressors so long as a sufficient number of strictly exogenous instruments are available (in particular, instruments that can be used for the lagged dependent variables). By applying our forward-filtering procedure, this condition is relaxed to the requirement that sufficient predetermined instruments be available. Then the y_{is} for $s \leq t - 1$ are in the set of valid instruments.

In applied panel-data work it is, of course, crucial to determine whether fixed effects, random effects, or no individual effects are present. Methods for testing hypotheses concerning the nature of the individual effects were developed by Hausman (1978). Both the theoretical and applied work on such specification testing, however, has universally maintained the assumption of strict exogeneity. In this article, we show how to perform specification tests when instruments are predetermined and not strictly exogenous. We also show how to test for strict exogeneity.

These tests are of practical importance, for two reasons. First, with failure of strict exogeneity, the inconsistent fixed-effects estimates obtained by demeaning will tend to differ from random-effects estimates even when random effects or no individual effects are present. Since the specification tests for fixed effects that have been applied by other researchers are based on the difference between these two estimators, failure of strict exogeneity can falsely lead researchers to conclude that fixed effects are present when they are not. Use of our tests avoids this problem. Second, many researchers have unnecessarily reduced the efficiency of their parameter estimates by using first-differenced estimators in panel-data models with predetermined instruments to avoid the parameter inconsistency that would occur if fixed effects were present. Our tests would result in potentially more efficient estimates if the individual effects were random, because they would indicate that first-differencing is unnecessary.

Finally, we use our estimator based on the forward-filtering procedure to estimate the consumption Euler equation for a simple version of the rational-expectations–life-cycle consumption model. We show that instruments are not strictly exogenous in this model and that incorrect application of a specification test that assumes strict exogeneity leads to false acceptance of the fixed-effects hypothesis. The incorrect application of a fixed-effects estimator obtained by demeaning leads to false rejection of the model. We show, however, that with proper application of our forward-filtering estimation procedure the simple life-cycle model cannot be rejected.

1. A REVIEW OF STANDARD PANEL–DATA ESTIMATION METHODS

Suppose that we have a panel of N people (indexed by i), for whom we observe the variables $Y_{i,t}$ and $X_{i,t}$ in each of time T periods (indexed by t). Consider the linear model

$$Y_{i,t} = X_{i,t}\beta + \varepsilon_{i,t}, \qquad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T, \tag{1'}$$

where $\varepsilon_{i,t}$ is a mean-zero residual. Estimating this model is simple if $X_{i,t}$ is exogenous and $\varepsilon_{i,t}$ is homoscedastic and serially uncorrelated ($E(\varepsilon_{i,t}|X_{i,t}) = 0$, $E(\varepsilon^2_{i,t}) = \sigma^2_\varepsilon$, and $E(\varepsilon_{i,t}\varepsilon_{j,s}) = 0$ for all $i \neq j$ or $t \neq s$). In that case, the model can be estimated using OLS. The resulting coefficient estimates and standard errors will be consistent.

Researchers have long recognized, however, that the strong conditions necessary to use OLS estimation on this model are not likely to be satisfied in most empirical applications using panel data. In particular, with unobserved individual heterogeneity the errors in Equation (1′) are likely to be correlated across time for each individual, invalidating the assumption that $E(\varepsilon_{i,t}\varepsilon_{i,s}) = 0$, for all $t \neq s$. Balestra and Nerlove (1966) proposed instead the assumption that the error term $\varepsilon_{i,t}$ can be decomposed into an individual-specific component η_i and the remaining time-varying error component $\nu_{i,t}$, where $E(\eta_i|X_{i,t}) = 0$, $E(\eta_i^2) = \sigma^2_\eta$, $E(\eta_i\eta_j) = 0$ for all $i \neq j$, $E(\nu^2_{i,t}) = \sigma^2_\nu$, $E(\nu_{i,t}\nu_{j,s}) = 0$ for all $i \neq j$ or $t \neq s$, and where the strict exogeneity assumption

$E(\nu_{i,t}|X_{i,s}) = 0$ for all t and s holds. The individual-specific component captures persistent deviations of $Y_{i,t}$ from its predicted value, based on the explanatory variables $X_{i,t}$. For example, if Equation (1′) were explaining individual wages, η_i would represent those aspects of individual ability that are not captured by observable variables such as experience, education, and past employment status.

If the Balestra–Nerlove assumptions are correct, then OLS will provide consistent but inefficient parameter estimates, and the OLS covariance matrix will be inconsistent. (Of course, a correction exists that provides consistent but inefficient standard errors.) However, the GLS estimator

$$Y_{i,t} = \gamma \overline{Y}_i = (X_{it} - \gamma \overline{X}_i)\beta + (\varepsilon_{it} - \gamma \overline{\varepsilon}_i), \quad (2)$$

where $\gamma = 1 - \sigma_\nu / \sqrt{\sigma_\nu^2 + T\sigma_\eta^2}$ provides both efficient parameter estimates and consistent estimates of the covariance matrix of the parameters. The Balestra–Nerlove estimator has often been called a *random-effects* estimator because of its assumption that the individual effect is random with respect to the observed explanatory variables [meaning that $E(\eta_i|X_{i,t}) = 0$].

But if $E(\eta_i|X_{i,t}) \neq 0$, then the individual effect is correlated with the explanatory variables and, as Maddala (1971) first explained, neither OLS nor the random-effects estimator would be consistent. In this case, as long as $X_{i,t}$ is strictly exogenous with respect to $\nu_{i,t}$, consistent parameter estimates can be obtained by taking deviations from individual means in (1) to obtain the transformed equation

$$Y_{i,t} - \overline{Y}_i = (X_{i,t} - \overline{X}_i)\beta + (\varepsilon_{it} - \overline{\varepsilon}_i),$$
$$i = 1, 2, \ldots, N; t = 1, 2, \ldots, T, \quad (3)$$

where $\overline{Y}_i$ and $\overline{X}_i$ are the individual means for $Y_{i,t}$ and $X_{i,t}$. Note that subtracting individual means eliminates any fixed effect from Equation (1). (Exactly the same results would be obtained by estimating individual-specific intercepts using dummy variables.) Because of the assumption that the individual effect is correlated with the explanatory variables, which leads to the interpretation of the individual effects as individual constants, Equation (2) is often called the *fixed-effects* estimator. Although the fixed-effects estimates are consistent, that consistency comes at a price: Coefficients cannot be estimated for variables that are constant for each individual across all time periods, and the remaining estimates are likely to have large standard errors.

Although Equations (1′), (2), and (3) may be consistently estimated by OLS if $X_{i,t}$ is exogenous, in the more general case $X_{i,t}$ is endogenous and (1′), (2), and (3) must be estimated by 2SLS. Suppose we have available instruments $Z_{i,t}$ that satisfy $E(\nu_{i,t}|Z_{i,t}) = 0$. In the case of no individual effects, Equation (1′) may be estimated consistently by 2SLS using the instrument $Z_{i,t}$. In the fixed- and random-effects cases, however, Equations (2) and (3) cannot generally be estimated consistently using such instruments. This is because the errors of these equations involve the term $\overline{\nu}_i$. This point is crucial. To have $E(\overline{\nu}_i|Z_{i,t}) = 0$, it is not sufficient to have the contemporaneous no-correlation condition $E(\nu_{i,t}|Z_{i,t}) = 0$. Rather, we need the much stronger strict-exogeneity condition $E(\nu_{i,s}|Z_{i,t}) = 0$ for *all* t and s.

Unfortunately, there are many cases in which such a strict exogeneity condition will not hold. One example is the case of a lagged dependent variable. Suppose we have the equation

$$Y_{i,t} = \gamma Y_{i,t-1} + Z_{i,t}\beta + \eta_i + \nu_{i,t}. \quad (4)$$

If demeaning or quasi-demeaning is applied to this equation, then lagged $Y_{i,t}$ are not valid instruments because they are correlated with $\overline{\nu}_i$ by construction.

As noted in the introduction, several authors have observed that if Equation (4) is first-differenced, giving

$$Y_{i,t} - Y_{i,t-1} = \gamma(Y_{i,t-1} - Y_{i,t-2}) + (X_{i,t} - X_{i,t-1})\beta + (\nu_{i,t} - \nu_{i,t-1}), \quad (5)$$

then the predetermined variable $Y_{i,t-2}$ is a valid instrument. This observation raises an important point: There are some transformations of regression equations (e.g., demeaning) that render predetermined variables such as $Y_{i,t-2}$ invalid as instruments, leaving only strictly exogenous variables as valid instruments. But there are other transformations (like differencing) that leave predetermined variables valid as instruments. In Section 2, we describe a forward-filtering transformation that also leaves predetermined variables valid as instruments but that has some important advantages over first-differencing.

2. GLS ESTIMATORS WHEN INSTRUMENTS ARE PREDETERMINED BUT NOT STRICTLY EXOGENOUS

Suppose that we want to estimate the equation

$$Y_{i,t} = X_{i,t}\beta + \varepsilon_{i,t},$$
$$i = 1, 2, \ldots, N; t = 1, 2 \ldots, T, \quad (6)$$

using instruments $Z_{i,t}$ that are predetermined but not strictly exogenous; that is, $E(\varepsilon_{i,t}|Z_{i,s}) = 0$ for all $s \leq t$, but $E(\varepsilon_{i,t}|Z_{i,s}) \neq 0$ for all $s > t$. If the errors in Equation (6) are uncorrelated with the instruments, that equation can be estimated using 2SLS. Given random effects or other sources of serial correlation, however, $\Omega_{TS} = (I_N \otimes \Sigma_{TS}) = E(\varepsilon\varepsilon')$ will not be diagonal and 2SLS will be inefficient.

We propose a new GLS estimator that remains consistent if the instruments in Equation (6) are predetermined rather than strictly exogenous but that is potentially more efficient than 2SLS when the errors in Equation (6) are serially correlated. The estimator is constructed by first obtaining a consistent estimate of

Σ_{TS}^{-1} and then computing its *upper-triangular* Cholesky decomposition, which we will call $\hat{P}_{TS}$. Then premultiply Equation (6) by $\hat{Q}_{TS} = (I_N \otimes \hat{P}_{TS})$ and estimate the transformed equation using 2SLS, while still using the original instruments. We call this new estimator $\hat{\beta}_{KR}$. Note that

$$\hat{\beta}_{KR} = (X'\hat{Q}_{TS}'Z(Z'Z)^{-1}Z'\hat{Q}_{TS}X)^{-1} \times X'\hat{Q}_{TS}'Z(Z'Z)^{-1}\hat{Q}_{TS}Y. \quad (7)$$

This estimator does not impose an equicorrelation assumption on Ω as the fixed-effects and random-effects estimators do.

This new estimator is derived by applying the insights of Hayashi and Sims (1983) concerning time series models to panel data. They showed that, if a time series equation has serially correlated errors and predetermined instruments, serial correlation can be eliminated by a transformation that makes the transformed dependent variable for time t a linear combination of the values of the original dependent variable for time periods t and later. So long as the dating of the instruments is left unchanged, this transformation preserves the orthogonality conditions implied by the time series model and yields consistent and potentially more efficient estimates of the parameters. Note that it was exactly these considerations that led Arellano and Bover (1990) to suggest forward demeaning (i.e., taking deviations from means taken only over current and future values) in models with predetermined but not strictly exogenous instruments. Unlike premultiplication by $\hat{Q}_{TS}$, however, their procedure does not eliminate all forms of serial correlation. Thus forward filtering has more general applicability.

In time series models, the covariance matrix $\hat{\Omega}$ must be tightly parameterized because the number of elements in $\hat{\Omega}$ is much larger than the number of observations available in the time series model. In a panel-data model, however, the number of unique elements in Ω_{TS}—namely, $T(T + 1)/2$—is usually far smaller than N, so $\hat{\Omega}_{TS}$ can be estimated directly. Denoting the residuals for individual i in the 2SLS equation as $\hat{U}_{IS}^{i}$, a consistent estimate of $\hat{\Sigma}_{TS}$ is obtained by constructing

$$\hat{\Sigma}_{TS} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}_{TS}^{i}\hat{U}_{TS}^{i\prime}.$$

As a result, a consistent estimate of Ω_{TS} would be $\hat{\Omega}_{TS} = (I_N \otimes \hat{\Sigma}_{TS})$. Note that we did not have to specify the covariance structure of the residuals for each individual to compute the estimates of $\hat{\Sigma}_{TS}$ that we will use in computing $\hat{\beta}_{KR}$. (Of course, we could parameterize $\hat{\Sigma}_{TS}$ as a Toeplitz matrix or include individual effects as the only source of serial correlation.)

The key difference between our GLS estimator and those suggested by Hausman and Taylor (1981), Amemiya and MaCurdy (1986), and Breusch et al. (1989), is the form of $\hat{P}_{TS}$ that we use to create $\hat{Q}_{TS}$. Those authors use $\Sigma_{TS}^{-1/2}$ to premultiply Equation (1), where $\Sigma_{TS}^{-1/2} = Q_\nu + \delta P_\nu$, $\delta^2 = \sigma_v^2/(\sigma_v^2 + T\sigma_n^2)$, ν is the $NT \times N$ matrix of individual dummy variables, $P_\nu \equiv \nu(\nu'\nu)^{-1}\nu'$, and $Q_\nu \equiv I - P_\nu$. This transformation leads to Equation (2). As was noted previously, the error in Equation (2) for person i in time t is not orthogonal to $Z_{i,t}$, because that error is a linear combination of the errors for person i from all different time periods, and $E(\varepsilon_{i,t}|Z_{i,s}) \neq 0$ for all $s > t$. Therefore, the estimators proposed by those authors will lead to inconsistent parameter estimates if the instruments are predetermined and not strictly exogenous, because the transformed equation will violate the orthogonality conditions of the original equation.

Although our new estimator is certainly useful when there are random effects, it may also be used to obtain more efficient estimates of the fixed-effects first-difference model. Suppose that the instruments in Equation (6) are predetermined but that the individual effects in that equation are also correlated with the instruments. In this case, we would want to estimate a first-differenced version of Equation (6)—namely,

$$Y_{i,t} - Y_{i,t-1} = (X_{i,t} - X_{i,t-1})\beta + (\nu_{i,t} - \nu_{i,t-1}),$$
$$i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T - 1, \quad (8)$$

using instruments from time $t - 1$ and before. As we noted previously, (8) may be estimated consistently by 2SLS even when instruments are not strictly exogenous. As is obvious from Equation (8), however, the residuals in the transformed equation are serially correlated. In fact, the serial correlation in this equation is (moving average) MA(1) if $\nu_{i,t}$ is itself serially uncorrelated and will take the form of a higher order autoregressive moving average process if ν_{it} is serially correlated. Thus $\hat{\beta}_{KR}$ may be more efficient than the 2SLS estimator. To obtain $\hat{\beta}_{KR}$, simply estimate $\hat{\Sigma}_{FD}$ and premultiply Equation (8) by $\hat{Q}_{FD} = (I_N \otimes \hat{P}_{FD})$. Then estimate the transformed equation by 2SLS using the original instruments.

3. SPECIFICATION TESTS

There are two problems facing econometricians who want to estimate a panel-data model: First, they must determine whether the instruments are merely predetermined or whether they are strictly exogenous. Second, they must determine whether the individual effects are correlated with the instruments.

We can test whether the instruments are strictly exogenous by comparing the results of two different estimators: a first-difference estimator and a fixed-effects estimator. Consider the first-difference equation (8). If we use instruments from time $t - 1$ or before in estimating this equation, we can consistently estimate β whether or not the instruments are strictly exogenous. Since any potential individual effect has been eliminated by differencing, there will also be no problem caused by correlation of an individual effect with the instruments. In contrast, the fixed-effects estimator (3) will give a consistent estimate of β only if the instruments are strictly exogenous. As previously noted, however, if the instruments are merely predetermined, the fixed-effects estimator will be inconsistent.

Since the probability limits of the estimates of β_{FE} and β_{FD} differ only if the instruments are not strictly exogenous, one simple specification test for strict exogeneity is to compute the statistic $(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}})'(V(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}}))^{-1}(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}})$, which should be distributed asymptotically as a χ_k^2 random variable if β_{FD} and β_{FE} each contain k parameters and the instruments are strictly exogenous.

Since no clear efficiency comparison is possible between the fixed-effects estimator and the first-difference estimator, computing $V(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}})$ is not as simple as it is for Hausman specification tests. Denote the residuals for individual i in the fixed-effects equation as $\hat{U}^i_{\text{FE}}$ and denote the residuals for individual i in the first-difference equation as $\hat{U}^i_{\text{FD}}$. Then consistent estimates of the covariances and cross-covariances of the residuals for each individual in those equations are given by

$$\hat{\Sigma}_{\text{FE}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{FE}}\hat{U}^{i\prime}_{\text{FE}},$$

$$\hat{\Sigma}_{\text{FD}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{FD}}\hat{U}^{i\prime}_{\text{FD}},$$

and

$$\hat{\Sigma}_{\text{FEFD}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{FE}}\hat{U}^{i\prime}_{\text{FD}}.$$

As a result, consistent estimates of the covariance and cross-covariance matrices of the residuals of these two equations would be $\hat{\Omega}_{\text{FE}} = (I_N \otimes \hat{\Sigma}_{\text{FE}})$, $\hat{\Omega}_{\text{FD}} = (I_N \otimes \hat{\Sigma}_{\text{FD}})$, and $\hat{\Omega}_{\text{FEFD}} = (I_N \otimes \hat{\Sigma}_{\text{FEFD}})$. Given these estimates, we can compute $V(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}})$ as

$$\begin{aligned} V(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{FD}}) &= (X_{\text{FE}}Z(Z'Z)^{-1}Z'Z_{\text{FE}})^{-1}(X_{\text{FE}}Z(Z'Z)^{-1}Z'\hat{\Omega}_{\text{FE}}Z(Z'Z)^{-1}Z'X_{\text{FE}}) \\ &\qquad \times (X_{\text{FE}}Z(Z'Z)^{-1}Z'X_{\text{FE}})^{-1} \\ &\quad - (X_{\text{FE}}Z(Z'Z)^{-1}Z'X_{\text{FE}})^{-1}(X_{\text{FE}}Z(Z'Z)^{-1}Z'\hat{\Omega}_{\text{FEFD}}Z(Z'Z)^{-1}Z'X_{\text{FD}}) \\ &\qquad \times (X_{\text{FD}}Z(Z'Z)^{-1}Z'X_{\text{FD}})^{-1} \\ &\quad - (X_{\text{FD}}Z(Z'Z)^{-1}Z'X_{\text{FD}})^{-1}(X_{\text{FD}}Z(Z'Z)^{-1}Z'\hat{\Omega}'_{\text{FEFD}}Z(Z'Z)^{-1}Z'X_{\text{FE}}) \\ &\qquad \times (X_{\text{FE}}Z(Z'Z)^{-1}Z'X_{\text{FE}})^{-1} \\ &\quad + (X_{\text{FD}}Z(Z'Z)^{-1}Z'X_{\text{FD}})^{-1}(X_{\text{FD}}Z(Z'Z)^{-1}Z'\hat{\Omega}_{\text{FD}}Z(Z'Z)^{-1}Z'X_{\text{FD}}) \\ &\qquad \times (X_{\text{FD}}Z(Z'Z)^{-1}Z'X_{\text{FD}})^{-1}. \end{aligned}$$

With this estimate of the covariance matrix, we can compute the specification test to determine whether the instruments are strictly exogenous or merely predetermined. (Runkle [1991] showed how to construct an estimate of $Z'\Omega_{\text{FE}}Z$ and similar terms that are robust to conditional heteroscedasticity.) Simple extensions to deal with missing data are also available.

Since the fixed-effects estimator would unnecessarily reduce efficiency if the individual effects were uncorrelated with the regressors, it is important to test directly the assumption that $E(\eta_i|X_{i,t}) = 0$. Hausman (1978) first developed such a test. Assuming strict exogeneity, he noted that, under the null hypothesis that $E(\eta_i|X_{i,t}) = 0$, both the random-effects and the fixed-effects estimators are consistent, but the random-effects estimator is efficient. Under the alternative hypothesis that $E(\eta_i|X_{i,t}) \neq 0$, the fixed-effects estimator is consistent, but the random-effects estimator is inconsistent. He proposed a test of the null hypothesis based on the difference between the random-effects and the fixed-effects parameter estimates.

It is necessary to know the outcome of the strict exogeneity test, however, to properly test for correlation between individual effects and the instruments. If the instruments are strictly exogenous, then Hausman and Taylor's (1981) specification tests can be used to determine whether there is an individual effect that is correlated with the instruments. But if the instruments are merely predetermined, the Hausman and Taylor tests may lead one to believe that fixed-effects are present when in fact they are not.

With predetermined but not strictly exogenous instruments, a valid specification test for fixed effects can be based on the difference between the common parameters from a two-stage first-difference estimator and a 2SLS estimator of Equation (6). Under the null hypothesis that there is no individual effect that is correlated with the instruments, both $\hat{\beta}_{\text{FD}}$ and $\hat{\beta}_{\text{TS}}$ will be consistent even when instruments are merely predetermined. If the null is incorrect, then $\hat{\beta}_{\text{FD}}$ will still be consistent, but $\hat{\beta}_{\text{TS}}$ will not. Consequently, we can test the null by forming the statistic $(\hat{\beta}_{\text{TS}} - \hat{\beta}_{\text{FD}})'(V(\hat{\beta}_{\text{TS}} - \hat{\beta}_{\text{FD}}))^{-1}(\hat{\beta}_{\text{TS}} - \hat{\beta}_{\text{FD}})$, which should be distributed asymptotically as a χ_k^2 random variable under the null.

To construct the test, a consistent estimate of $V(\hat{\beta}_{\text{TS}} - \hat{\beta}_{\text{FD}})$ is needed. Let the residuals for individual i in the 2SLS equation be denoted as $\hat{U}^i_{\text{TS}}$, and let the residuals for individual i in the first-difference equation be denoted as $\hat{U}^i_{\text{FD}}$. Then consistent estimates of the covariances and cross-covariances of the residuals for each individual in those equations are

$$\hat{\Sigma}_{\text{TS}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{TS}}\hat{U}^{i\prime}_{\text{TS}},$$

$$\hat{\Sigma}_{\text{FD}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{FD}}\hat{U}^{i\prime}_{\text{FD}},$$

and

$$\hat{\Sigma}_{\text{TSFD}} = \frac{1}{N}\sum_{i=1}^{N} \hat{U}^i_{\text{TS}}\hat{U}^{i\prime}_{\text{FD}}.$$

Thus consistent estimates of the covariance and cross-covariance matrices of the residuals of these two equations would be $\hat{\Omega}_{TS} = (I_N \otimes \hat{\Sigma}_{TS})$, $\hat{\Omega}_{FD} = (I_N \otimes \hat{\Sigma}_{FD})$, and $\hat{\Omega}_{TSFD} = (I_N \otimes \hat{\Sigma}_{TSFD})$. Given these estimates, we can compute an estimate of $(V(\hat{\beta}_{TS} - \hat{\beta}_{FD}))$ that is guaranteed to be positive definite as follows:

$$
\begin{aligned}
V(\hat{\beta}_{TS} - \hat{\beta}_{FD}) \\
&= (X'_{TS}Z(Z'Z)^{-1}Z'X_{TS})^{-1}(X'_{TS}Z(Z'Z)^{-1}Z'\hat{\Omega}_{TS}Z(Z'Z)^{-1}Z'X_{TS}) \\
&\qquad \times (X'_{TS}Z(Z'Z)^{-1}Z'X_{TS})^{-1} \\
&- (X'_{TS}Z(Z'Z)^{-1}Z'X_{TS})^{-1}(X'_{TS}Z(Z'Z)^{-1}Z'\hat{\Omega}_{TSFD}Z(Z'Z)^{-1}Z'X_{FD}) \\
&\qquad \times (X'_{-FD}Z(Z'Z)^{-1}Z'X_{FD})^{-1} \\
&- (X_{FD}Z(Z'Z)^{-1}Z'X_{FD})^{-1}(X'_{FD}Z(Z'Z)^{-1}Z'\hat{\Omega}'_{TSFD}Z(Z'Z)^{-1}Z'X_{TS}) \\
&\qquad \times (X'_{TS}Z(Z'Z)^{-1}Z'X_{TS})^{-1} \\
&+ (X'_{FD}Z(Z'Z)^{-1}Z'X_{FD})^{-1}(X'_{FD}Z(Z'Z)^{-1}Z'\hat{\Omega}_{FD}Z(Z'Z)^{-1}Z'X_{FD}) \\
&\qquad \times (X'_{FD}Z(Z'Z)^{-1}Z'X_{FD})^{-1}.
\end{aligned}
$$

This estimate of the covariance matrix will allow us to compute the specification test to determine whether there is an individual effect that is correlated with instruments. (Here, as previously, a heteroscedastic-consistent version is available by using the estimator for $Z'\Omega_{TS}Z$, and similar terms, suggested by Runkle [1991].)

4. EMPIRICAL EXAMPLE: TESTING THE RATIONAL-EXPECTATIONS-LIFE-CYCLE CONSUMPTION MODEL

The following example will illustrate why failing to determine whether instruments are strictly exogenous or merely predetermined can cause problems with statistical inference in panel-data models. Several recent articles have used panel data to test the permanent-income hypothesis. Among them are those of Shapiro (1984), Zeldes (1989), and Runkle (1991). Since the permanent-income hypothesis states that consumption growth from period t to period $t + 1$ should depend only on the real-interest rate from period t to period $t + 1$, these authors have all estimated some version of the equation

$$
\begin{aligned}
\Delta C_{i,t+1} &= \ln(C_{i,t+1}) - \ln(C_{i,t}) \\
&= \beta_0 + \beta_1 r_{i,t} + \varepsilon_{i,t+1}, \\
&\quad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T - 1, \qquad (9)
\end{aligned}
$$

where $C_{i,t}$ is the level of real consumption for person i in period t and $r_{i,t}$ is the one-period after-tax real interest rate for person i from period t to period $t + 1$. (Of course, this equation may also include demographic factors such as age.) The variable $r_{i,t}$ is uncertain because the price level at time $t + 1$ is unknown at time t. Therefore, Equation (9) must be estimated using some IV method. A list of valid instruments for estimating Equation (9) can be found by invoking the assumption of rational expectations—namely, $E(\varepsilon_{i,t+1}|I_{i,t}) = 0$, where $I_{i,t}$ is the information available to person i at time t.

If there is no serial correlation in $\varepsilon_{i,t+1}$, Equation (9) can be estimated using 2SLS. But serial correlations could exist if there were an error in the measurement of $\ln(C_{i,t})$—an unnecessary complication here (see Runkle 1991)—or if there were persistent individual differences in the discount rate. Such differences in the discount rate would cause individual-specific variations in β_0, which would cause a persistent individual effect in $\varepsilon_{i,t+1}$.

If there is a persistent individual effect η_i in $\varepsilon_{i,t+1}$ in Equation (9), the standard 2SLS estimator will be inconsistent or, at best, inefficient, depending on whether η_i is a fixed or a random effect. But standard GLS transformations cannot be used to obtain consistent and efficient estimates. Because of the rational-expectations assumption needed to estimate Equation (9), both the GLS random-effects estimator and the fixed-effects estimator will be inconsistent because the available instruments are predetermined, rather than strictly exogenous. Specifically $\bar{\varepsilon}_i$ is correlated with elements of *all* the information sets I_{is} for $s = 1, \ldots, T - 1$, so no valid instruments are available to estimate a standard GLS transformed version of (9).

It has long been noted in the time-series literature (for example by Hansen and Hodrick 1980) that conventional GLS estimators of linear rational-expectations models will produce inconsistent parameter estimates because those estimators violate some of the orthogonality conditions imposed by rational expectations. For exactly the same reasons, the IV GLS estimators proposed by Hausman and Taylor (1981), Amemiya and MaCurdy (1986), and Breusch et al. (1989) will be inconsistent for estimating Equation (9). All of those estimators would start by quasi-demeaning the equation, as in the work of Maddala (1971). Then they would use an IV estimator that requires all instruments to be strictly exogenous. But rational-expectations models have no such instruments; rational expectations imposes only predeterminedness. And the GLS transformations that all of the estimators employ would violate the orthogonality conditions imposed by Equation (9) because those transformations assume that a linear combination of current and past errors is orthogonal to current instruments. That condition is not satisfied in Equation (9).

For the same reason, a standard fixed-effects estimator will yield inconsistent estimates of Equation (9). (A similar point was made by Chamberlain [1984] and Runkle [1991]). Writing down a fixed-effects version of Equation (9) shows why this is true. That equation is simply

$$
\begin{aligned}
\Delta C_{i,t+1} - \overline{\Delta C}_i &= \beta_1(r_{i,t} - \bar{r}_i) + \varepsilon_{i,t+1} - \bar{\varepsilon}_i, \\
&\quad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T - 1, \qquad (10)
\end{aligned}
$$

which would be estimated using instruments from time t and before. Unfortunately, the error term for person i in period t in this transformed equation, $\varepsilon_{i,t+1} - \bar{\varepsilon}_i$, is a function of the errors for person i in each period in Equation (9). As a result, the errors in the transformed equation are not orthogonal to the proposed instruments, and the parameter estimates will be inconsistent.

Thus, in rational-expectations panel-data models, neither conventional random-effects estimates nor conventional fixed-effects estimators will be consistent, because instruments are predetermined rather than strictly exogenous. Furthermore, the specification tests described by Hausman (1978) and Hausman and Taylor (1981) will give misleading results. Since each of the estimators used in those tests will be inconsistent when estimating rational-expectations panel-data models, those tests will also be inconsistent.

Because of these problems, we have reexamined the rational-expectations–life-cycle consumption model using the new estimation methods and specification tests described in Sections 2 and 3. As with all of the studies we have cited, we use data from the Michigan Panel Study on Income Dynamics (PSID). Our sample includes 3,762 observations on 627 households surveyed between 1975 and 1982. For a description of our data-screening criteria and an explanation of our constructed variables, see the Appendix. These computations closely follow Runkle (1991) and Zeldes (1989).

We estimate a modified version of Equation (9),

$$\ln(C_{i,t+1}) - \ln(C_{i,t}) = \beta_0 + \beta_1 r_{i,t} + \beta_2 \text{age}_{i,t} + \varepsilon_{i,t+1},$$
$$i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T-1, \qquad (9')$$

where $C_{i,t}$ is the level of real consumption for household i in period t, and $r_{i,t}$ is the one-period after-tax real interest rate for household i from period t to period $t + 1$. In the PSID, the only measure of consumption is food consumption. We use that as our measure of consumption.

We examine three sets of results in this example. First, we test to see whether the instruments for estimating Equation (9′) are predetermined or strictly exogenous. Second, we test whether there is an individual effect that is correlated with the instruments. Finally, we examine the implications of these tests for previous work testing for liquidity constraints using panel data. All reported standard errors and test statistics are corrected for conditional heteroscedasticity and serial correlation. (For a discussion of the source of the serial correlation in this model, see Runkle [1991].)

Table 1 shows the results of estimating Equation (9′). Four estimators are reported, 2SLS (col. 1), two-stage fixed-effects (col. 2), two-stage first-difference (col. 3), and our new estimator (col. 4). The estimates from the fixed-effects estimator are very different from the other three estimators. This suggests that the instruments may not be strictly exogenous.

Table 1. The Results of Estimating Equation (9′)

	Methods			
Estimator	*(1) 2SLS*	*(2) FE*	*(3) FD*	*(4) KR*
β_0	.103	—	—	.096
	(.013)			(.012)
β_1	.486	1.551	.719	.439
	(.145)	(.419)	(.233)	(.139)
β_2	−.002	−.022	.003	−.002
	(.0003)	(.007)	(.003)	(.0002)

NOTE: Standard errors are in parentheses. The number of observations is 3,762.

Our specification test for strict exogeneity rejects exogeneity. If we compute that test based on the difference between the parameter estimates of the fixed-effects and the first-difference models, we find that the value of the test statistic is 12.05. Under the null hypothesis of exogeneity, that statistic should be distributed asymptotically as a χ^2_2 random variable. Thus we must reject the null hypothesis of exogeneity. This means that it is *not* legitimate to estimate any version of Equation (9′) using a standard fixed-effects estimator.

Comparing the 2SLS estimates with the first-differenced estimates allows us to test whether there is an individual effect that is correlated with the instruments. The estimates appear quite close, and a specification test reveals no significant difference between the two sets of parameters. If we compute our specification test based on the difference between the common parameters in the 2SLS and first-difference estimators, the value of the statistic is .55. Under the null hypothesis of no correlation, that test statistic is distributed asymptotically as a χ^2_2 random variable. Therefore, we cannot reject the null hypothesis of no correlation between the individual effect and the instruments. This means that it is unnecessary to use a first-difference estimator for estimating (9′) and that severe efficiency losses will result if one is used. The difference in the standard errors between columns 1 and 3 shows how severe those losses are.

Note that the failure of strict exogeneity causes the 2SLS and two-stage fixed-effects estimates to be quite different even though no fixed effects are present. Given this type of bias in two-stage fixed-effects estimates, traditional Hausman–Taylor type specification tests would lead one to falsely conclude that fixed effects are present.

The results of these two specification tests also suggest that our new estimator is appropriate to use in this case and that it may increase efficiency. A comparison of columns 1 and 4 shows the efficiency gains from using $\hat{\beta}_{\text{KR}}$. The standard errors are smaller for every coefficient using the new estimator than using 2SLS. The reductions in the estimated standard deviations of the coefficients range from 7% to 13%.

We have assumed here, as does all of the literature, that there are no time-period-specific error components. If such error components were present, they would cause problems for our new estimator, but not for the specification tests. Runkle (1991), however, failed to reject the hypothesis that there were no such time-period-specific errors in this model, so our assumption seems appropriate.

Although Table 1 and the specification tests showed the statistical importance of the assumption of exogeneity, we have not yet demonstrated its economic importance. We do that now by considering tests for liquidity constraints using a second modification to Equation (9). This final equation, which we will call Equation (9″), is as follows:

$$\ln(C_{i,t+1}) - \ln(C_{i,t}) = \beta_0 + \beta_1 r_{i,t} + \text{age}_{i,t} + \beta_3 \ln(Y_{i,t}) + \varepsilon_{i,t+1},$$
$$i = 1, 2, \ldots, N; t = 1, 2, \ldots, T - 1. \quad (9'')$$

Both Runkle (1991) and Zeldes (1989) estimated Equation (9″) using samples that are similar to the one used in this article. Table 2 reports estimates of Equation (9″) using $\hat{\beta}_{\text{KR}}$, which eliminates serial correlation by transforming Equation (9″), as well as estimates obtained using a standard two-stage fixed-effects estimator. The difference in the results is striking. In fact, the value of the χ_3^2 test statistic comparing the common coefficients is 11.07. Thus we must reject the hypothesis that the common parameters are the same.

The inconsistent fixed-effects estimates suggest that lagged income is significant, both statistically and economically, in explaining consumption growth; that is, there are important liquidity constraints. The results imply that consumption grows faster from this period to next period if this period's income is lower, because an inability to borrow constrains today's consumption. These estimates are qualitatively similar to those in Zeldes's (1989) article, but the estimated effect of income on consumption growth is even larger than the one he found. The consistent estimator $\hat{\beta}_{\text{KR}}$, however, shows that lagged income is neither statistically nor economically significant in explaining consumption growth. These results are similar to those of Runkle (1991). When coupled with the results in Table 1 this suggests that one possible reason for the difference between Zeldes's and Runkle's estimates stems from Zeldes's use of a fixed-effects estimator in a case that yields inconsistent parameter estimates.

Table 2. The Results of Estimating Equation (9″)

	Methods	
Estimator	KR (1)	FE (2)
β_0	.192 (.067)	—
β_1	.451 (.140)	1.211 (.340)
β_2	−.002 (.0002)	−.017 (.005)
β_3	−.011 (.008)	−.375 (.176)

NOTE: Standard errors are in parentheses. The number of observations is 3,762.

5. CONCLUSION

This article developed two new specification tests for panel-data models. The first is a test to determine whether a panel-data model with individual-specific effects can be estimated using conventional estimators that assume that all instruments are strictly exogenous. The second is a test for the presence of individual fixed effects that is valid even when instruments are predetermined but not strictly exogenous. It also developed a new estimator that may yield more efficient estimates for panel-data models when instruments are predetermined but not strictly exogenous. Our empirical example demonstrated the importance of this work for determining the validity of the permanent-income hypothesis.

APPENDIX: DATA CONSTRUCTION

It is important to understand both the criteria used to exclude specific observations and the methods used to construct variables used in the empirical analysis. As mentioned in the text of the article, the data for this study come from the PSID. The sample used in the following analysis consists of a balanced panel of 3,762 observations on 627 households between 1975 and 1982. Because the model is estimated in first differences and we use lagged variables, eight years of data yield six annual observations per family. Since this article is concerned with consumption, our criteria for sample selection minimize the noise in the consumption data. We included an observation for a household only if all data on consumption and income were available for that period. Since all data records were kept for heads of households, measurement error in the consumption series would occur if the head of a household divorced, stayed single for a year, and remarried. Therefore, if a couple married or divorced in a given year, we discarded the data for that year and treated the resulting household as a new household. To reduce errors in the measurement of income, we excluded farmers and self-employed heads of households. Since the selection is based on variables exogenous to the estimated equations, no sample selection bias will occur.

The most important household variables used in this study were food consumption, disposable income, the annual number of hours worked by the householder, and the household's after-tax real interest rate. Annual hours worked are provided directly in the survey, but all of the other variables must be computed from data in the survey.

Real food consumption was computed as the sum of real food consumption at home and real food consumption away from home. The nominal data for each element of food consumption was deflated by the appropriate Consumer Price Index (CPI) component. Since the food-consumption data refer to consumption during a week in the first quarter of the survey year, the average CPI component for the first three months of the year was used to deflate the nominal quantities. The net cash value of food stamps was included in the nominal value of food consumption at home.

Disposable income was computed as reported family-unit income plus the net cash value of food stamps minus federal income and Social Security taxes paid by the householders. Taxes are computed for both husband and wife if both are present in the family. Social Security taxes are computed from published Social Security tax schedules and reported labor income.

The after-tax interest rate for each household was computed by multiplying the interest rate by $(1 - \theta_{i,t})$, where $\theta_{i,t}$ is the marginal tax rate for household i in period t. The average annual passbook savings rate for the year before the panel interview was used as the interest rate. The real after-tax interest rate for each household was computed by subtracting the ex post inflation rate from the after-tax interest rate.

For the equations in Table 1, the instrument list includes a constant, the householder's hours worked in period $t - 2$, the natural log of the family's disposable income in period $t - 2$, and the value of the after-tax real interest rate for passbook and T-bill interest rates in period $t - 2$. This common instrument list is chosen because all information must be from period $t - 2$ or before the first-difference estimator to be consistent.

For the equations in Table 2, the instrument list includes a constant, the householder's age, the householder's hours worked in period $t - 1$, the natural log of the family's disposable income in period $t - 1$, the value of the after-tax real interest rate for passbook and T-bill interest rates in period $t - 1$, and the log-difference of the family's disposable income in periods $t - 1$ and $t - 2$. The instrument list is different from that used for Table 1 because the information constraints are not as strict as those for estimating the first-difference model in Table 1.

[Received January 1991. Revised August 1991.]

REFERENCES

Ahn, S., and Schmidt, P. (1990), "Efficient Estimation of Models for Dynamic Panel Data," unpublished manuscript, Michigan State University, Dept. of Economics.

Amemiya, T., and MaCurdy, T. E. (1986), "Instrumental-Variables Estimation of an Error-Components Model," *Econometrica*, 54, 869–880.

Anderson, T. W., and Hsiao, C. (1981), "Estimation of Dynamic Models With Error Components," *Journal of the American Statistical Association*, 76, 598–606.

Arellano, M., and Bover, O. (1990), "Another Look at the Instrumental-Variable Estimation of Error-Components Models," Discussion Paper 7, London School of Economics, Centre for Economic Performance.

Balestra, P., and Nerlove, M. (1966), "Pooling Cross Section and Time Series Data in the Estimation of a Dynamic Model: The Demand for Natural Gas," *Econometrica*, 34, 585–612.

Bhargava, A., and Sargan, J. D. (1983), "Estimating Dynamic Random Effects Models From Panel Data Covering Short Time Periods," *Econometrica*, 51, 1635–1659.

Breusch, T., Mizon, G. E., and Schmidt, P. (1989), "Efficient Estimation Using Panel Data," *Econometrica*, 57, 695–700.

Chamberlain, G. (1984), "Panel Data," in *Handbook of Econometrics* (Vol. 2), eds. Z. Griliches and M. D. Intriligator, Amsterdam: Elsevier, pp. 1247–1313.

Hansen, L. P., and Hodrick, R. J. (1980), "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis," *Journal of Political Economy*, 88, 829–53.

Hausman, J. (1978), "Specification Tests in Econometrics," *Econometrica*, 46, 1251–1272.

Hausman, J., and Taylor, W. (1981), "Panel Data and Unobservable Individual Effects," *Econometrica*, 49, 1377–1398.

Hayashi, F., and Sims, C. (1983), "Nearly Efficient Estimation of Time Series Models With Predetermined but not Exogenous Instruments," *Econometrica*, 51, 783–792.

Holtz-Eakin, D., Newey, W., and Rosen, H. (1988), "Estimating Vector Autoregressions With Panel Data," *Econometrica*, 56, 1371–1395.

Maddala, G. S. (1971), "The Use of Variance Components Models in Pooling Cross Section and Time Series Data," *Econometrica*, 39, 341–358.

Runkle, D. E. (1991), "Liquidity Constraints and the Permanent Income Hypothesis: Evidence from Panel Data," *Journal of Monetary Economics*, 97, 73–98.

Shapiro, M.D. (1984), "The Permanent Income Hypothesis and the Real Interest Rate: Some Evidence From Panel Data," *Economic Letters*, 14, 93–100.

Zeldes, S. (1989), "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy*, 97, 305–346.

LINKED CITATIONS

You have printed the following article:

On the Estimation of Panel-Data Models with Serial Correlation When Instruments Are Not Strictly Exogenous
Michael P. Keane; David E. Runkle
Journal of Business & Economic Statistics, Vol. 10, No. 1. (Jan., 1992), pp. 1-9.
Stable URL:
http://links.jstor.org/sici?sici=0735-0015%28199201%2910%3A1%3C1%3AOTEOPM%3E2.0.CO%3B2-D

This article references the following linked citations:

References

Instrumental-Variable Estimation of an Error-Components Model
Takeshi Amemiya; Thomas E. MaCurdy
Econometrica, Vol. 54, No. 4. (Jul., 1986), pp. 869-880.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198607%2954%3A4%3C869%3AIEOAEM%3E2.0.CO%3B2-6

Estimation of Dynamic Models with Error Components
T. W. Anderson; Cheng Hsiao
Journal of the American Statistical Association, Vol. 76, No. 375. (Sep., 1981), pp. 598-606.
Stable URL:
http://links.jstor.org/sici?sici=0162-1459%28198109%2976%3A375%3C598%3AEODMWE%3E2.0.CO%3B2-Q

Pooling Cross Section and Time Series Data in the Estimation of a Dynamic Model: The Demand for Natural Gas
Pietro Balestra; Marc Nerlove
Econometrica, Vol. 34, No. 3. (Jul., 1966), pp. 585-612.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28196607%2934%3A3%3C585%3APCSATS%3E2.0.CO%3B2-F

Estimating Dynamic Random Effects Models from Panel Data Covering Short Time Periods
Alok Bhargava; J. D. Sargan
Econometrica, Vol. 51, No. 6. (Nov., 1983), pp. 1635-1660.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198311%2951%3A6%3C1635%3AEDREMF%3E2.0.CO%3B2-X

LINKED CITATIONS

Efficient Estimation Using Panel Data
Trevor S. Breusch; Grayham E. Mizon; Peter Schmidt
Econometrica, Vol. 57, No. 3. (May, 1989), pp. 695-700.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198905%2957%3A3%3C695%3AEEUPD%3E2.0.CO%3B2-C

Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis
Lars Peter Hansen; Robert J. Hodrick
The Journal of Political Economy, Vol. 88, No. 5. (Oct., 1980), pp. 829-853.
Stable URL:
http://links.jstor.org/sici?sici=0022-3808%28198010%2988%3A5%3C829%3AFERAOP%3E2.0.CO%3B2-J

Specification Tests in Econometrics
J. A. Hausman
Econometrica, Vol. 46, No. 6. (Nov., 1978), pp. 1251-1271.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28197811%2946%3A6%3C1251%3ASTIE%3E2.0.CO%3B2-X

Panel Data and Unobservable Individual Effects
Jerry A. Hausman; William E. Taylor
Econometrica, Vol. 49, No. 6. (Nov., 1981), pp. 1377-1398.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198111%2949%3A6%3C1377%3APDAUIE%3E2.0.CO%3B2-3

Nearly Efficient Estimation of Time Series Models with Predetermined, but not Exogenous, Instruments
Fumio Hayashi; Christopher Sims
Econometrica, Vol. 51, No. 3. (May, 1983), pp. 783-798.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198305%2951%3A3%3C783%3ANEEOTS%3E2.0.CO%3B2-U

Estimating Vector Autoregressions with Panel Data
Douglas Holtz-Eakin; Whitney Newey; Harvey S. Rosen
Econometrica, Vol. 56, No. 6. (Nov., 1988), pp. 1371-1395.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28198811%2956%3A6%3C1371%3AEVAWPD%3E2.0.CO%3B2-V

LINKED CITATIONS

The Use of Variance Components Models in Pooling Cross Section and Time Series Data
G. S. Maddala
Econometrica, Vol. 39, No. 2. (Mar., 1971), pp. 341-358.
Stable URL:
http://links.jstor.org/sici?sici=0012-9682%28197103%2939%3A2%3C341%3ATUOVCM%3E2.0.CO%3B2-A

Consumption and Liquidity Constraints: An Empirical Investigation
Stephen P. Zeldes
The Journal of Political Economy, Vol. 97, No. 2. (Apr., 1989), pp. 305-346.
Stable URL:
http://links.jstor.org/sici?sici=0022-3808%28198904%2997%3A2%3C305%3ACALCAE%3E2.0.CO%3B2-M