Chapter 17

PANEL AND CROSS-SECTIONAL DATA

Many recent macroeconomic applications use panel and cross-sectional data. For example, macroeconomic hypotheses are tested in micro data sets for households, industries, and business firms and in aggregate data sets for many countries. This chapter focuses on econometric issues that are particularly relevant for macroeconomic applications.

17.1 Generalized Method of Moments

This section discusses GMM from the cross-sectional average rather than from the time series average as in Chapter 9. The method here can be applied to both cross-sectional and panel data with many cross-sectional observations and to those with a relatively small number of observations over time. Given cross-sectional data for $\mathbf{x}_i$, let $\mathbf{b}_0$ be a p-dimensional vector of the parameters to be estimated, and $f(\mathbf{x}_i, \mathbf{b})$ a q-dimensional vector of functions. We refer to $\mathbf{u}_i = f(\mathbf{x}_i, \mathbf{b}_0)$ as the disturbance of GMM. We assume that $\mathbf{x}_i$ is i.i.d. Consider the (unconditional) moment restrictions

$$E(f(\mathbf{x}_i, \mathbf{b}_0)) = 0. \tag{17.1}$$

Note that $E(\mathbf{u}_i\mathbf{u}_j')=0$ for $i \neq j$. Suppose that a law of large numbers can be applied to $f(\mathbf{x}_i,\mathbf{b})$ for all admissible $\mathbf{b}$, so that the sample mean of $f(\mathbf{x}_i,\mathbf{b})$ converges to its population mean:

$$\lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N} f(\mathbf{x}_i,\mathbf{b}) = E(f(\mathbf{x}_i,\mathbf{b})) \tag{17.2}$$

with probability one (or in other words, almost surely). The basic idea of GMM estimation is to mimic the moment restrictions (17.2) by minimizing a quadratic form of the sample means

$$J_N(\mathbf{b}) = \{\frac{1}{N}\sum_{i=1}^{N} f(\mathbf{x}_i,\mathbf{b})\}' W_N \{\frac{1}{N}\sum_{i=1}^{N} f(\mathbf{x}_i,\mathbf{b})\} \tag{17.3}$$

with respect to $\mathbf{b}$; where W_N is a positive definite matrix, which satisfies

$$\lim_{N\to\infty} W_N = W_0 \tag{17.4}$$

with probability one for a positive definite matrix W_0. The matrices W_N and W_0 are both referred to as the distance or weighting matrix. The GMM estimator, $\mathbf{b}_N$, is the solution of the minimization problem (17.3). Under fairly general regularity conditions, the GMM estimator $\mathbf{b}_N$ is a consistent estimator for arbitrary distance matrices. The optimal choice of the distance matrix is $W_0 = E(\mathbf{u}_i\mathbf{u}_i')^{-1}$.

The GMM for cross-sectional data can be applied to panel data with large N and short T in order to allow for a general serial correlation structure. Let $\mathbf{x}_{it}$ be a random vector of economic variables for an individual i at period t and $f_t(\mathbf{x}_{it},\mathbf{b})$ be a q^*-dimensional vector of functions, and let $\mathbf{u}_{it} = f_t(\mathbf{x}_{it},\mathbf{b}_0)$. Let $q = Tq^*$, $\mathbf{x}_i = (\mathbf{x}_{i1}',\cdots,\mathbf{x}_{iT}')'$ and $f(\mathbf{x}_i,\mathbf{b}) = (f_1(\mathbf{x}_{i1},\mathbf{b})',\cdots,f_T(\mathbf{x}_{iT},\mathbf{b})')'$. In this framework,

$E(\mathbf{u}_i\mathbf{u}_i')$ can be estimated by $\frac{1}{N}\sum_{i=1}^{N}\mathbf{u}_i\mathbf{u}_i'$. Since

$$E(\mathbf{u}_i\mathbf{u}_i') = \begin{bmatrix} E(\mathbf{u}_{i1}\mathbf{u}_{i1}') & \cdots & E(\mathbf{u}_{i1}\mathbf{u}_{iT}') \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ E(\mathbf{u}_{iT}\mathbf{u}_{i1}') & \cdots & E(\mathbf{u}_{iT}\mathbf{u}_{iT}') \end{bmatrix}, \tag{17.5}$$

where some entries of $E(\mathbf{u}_i\mathbf{u}_i')$ represent autocovariances of $\mathbf{u}_{it}$. Thus a general form of serial correlation is allowed by stacking disturbance terms with different dates as different disturbance terms rather than treating them as different observations of one disturbance term. Unlike GMM for the time series average in Chapter 9, there is no need to use kernel estimators to allow for a general form of serial correlation.

17.2 Tests of Risk Sharing

As in Chapter 7, consider an economy with a single good, in which the current and past values of a random vector $\mathbf{x}_t$ generate the information set I_t, which is available to the economic agents. The random vector $\mathbf{H}_t = [\mathbf{x}_0', \mathbf{x}_1', \cdots, \mathbf{x}_t']'$ summarizes I_t. Let $Prob(\mathbf{H}_t)$ denote the probability of $\mathbf{H}_t$. For simplicity, we assume that the economy ends at date T, and that there exist N possible values of $\mathbf{H}_T$.

We assume that consumer h maximizes the lifetime utility function

$$U^h = \sum_{t=0}^{T}\sum_{\mathbf{H}_t} Prob(\mathbf{H}_t)\beta^t u(C_t^h(\mathbf{H}_t)), \tag{17.6}$$

where β is a discount factor, $u(\cdot)$ is the utility function, and $C_t^h(\mathbf{H}_t)$ is the consumption at date t with history $\mathbf{H}_t$. As a bench mark case, we assume that there exists a complete set of contingent security markets at date 0. Assuming the existence of a complete set of markets, we obtain

$$\frac{\beta^1 Prob(\mathbf{H}_{t+1}) mu(C_{t+1}^h(\mathbf{H}_{t+1}))}{Prob(\mathbf{H}_t) mu(C_t^h(\mathbf{H}_t))} = \frac{P_{t+1}(\mathbf{H}_{t+1})}{P_t(\mathbf{H}_t)} \tag{17.7}$$

which we call the *state-by-state intertemporal first order condition.*

The first order condition (17.7) implies that the ratio of the marginal utilities, $\frac{mu(C^h_{t+1}(\mathbf{H}_{t+1}))}{mu(C^h_t(\mathbf{H}_t))}$ is identical for all consumers for all possible histories. When this condition is satisfied, consumers are said to be completely risk sharing. The hypothesis of complete risk sharing has been tested by Altug and Miller (1990), Deaton (1990), Cochrane (1991), Mace (1991), Townsend (1994), and Hayashi, Altonji, and Kotlikoff (1996) among others.

The implications of complete risk sharing on consumption depend on the functional form of the utility function. With an isoelastic utility function, $u(C_t) = \frac{C_t^{1-\alpha}-1}{1-\alpha}$, $mu(C^h_t) = (C^h_t)^{-\alpha}$. Hence complete risk sharing implies that consumption growth, $\frac{C^h_{t+1}(\mathbf{H}_{t+1})}{C^h_t(\mathbf{H}_t)}$, is identical for all consumers for all possible histories. With a constant absolute risk aversion utility function, $u_t(C_t) = \exp(\alpha C_t)$, $mu_t = \alpha\exp(\alpha C_t)$. Hence (17.7) implies that $\exp(\alpha(C^h_{t+1}(\mathbf{H}_{t+1}) - C^h_t(\mathbf{H}_t)))$ is identical for all consumers in all possible histories. Therefore, complete risk sharing implies that the change in consumption is identical for all consumers.

These implications hold exactly without any errors. For tests of complete risk sharing with household data, errors are introduced either as preference shocks or measurement errors. Since measurement errors are likely to be important for household data, we consider them.

With the isoelastic utility function, assume that consumption is measured with multiplicative errors: $C^{mh}_t = C^h_t e^h_t$, where C^{mh}_t is the measured level of consumption. Then let ϕ_t be the logarithm of the growth rate of consumption that is common to all consumers: $\ln(C^h_{t+1}) - \ln(C^h_t) = \phi_t$. Substituting $\ln(C^h_t) = \ln(C^{mh}_t) - \ln(e^h_t)$ into this equation, we obtain

$$\ln(C^{mh}_{t+1}) - \ln(C^{mh}_t) = \phi_t + e^h_t, \tag{17.8}$$

where $e^h_t = -\ln(e^h_{t+1}) + \ln(e^h_t)$. Consider the regression

$$\ln(C^{mh}_{t+1}) - \ln(C^{mh}_t) = bd_t + \mathbf{x}^{h\prime}_t\mathbf{a} + e^h_t, \tag{17.9}$$

where d_t is a time dummy and $\mathbf{x}^h_t$ contains variables that are uncorrelated with the logarithm of the measurement error in consumption. Typically, income growth of consumer h is used as $\mathbf{x}^h_t$. Wealth, unemployment, and sickness are other examples. The null hypothesis of complete risk sharing can be tested by testing $\mathbf{a} = \mathbf{0}$.

With the exponential utility function, assume that consumption is measured with additive errors: $C^{mh}_t = C^h_t + e^h_t$, where C^{mh}_t is the measured level of consumption. Then let ϕ_t be the common first difference of consumption. Then

$$C^{mh}_{t+1} - C^{mh}_t = \phi_t + e^h_t, \tag{17.10}$$

where $e^h_t = -e^h_{t+1} + e^h_t$. Consider the regression

$$C^{mh}_{t+1} - C^{mh}_t = bd_t + \mathbf{x}^{h\prime}_t\mathbf{a} + e^h_t, \tag{17.11}$$

where d_t is a time dummy and $\mathbf{x}^h_t$ contains variables that are uncorrelated with the measurement errors in consumption. Then the null hypothesis of complete risk sharing can be tested by testing $\mathbf{a} = \mathbf{0}$.

17.3 Decreasing Relative Risk Aversion and Risk Sharing

Ogaki and Zhang (2001) argue that decreasing relative risk aversion is more plausible than constant relative risk aversion and increasing relative risk aversion. A parsimonious parameterization of the utility function which contains decreasing, constant, and increasing relative risk aversion as special cases is

$$u(C_t) = \frac{1}{1-\alpha}((C_t - \gamma)^{1-\alpha} - 1) \tag{17.12}$$

which is called the Hyperbolic Absolute Risk Aversion (HARA) utility function.

Then the relative risk aversion coefficient is

$$-\frac{u'' C_t^h}{u'} \alpha (1 - \frac{\gamma}{C_t^h})^{-1}. \tag{17.13}$$

Thus relative risk aversion is decreasing (increasing) in consumption if γ is positive (negative).

For the HARA utility function $mu(C_t^h) = (C_t^h - \gamma)^{-\alpha}$. Hence the complete risk sharing hypothesis implies that $C_t^h - \gamma$ grows at the same rate for all consumers. Let ϕ_t be the common growth rate:

$$\frac{C_{t+1}^h - \gamma}{C_t^h - \gamma} = \phi_t. \tag{17.14}$$

Assume that consumption is measured with additive errors: $C_t^{mh} = C_t^h + e_t^h$ where C_t^{mh} is the measured level of consumption. Multiplying both sides of (17.14) by $C_t^h - \gamma$, substituting $C_t^h = C_t^{mh} - e_t^h$, and rearranging terms, we obtain

$$C_{t+1}^{mh} - \phi_t C_t^{mh} + (\phi_t - 1)\gamma = \nu_t^h, \tag{17.15}$$

where

$$\nu_t^h = e_{t+1}^h - e_t^h. \tag{17.16}$$

Let $\mathbf{z}_t^h$ be a vector of instrumental variables that are uncorrelated with the consumption measurement errors. Then GMM can be applied to the moment conditions that $E(\mathbf{z}_t^h \nu_t^h) = \mathbf{0}$.

17.4 Euler Equation Approach

As in Chapter 7, the state-by-state intertemporal first order condition can be used to derive the Euler equation

$$\frac{E(\beta mu(C^h_{t+1})R_{t+1}|\mathrm{I}_t)}{mu(C^h_t)} = 1 \tag{17.17}$$

for any asset return, R_{t+1}.

Imagine that a panel data set of C^h_t and R_t is available for $t = 1, \cdots, T$ and $h = 1, \cdots, N$. In order to estimate and test the Euler equation with the panel data set, it is important to distinguish the time average and the cross-sectional average. In many panel data sets, N is large but T is small. Chamberlain (1984) criticized the use of such a panel data set for the Euler equation approach by pointing out a difficulty in such applications. This difficulty is often refereed to as *Chamberlain's critique.*

For example, assume that the intraperiod utility function is $u(C_t) = \frac{C_t^{1-\alpha}-1}{1-\alpha}$, so that $mu(C^h_t) = (C^h_t)^{-\alpha}$, and the Euler equation is

$$E[\beta(\frac{C^h_{t+1}}{C^h_t})^{-\alpha}R_{t+1}|\mathrm{I}_t] = 1. \tag{17.18}$$

Removing the conditional expectation yields

$$\beta(\frac{C^h_{t+1}}{C^h_t})^{-\alpha}R_{t+1} - 1 = e^h_t, \tag{17.19}$$

where $E(e^h_t|\mathrm{I}_t) = 0$. It should be noted that $E(e^h_t|\mathrm{I}_t) = 0$ does not imply that the probability limit of the cross-sectional average of e^h_t is zero even though it implies that the probability limit of the time-series average of e^h_t is zero. In order to see this, recall that consumption growth is identical for all consumers under complete risk sharing. Hence (17.19) implies that e_t^h is identical, and $\frac{1}{N}\sum_{h=1}^{\infty} e_t^h = e_t^1$ for any N. In a panel data set with large N and small T, an appropriate asymptotic theory fixes T and drives N to infinity to derive asymptotic results. In this example, the estimators based on $E(e_t^h|\mathrm{I}_t) = 0$ are inconsistent because $\frac{1}{N}\sum_{h=1}^{\infty} e_t^h$ does not converge to zero in probability when N is driven to infinity. This example illustrates Chamberlain's critique.

17.5 Panel Unit Root Tests

Panel data allows researchers to effectively increase the number of observations. Levin, Lin, and Chu (2002) developed unit root tests for panel data. Their null hypothesis is that all series in the panel data are difference stationary against all series are stationary. Their test is a panel version of the Augmented Dickey-Fuller test. For a panel data set of a variable $x_{i,t}$ for $i = 1, ..., N$ and $t = 1, ..., T$, they consider N time series regressions of the form:

$$\Delta\tilde{x}_{i,t} = \theta_i + \mu_i t \ + \rho\tilde{x}_{i,t-1} + \beta_{i,1}\Delta\tilde{x}_{i,t-1} + \cdots + \beta_{i,p}\Delta\tilde{x}_{t-p} + \nu_t, \tag{17.20}$$

where $\tilde{x}_{i,t} = x_{i,t} - (1/N)\sum_{i=1}^{N} x_{i,t}$. Here the cross-sectional average is subtracted from $x_{i,t}$ in each period in order to take into account the cross-sectional dependence or a common time effect. It should be noted that they assumed that ρ is common to all i under both null and alternative hypotheses. Their test statistic, which is basically the t-statistic for $\rho = 0$, is called the adjusted t-statistic. When N and T go to infinity, the test statistic has an asymptotic standard normal distribution. Im, Pesaran, and Shin (2003) relaxed Levin and Lin's assumption that ρ is common to all i. Their test is based on regressions

$$\Delta \tilde{x}_{i,t} = \theta_i + \mu_i t \ + \rho_i \tilde{x}_{i,t-1} + \beta_{i,1} \Delta \tilde{x}_{i,t-1} + \cdots + \beta_{i,p} \Delta \tilde{x}_{t-p} + \nu_t. \tag{17.21}$$

For their test, the null hypothesis is that $\rho_i = 0$ for all i, and the alternative hypothesis is that $\rho_i < 0$ at least one i. Their test statistic is based on the average of the t-statistics for the hypothesis that $\rho_i = 0$. Its asymptotic distribution is the standard normal distribution.

Maddala and Wu (1999) also relaxed Levin and Lin's assumption that ρ is common to all i. Their test statistic is based on the p-values and can be used for an unbalanced panel in which T is different for different i. However, this test is computationally more involved than the other two tests mentioned above because the p-values need to be computed by simulations for each application.

The alternative hypothesis of both Im, Pesaran, and Shin's and Maddala and Wu's tests is that at least one series is stationary. Therefore, rejection of the null hypothesis should not be regarded as evidence that all series are stationary unless there is a reason to believe that all series are either difference stationary or stationary.

Most panel unit root tests assume that the error terms are cross-sectionally uncorrelated. If this assumption is violated, then the tests can show severe size distortions (see, e.g., O'Connell, 1998). A certain degree of cross-sectional dependence can be removed by subtracting the cross-sectional mean for each time period. However, if the true cross-sectional dependence exhibits substantial heterogeneity, then this method will not work very well. Moreover, if the series share a common stochastic trend, then the subtraction of the cross-sectional mean can transform a difference stationary series into a stationary series. A recent work by Chang (2000) has solved this problem.

The tests described so far take difference stationarity as the null hypothesis. There are tests for the null hypothesis of stationarity for panel data. Nyblom and Harvey (2000) extended Kwiatkowski, Phillips, Schmidt, and Shin (1992, KPSS for short) test for stationarity to panel data. The null hypothesis is that all series in the panel are stationary, and the alternative hypothesis is that at least one of them is difference stationary. Choi (2000) extended Park and Choi's (1988) G test to panel data. Choi (2000) reports Monte Carlo results that the panel G test is more powerful than the panel KPSS test for most data generation processes.

17.6 Cointegration and Panel Data

Pedroni (2001) developed residual based tests for the null hypothesis of no cointegration for panel data while allowing for estimated slope coefficients to vary across individual members of panel. Pedroni (2000) and Phillips and Moon (1999) extended Phillips and Hansen's (1990) fully modified OLS estimator to panel data. Mark and Sul (2002) extended the dynamic OLS technique to panel data. The dynamic OLS estimator is much computationally simpler to calculate in the panel data setting. These estimators assume that the regression errors are cross-sectionally uncorrelated after removing common time effects. Seemingly unrelated cointegration techniques explained in Chapter 15 (see, e.g., Mark, Ogaki, and Sul, 2003) can be used to allow for a general form of cross-sectional dependence in regression errors. However, these techniques cannot be used when N is large because too many free parameters for cross-sectional dependence need to be estimated.

Exercises

17.1 Suppose that each consumer maximizes the identical lifetime utility function

$$\mathrm{U} = \sum_{t=0}^{T} \sum_{e_t} Prob(e_t)\beta^t U(c_t) \tag{17.E.1}$$

at time 0 in an Arrow-Debreu complete market, where $e_t = (s_0, \cdots, s_t)$ is the history of the economy, $s_t \in \{1, \cdots, S\}$ is the state of the economy at t, and $Prob(e_t)$ denotes the probability of e_t conditioned on e_0. The intra-period utility function is assumed to be

$$U(c_t) = \frac{\{c_t - \gamma\}^{1-\alpha} - 1}{1 - \alpha} \tag{17.E.2}$$

where c_t is consumption at time t

(**a**) Write down a complete market budget constraint.

(**b**) Derive a parameterized formula for a state-by-state intertemporal first order condition for c_t and c_{t+1}. Discuss the complete risk sharing implication of the first order condition. Then use the first order condition to derive an asset pricing formula for an asset that pays off d_{t+1} at $t+1$ (d_{t+1} varies depending on e_{t+1}).

(**c**) Imagine that you have panel data set for $\{c_t^h : t = 1, \cdots, T, h = 1, \cdots, N\}$ and real bond returns $\{R_t : t = 1, \cdots, T\}$ (without measurement error) in this village. Suppose that these variables are stationary. Discuss how you set up the GMM estimation to estimate β, α, and γ in this case, assuming $T = 200$ and $N = 300$. If $T = 2$ and $N = 300$, do you think that you can use the GMM to estimate these parameters for this model? Explain your answer.

(d) Now assume that there exist multiplicative measurement errors with unknown serial correlation in the consumption data $\{c_t^h : t = 1, \cdots, T, h = 1, \cdots, N\}$ in this panel data set of the following form:

$$c_t^h - \gamma = (c_t^{h*} - \gamma)\epsilon_t^h \tag{17.E.3}$$

where c_t^{h*} is the true consumption and $\ln(\epsilon_t^h)$ has mean zero and is uncorrelated across the consumers and with any income variables. Also assume that there are no asset return data and that $T = 6$ and $N = 300$. Discuss how you set up GMM estimation to estimate γ (parameterized disturbance and weighting matrix). In particular, discuss why the expected value of the parameterized GMM disturbance is zero.

(e) Now assume that there exist additive measurement errors with unknown serial correlation in the consumption data $\{c_t^h : t = 1, \cdots, T, h = 1, \cdots, N\}$ in this panel data set of the following form:

$$c_t^h = c_t^{h*} + \epsilon_t^h \tag{17.E.4}$$

where c_t^{h*} is the true consumption and ϵ_t^h has mean zero and is uncorrelated across consumers and with any income variables. Also assume that there are no asset return data and that $T = 6$ and $N = 300$. Discuss how you set up GMM estimation to estimate γ in terms of the parameterized disturbance. In particular, discuss why the expected value of the parameterized GMM disturbance is zero. You do not have to explain the weighting matrix for this question.

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