Table 10.3
TFP Growth Adjusted for Endogenous Responses of Capital

Country	(1) GDP Growth Rate	(2) TFP Growth Rate	(3) TFP Growth Adjusted for Physical Capital	(4) TFP Growth Adjusted for Broad Capital
Hong Kong	0.073	0.027 (37%)	0.043 (59%)	0.090 (123%)
Singapore	0.087	0.022 (25%)	0.043 (49%)	0.073 (84%)
South Korea	0.103	0.015 (14%)	0.021 (20%)	0.050 (49%)
Taiwan	0.094	0.037 (39%)	0.050 (53%)	0.123 (131%)

Notes: Column 1 shows the growth rate of GDP as given in table 10.1, panel D. Column 2 shows the TFP growth rate indicated for the dual column in table 10.2. Column 3 adjusts for responses of physical capital by multiplying the TFP growth rate by $1/(1-\alpha)$, where α is the capital share shown in table 10.1, panel D. Column 4 adjusts for responses of physical and human capital by multiplying the TFP growth rate by 1/0.3, that is, by assuming a broad capital share of $\alpha = 0.7$. The numbers in parentheses show the percentages of the growth rate of GDP accounted for by each measure of TFP growth.

The corrections made in this section surely overstate the importance of technological progress because they assume that all of the endogenous responses of capital occur within the period of observation. The calculations are not meant to offer a realistic way of adjusting the TFP estimates to make causality statements about ultimate sources of growth but, rather, to warn the reader that such claims should be avoided. A small positive number for $\hat{g}$ is, in principle, consistent with a situation in which technological progress is ultimately responsible for a small part of GDP growth, but it is also consistent with a situation in which it is ultimately responsible for the entirety of GDP growth. Thus the same accounting decomposition is consistent with two entirely different visions of growth.

Growth accounting may be able to provide a mechanical decomposition of the growth of output into growth of an array of inputs and growth of total factor productivity. Successful accounting of this sort is likely to be useful and may stimulate the development of useful economic theories of growth. Growth accounting does not, however, constitute a theory of growth because it does not attempt to explain how the changes in inputs and the improvements in total factor productivity relate to elements—such as aspects of preferences, technology, and government policies—that can reasonably be viewed as fundamentals.

11 Empirical Analysis of Regional Data Sets

A key property of the neoclassical growth model is its prediction of conditional convergence, a concept that applies when the growth rate of an economy is positively related to the distance between this economy's level of income and its own steady state. Conditional convergence should not be confused with absolute convergence, a concept that applies when poor economies tend to grow faster than rich ones (and, therefore, the poor tend to "catch up"). It is possible that two economies converge in the conditional sense (the growth rate of each economy declines as it approaches its own steady state) but not in the absolute sense (the rich economy can grow faster than the poor one if the former is further below its own steady state). The two concepts are identical if a group of economies tend to converge to the same steady state. We found in chapters 1 and 2 that neoclassical economies with similar tastes and technologies converge to the same steady state. Therefore, in this case, the neoclassical growth model predicts absolute convergence; that is, poor economies tend to grow faster than rich ones. Thus one way to test the convergence hypothesis is to check whether economies with similar tastes and technologies—economies that are likely to converge to the same steady state—converge in an absolute sense.

In this chapter, we test the convergence predictions of the neoclassical growth model by looking at the behavior of regions within countries. Although differences in technology, preferences, and institutions exist across regions, these differences are likely to be smaller than those across countries. Firms and households of different regions within a single country tend to have access to similar technologies and have roughly similar tastes and cultures. Furthermore, the regions share a common central government and therefore have similar institutional setups and legal systems. This relative homogeneity means that regions are more likely to converge to similar steady states. Hence, absolute convergence is more likely to apply across regions within countries than across countries.

It can be argued that using regions to test the convergence hypothesis is incorrect because inputs tend to be more mobile across regions than across countries. Legal, cultural, linguistic, and institutional barriers to factor movements tend to be smaller across regions within a country than across countries. Hence, the assumption of a closed economy—a standard condition of the neoclassical growth model—is likely to be violated for regional data sets. However, we found in chapter 3 that the dynamic properties of economies that are open to capital movements can be similar to those of closed economies if a fraction of the capital stock—which includes human capital—is not mobile or cannot be used as collateral in interregional or international credit transactions. The speed of convergence is increased by the existence of capital mobility but remains within a fairly narrow range for reasonable values of the fraction of capital that is mobile. Another result is that a technology without diminishing returns to capital—that is, some version of the AK technology—implies a zero convergence speed whether the economy is open or closed.

We also found in chapter 9 that the allowance for migration in neoclassical growth models tends to accelerate the process of convergence. The change is, again, a quantitative modification to the speed of convergence. The main point, therefore, is that although regions within a country are relatively open to flows of capital and persons, the neoclassical growth model still provides a useful framework for the empirical analysis.

11.1 Two Concepts of Convergence

Two concepts of convergence appear in discussions of economic growth across countries or regions. In one view (Barro, 1984, chapter 12; Baumol, 1986; DeLong, 1988; Barro, 1991a; Barro and Sala-i-Martin, 1991, 1992a, 1992b), convergence applies if a poor economy tends to grow faster than a rich one, so that the poor country tends to catch up to the rich one in terms of levels of per capita income or product. This property corresponds to our concept of β *convergence*.[1] The second concept (Easterlin, 1960a; Borts and Stein, 1964, chapter 2; Streissler, 1979; Barro, 1984, chapter 12; Baumol, 1986; Dowrick and Nguyen, 1989; Barro and Sala-i-Martin, 1991, 1992a, 1992b) concerns cross-sectional dispersion. In this context, convergence occurs if the dispersion—measured, for example, by the standard deviation of the logarithm of per capita income or product across a group of countries or regions—declines over time. We call this process σ *convergence*. Convergence of the first kind (poor countries tending to grow faster than rich ones) tends to generate convergence of the second kind (reduced dispersion of per capita income or product), but this process is offset by new disturbances that tend to increase dispersion.

To make the relation between the two concepts more precise, we consider a version of the growth equation predicted by the neoclassical growth model of chapter 2. Equation (2.35) relates the growth rate of income per capita for economy i between two points in time to the initial level of income. We apply equation (2.35) here to discrete periods of unit length (say years), and we also augment it to include a random disturbance:

$$\log(y_{it}/y_{i,t-1}) = a_{it} - (1 - e^{-\beta}) \cdot \log(y_{i,t-1}) + u_{it} \tag{11.1}$$

where the subscript t denotes the year, and the subscript i denotes the country or region. The theory implies that the intercept, a_{it}, equals $x_i + (1-e^{-\beta}) \cdot [\log(\hat{y}_i^*) + x_i \cdot (t-1)]$, where $\hat{y}_i^*$ is the steady-state level of $\hat{y}_i$ and x_i is the rate of technological progress. We assume that the random variable u_{it} has 0 mean, variance σ_{ut}^2, and is distributed independently of $\log(y_{i,t-1})$, u_{jt} for $j \neq i$, and lagged disturbances.

1. This phenomenon is sometimes described as "regression toward the mean."

We can think of the random disturbance as reflecting unexpected changes in production conditions or preferences. We begin by treating the coefficient a_{it} as the same for all economies so that $a_{it} = a_t$. This specification means that the steady-state value, $\hat{y}_i^*$, and the rate of exogenous technological progress, x_i, are the same for all economies. This assumption is more reasonable for regional data sets than for international data sets; it is plausible that different regions within a country are more similar than different countries with respect to technology and preferences.

If the intercept a_{it} is the same in all places and $\beta > 0$, equation (11.1) implies that poor economies tend to grow faster than rich ones. The neoclassical growth models of chapters 1 and 2 made this prediction. The AK model discussed in chapter 4 predicts, in contrast, a 0 value for β and, consequently, no convergence of this type. The same conclusion holds for various endogenous growth models (chapters 6 and 7) that incorporate a linearity in the production function.[2]

Since the coefficient on $\log(y_{i,t-1})$ in equation (11.1) is less than 1, the convergence is not strong enough to eliminate the serial correlation in $\log(y_{it})$. Put alternatively, in the absence of random shocks, convergence to the steady state is direct and involves no oscillations or overshooting. Therefore, for a pair of economies, the one that starts out behind is predicted to remain behind at any future date.

Let σ_t^2 be the cross-economy variance of $\log(y_{it})$ at time t. Equation (11.1) and the assumed properties of u_{it} imply that σ_t^2 evolves over time in accordance with the first-order difference equation[3]

$$\sigma_t^2 = e^{-2\beta} \cdot \sigma_{t-1}^2 + \sigma_{ut}^2 \tag{11.2}$$

where we have assumed that the cross section is large enough so that the sample variance of $\log(y_{it})$ corresponds to the population variance.

If the variance of the disturbance, σ_{ut}^2, is constant over time ($\sigma_{ut}^2 = \sigma_u^2$ for all t), the solution of the first-order difference equation (11.2) is

$$\sigma_t^2 = \frac{\sigma_u^2}{1 - e^{-2\beta}} + \left(\sigma_0^2 - \frac{\sigma_u^2}{1 - e^{-2\beta}}\right) \cdot e^{-2\beta t} \tag{11.3}$$

where σ_0^2 is the variance of $\log(y_{i0})$. (It can be readily verified that the solution in equation [11.3] satisfies equation [11.2].) Equation (11.3) implies that σ_t^2 monotonically approaches its steady-state value, $\sigma^2 = \sigma_u^2/(1 - e^{-2\beta})$, which rises with σ_u^2 but declines with

2. We showed, however, in chapter 4 that β convergence would apply if the technology were asymptotically AK but featured diminishing returns to capital for finite K.

3. To derive equation (11.2), add $\log(y_{i,t-1})$ to both sides of equation (11.1), compute the variance, and use the condition that the covariance between u_{it} and $\log(y_{i,t-1})$ is 0.

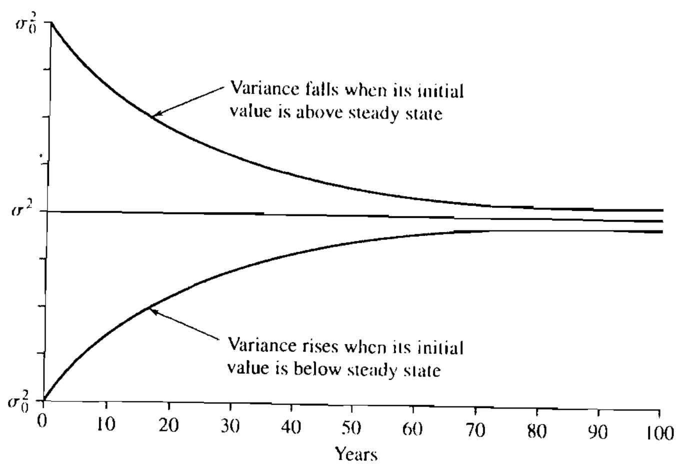

Figure 11.1
Theoretical behavior of dispersion. The figure shows the dispersion of per capita product, measured as the variance of the log of per capita product across economies. Although β convergence is assumed to apply, the dispersion may fall, rise, or remain constant, depending on whether it starts above, below, or at its steady-state value, σ^2. The figure assumes $\beta = 0.02$ per year.

the convergence coefficient, β. Over time, σ_t^2 falls (or rises) if the initial value σ_0^2 is greater than (or less than) the steady-state value, σ^2. Thus a positive coefficient β (β convergence) does not imply a falling σ_t^2 (σ convergence). To put it another way, β convergence is a necessary but not a sufficient condition for σ convergence.

Figure 11.1 shows the time pattern of σ_t^2 with σ_0^2 above or below σ^2. The convergence coefficient used, $\beta = 0.02$ per year, corresponds to the estimates that we report in a later section. With this value of β, the cross-sectional variance is predicted to fall or rise over time at a slow rate. In particular, if σ_0^2 departs substantially from the steady-state value, σ^2, then it takes about 100 years for σ_t^2 to get close to σ^2.

The cross-sectional dispersion of $\log(y_{it})$ is sensitive to shocks that have a common influence on subgroups of countries or regions. These kinds of disturbances violate the condition that u_{it} in equation (11.1) is independent of u_{jt} for $i \neq j$. To the extent that these shocks tend to benefit or hurt regions with high or low income (that is, to the extent that the shocks are correlated with the explanatory variable), the omission of such shocks from the regressions will tend to bias the estimates of β.

Examples are shocks that generate changes in the terms of trade for commodities. For the United States, an example is the sharp drop in the relative prices of agricultural goods during the 1920s. This disturbance had an adverse effect on the incomes of agricultural

regions relative to the incomes of industrial regions. We can think also of the two oil price increases of the 1970s and the price decline of the 1980s. These shocks had effects in the same direction on the incomes of oil-producing regions relative to other regions. Another example for the United States is the Civil War. This shock had a strong adverse impact on the incomes of southern states relative to the incomes of northern states.

Formally, let S_t be a random variable that represents an economy-wide disturbance for period t. For example, S_t could reflect the relative price of oil as determined on world markets. Then equation (11.1) can be modified to

$$\log(y_{it}/y_{i,t-1}) = a_{it} - (1 - e^{-\beta}) \cdot \log(y_{i,t-1}) + \varphi_i S_t + u_{it} \tag{11.4}$$

where φ_i measures the effect of the aggregate disturbance on the growth rate in region i. If a positive value of S_t signifies an increase in the relative price of oil, then φ_i would be positive for countries or regions that produce a lot of oil.[4] The coefficient φ_i would tend to be negative for economies that produce goods, such as automobiles, that use oil as an input. We think of the coefficient φ_i as distributed cross sectionally with mean $\bar{\varphi}$ and variance σ_φ^2.

If $\log(y_{i,t-1})$ and φ_i are uncorrelated, estimates of β in equation (11.4) would be consistent when the shock is omitted from the regression. If $\log(y_{i,t-1})$ and φ_i are positively correlated, the coefficient estimated by OLS on $\log(y_{i,t-1})$ in equation (11.4) would be positively or negatively biased as S_t is positive or negative. As an example, if oil producers have relatively high per capita income, an increase in oil prices will benefit the relatively rich states. Consequently, an OLS regression of growth on initial income will underestimate the true convergence coefficient. In the empirical analysis of the next sections, we hold constant proxies for S_t as an attempt to obtain consistent estimates of the convergence coefficients.

Equation (11.4) implies that the variance of the log of per capita income evolves as

$$\sigma_t^2 = e^{-2\beta} \cdot \sigma_{t-1}^2 + \sigma_{ut}^2 + S_t^2 \cdot \sigma_\varphi^2 + 2S_t \cdot e^{-\beta} \cdot \mathrm{cov}[\log(y_{i,t-1}), \varphi_i] \tag{11.5}$$

where the variances and covariances are conditioned on the current and past realizations of the aggregate shocks, $S_t, S_{t-1}, \ldots$. If $\mathrm{cov}[\log(y_{i,t-1}), \varphi_i]$ equals 0—that is, if the shock is uncorrelated with initial income—equation (11.5) corresponds to equation (11.2), except that realizations of S_t effectively move σ_{ut}^2 around over time. A temporarily large value of S_t raises σ_t^2 above the long-run value σ^2 that corresponds to a typical value of S_t. Therefore, in the absence of a new shock, σ_t^2 returns gradually toward σ^2, as shown in figure 11.1.

4. More precisely, this shock would have a positive effect on the real income derived from the countries or regions that produce a lot of oil. This income may be owned by "foreigners" and appear as part of the net factor payments from "abroad," the term that differentiates GNP from GDP. For example, a substantial fraction of the capital inputs of Wyoming is owned by residents of other states. A positive oil shock will increase Wyoming's nominal GDP (and raise the real value of this GDP when deflated by a national price index) but not necessarily raise its GNP or personal income. For the U.S. states, this distinction is important in a few cases, notably for oil producers.

11.2 Convergence Across the U.S. States

11.2.1 β Convergence

We now use the data on per capita income for the U.S. states to estimate the speed of convergence, β.[5] (The definitions and sources of the data are in the appendix, section 11.12.) Suppose, for the moment, that we have observations at only two points in time, 0 and T. Then equation (2.35) implies that the average growth rate of per capita income for economy i over the interval from 0 to T is given by

$$(1/T)\cdot\log(y_{iT}/y_{i0}) = x - [(1-e^{-\beta T})/T]\cdot\log(y_{i0}) + [(1-e^{-\beta T})/T]\cdot\log(\hat{y}_i^*) + u_{i0,T} \tag{11.6}$$

where $u_{i0,T}$ represents the effect of the error terms, u_{it}, between dates 0 and T; $\hat{y}_i^*$ is the steady-state level of income; and x is the rate of technological progress, which we assume is the same for all economies.

The coefficient on initial income in equation (11.6) is $(1-e^{-\beta T})/T$, an expression that declines with the length of the interval, T, for a given β. That is, if we estimate a linear relation between the growth rate of income and the log of initial income, the coefficient is predicted to be smaller the longer the time span over which the growth rate is averaged. The reason is that the growth rate declines as income increases (if $y_{i0} < \hat{y}_i^*$). Hence, if we compute the growth rate over a longer time span, it combines more of the smaller future growth rates with the initially larger growth rates. Hence, as the interval increases, the effect of the initial position on the average growth rate declines. The coefficient $(1-e^{-\beta T}/T)$ approaches 0 as T approaches infinity, and it tends to β as T approaches 0.

Notice that equation (11.6) includes the term $[(1-e^{-\beta T})/T]\cdot\log(\hat{y}_i^*)$ as an explanatory variable. That is, the growth rate of economy i depends on its initial level of income, y_{i0}, but it also depends on the steady-state level of income. This is why we use the concept of conditional rather than absolute convergence: the growth rate of an economy depends negatively on its initial level of income, after we "condition" on the steady state.

5. Barro and Sala-i-Martin (1992a) also use the data on gross state product (GSP), reported by the Bureau of Economic Analysis. GSP is analogous to GDP in that it assigns the product to the state in which it has been produced. In contrast, income (like GNP) assigns the product to the state in which the owners of the inputs reside. This distinction is potentially important if the economies are open and people tend to own capital in other states, or if there is a lot of interstate commuting (people live in one state and work in another). Barro and Sala-i-Martin (1992a) show that, in practice, the distinction turns out not to be that important; the estimates of the speed of convergence for GSP are similar to those for personal income. Since GSP data are available only starting in 1963, we limit attention in this chapter to the results that use the income data.

The usefulness of using regional data can be seen as follows: imagine that, instead of estimating the multivariate equation (11.6), we estimate the univariate regression

$$(1/T)\cdot\log(y_{iT}/y_{i0}) = a - [(1-e^{-\beta T})/T]\cdot\log(y_{i0}) + w_{i0,T} \tag{11.7}$$

Notice that, in equation (11.7), the term $[(1-e^{-\beta T})/T]\cdot\log(\hat{y}_i^*)$ is no longer an explanatory variable. If the term that multiplies initial income in equation (11.7) turns out to be negative, we will conclude that poor economies tend to grow faster than rich economies so that "absolute convergence" applies. It is for this reason that regressions like equation (11.7) have been used in the literature to test the absolute convergence hypothesis. The question is whether the failure to find a negative coefficient is reason to reject the neoclassical growth model. Remember that the neoclassical model predicts a multivariate relation such as equation (11.6). Suppose that, instead of equation (11.6), we estimate equation (11.7). If we analyze data sets in which the various economies converge to different steady states, that is $\hat{y}_i^* \neq \hat{y}_j^*$ for all i and j, then the univariate regression equation (11.7) is misspecified and the excluded term is incorporated into the error term: $w_{i0,T} = u_{i0,T} + [(1-e^{-\beta T})/T]\cdot\log(\hat{y}_i^*)$. If the steady-state level of income, $\hat{y}_i^*$, is correlated with the explanatory variable y_{i0}, the error term is correlated with the right-hand-side variable, and the univariate regression equation (11.7) will provide biased estimates of β. In particular, if currently richer economies tend to converge to a higher steady-state level of income (that is, if $\hat{y}_i^*$ and y_{i0} are positively correlated), the estimate of β in equation (11.7) is biased toward zero. In other words, researchers could find no relation between growth and the initial level of income, even though conditional convergence holds. Under these circumstances, the only way to get consistent estimates of β is to get measures of $\hat{y}_i^*$ and include them in the regression.

Imagine now that we have a data set in which the various economies converge to different steady states, but that there is no correlation between the initial and the steady-state level of income. Although the univariate regression is still misspecified, the error term (which again includes the missing variable, $\hat{y}_i^*$) is not correlated with the explanatory variable. Hence, the usual estimation of equation (11.7) can provide a consistent estimate of β. Finally, if we analyze a data set in which all economies have the same steady state, that is, if $\hat{y}_i^* = \hat{y}_j^*$ for all i and j, the term $[(1-e^{-\beta T})/T]\cdot\log(\hat{y}_i^*)$ is incorporated into the constant term, and the usual estimation of equation (11.7) will again provide a consistent estimate of β.

In sum, there are two ways to estimate the speed of convergence, β. The first is to use general data sets (that is, data sets for which there is no guarantee that the initial level of income is uncorrelated with the steady-state level of income) and find proxies for the steady-state level of income. The second is to use data sets in which the various economies tend to converge to similar steady states or that, at least, the steady states are unrelated to the initial level of income. This second context is the one in which regional data sets play an important role. Although differences in technology, preferences, and institutions exist across regions, these differences are likely to be smaller than those across countries. Firms and households of different regions within a single country tend to have access to similar technologies and have roughly similar tastes and cultures. Furthermore, the regions share a common central government and therefore have similar institutional setups and legal systems. This relative homogeneity means that absolute convergence is more likely to apply across regions within countries than across countries.

Table 11.1 shows nonlinear least-squares estimates in the form of equation (11.7) for 47 or 48 U.S. states or territories for various time periods. The rows of table 11.1 correspond to the different time periods. For example, the first row applies to the 120-year period between 1880 and 2000. The first column of the table refers to the equation with only one explanatory variable, the logarithm of income per capita at the beginning of the period. Column two adds four regional dummies, corresponding to the four main census regions: Northeast, South, Midwest, and West. Finally, column three includes sectoral variables that are meant to capture the aggregate shocks discussed in the previous section. We already argued that the inclusion of these auxiliary variables would help to obtain accurate estimates of β.

Each cell contains the estimate of β, the standard error of this estimate (in parentheses), the R^2, and the standard error of the regression (in brackets). All equations have been estimated with constant terms, which are not reported in table 11.1.

The point estimate of β for the long sample, 1880–2000, is 0.0172 (s.e. = 0.0024).[6] The high R^2, 0.92, can be appreciated from figure 11.2, which provides a scatter plot of the average growth rate of income per capita between 1880 and 2000 against the log of income per capita in 1880.

The second column of the first row presents the estimated speed of convergence when the four regional dummies are incorporated. The estimated β coefficient is 0.0160 (0.0034). The similarity between this estimate and the previous one suggests that the speed at which average incomes converge across the census regions is not substantially different from the speed at which average incomes converge for the states within each of the regions. We can check this result by computing the average income for each of the four regions. The growth rate of a region's average income between 1880 and 2000 is plotted against the log of the region's average income in 1880 in figure 11.3. The negative relation is clear (the correlation coefficient is −0.97). The estimated speed of convergence implied by this relation is 2.1 percent per year, about the same as the within-region rate shown in column 2.

The next ten rows of table 11.1 divide the sample into subperiods. The first two are twenty years long (1880 to 1900 and 1920 to 1940), because income data for 1890 and 1910 are unavailable. The remaining eight subperiods are ten years long.

6. This regression includes 47 states or territories. Data for the Oklahoma territory are unavailable for 1880.

Table 11.1
Regressions for Personal Income Across U.S. States

	(1) Basic Equation		(2) Equations with Regional Dummies		(3) Equations with Structural Variables and Regional Dummies	
Period	β	$R^2[\hat{\sigma}]$	β	$R^2[\hat{\sigma}]$	β	$R^2[\hat{\sigma}]$
1880–2000	0.0172 (0.0024)	0.92 [0.0012]	0.0160 (0.0034)	0.95 [0.0010]	—	—
1880–1900	0.0101 (0.0022)	0.36 [0.0068]	0.0224 (0.0043)	0.62 [0.0054]	0.0268 (0.0051)	0.65 [0.0053]
1900–20	0.0218 (0.0031)	0.62 [0.0065]	0.0209 (0.0065)	0.67 [0.0062]	0.0270 (0.0077)	0.71 [0.0060]
1920–30	−0.0149 (0.0051)	0.14 [0.0132]	−0.0128 (0.0078)	0.43 [0.0111]	0.0209 (0.0119)	0.64 [0.0089]
1930–40	0.0129 (0.0033)	0.28 [0.0079]	0.0072 (0.0052)	0.34 [0.0078]	0.0147 (0.0083)	0.37 [0.0078]
1940–50	0.0502 (0.0058)	0.73 [0.0087]	0.0512 (0.0062)	0.88 [0.0059]	0.0304 (0.0065)	0.91 [0.0052]
1950–60	0.0193 (0.0039)	0.40 [0.0051]	0.0191 (0.0056)	0.52 [0.0047]	0.0305 (0.0053)	0.74 [0.0035]
1960–70	0.0286 (0.0039)	0.61 [0.0040]	0.0181 (0.0046)	0.73 [0.0034]	0.0196 (0.0061)	0.74 [0.0035]
1970–80	0.0186 (0.0049)	0.27 [0.0044]	0.0079 (0.0055)	0.44 [0.0040]	0.0057 (0.0068)	0.46 [0.0040]
1980–90	0.0036 (0.0085)	0.01 [0.0077]	0.0095 (0.0074)	0.57 [0.0052]	0.0029 (0.0070)	0.69 [0.0045]
1990–2000	0.0016 (0.0035)	0.01 [0.0035]	−0.0005 (0.0045)	0.07 [0.0035]	0.0029 (0.0050)	0.14 [0.0034]
Joint, 9 subperiods	0.0150 (0.0015)	— —	0.0164 (0.0021)	— —	0.0212 (0.0023)	— —

Note: The regressions use nonlinear least squares to estimate equations of the form

$$(1/T)\cdot\log(y_{it}/y_{i,t-T}) = a - [\log(y_{i,t-T})]\cdot[(1-e^{-\beta T})/T] + \text{other variables}$$

where $y_{i,t-T}$ is per capita income in state i at the beginning of the period divided by the overall CPI, T is the length of the interval, and the other variables are regional dummies and structural measures (see the description in the text). See the appendix (section 11.12) for a discussion of the data on the U.S. states. The samples that begin in 1880 have 47 observations. The others have 48 observations. Each column contains the estimate of β, the standard error of this estimate (in parentheses), the R^2 of the regression, and the standard error of the equation (in brackets). The estimated coefficients for constants, regional dummies, and structural variables are not reported. The likelihood-ratio statistic refers to a test of the equality of the coefficients of the log of initial income over the nine subperiods. The p value comes from a χ^2 distribution with eight degrees of freedom.

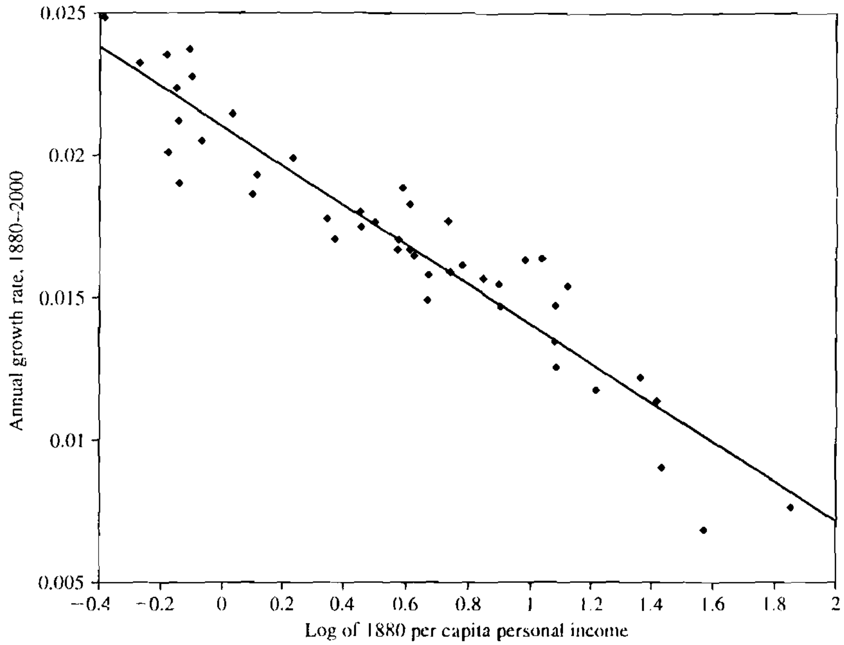

Figure 11.2
Convergence of personal income across U.S. states: 1880 personal income and 1880–2000 income growth. The average growth rate of state per capita income for 1880–2000, shown on the vertical axis, is negatively related to the log of per capita income in 1880, shown on the horizontal axis. Thus, absolute β convergence exists for the U.S. states.

The estimated β coefficient is significantly positive—indicating β convergence—for seven of the ten subperiods. The coefficient has the wrong sign ($\beta < 0$) for only one of the subperiods, 1920–30, a time of large declines in the relative price of agricultural commodities. A likely explanation for this result is that agricultural states tended to be poor states, and the agricultural states suffered the most from the fall in agricultural prices. The estimated coefficient is insignificant for the two most recent subperiods, the 1980s and the 1990s. If we constrain the β coefficients to be the same for all subperiods, the joint estimate for the basic equation is 0.0150 (0.0015).

Column 2 of Table 11.1 adds regional dummies, where the coefficients of these dummies are allowed to differ for each period. These regional variables capture effects that are common to all states within a region in a given period. The estimated β coefficient for the 1920s still has the wrong sign, as does the the coefficient for the 1990s, although they

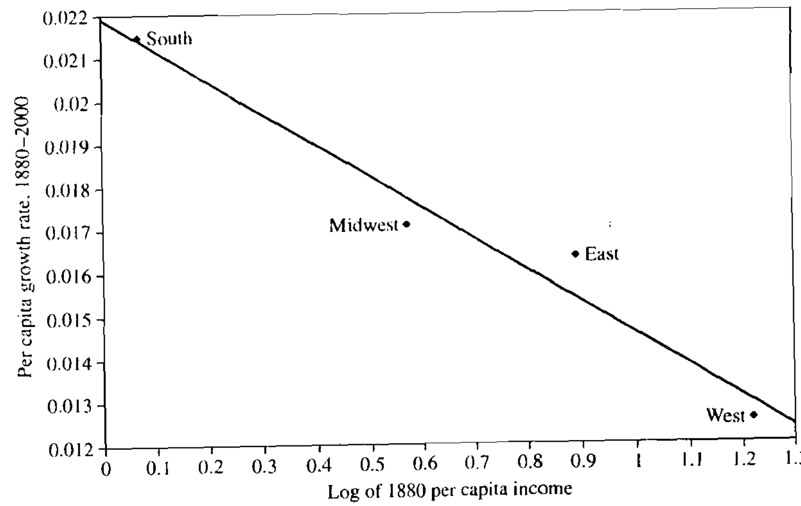

Figure 11.3
Convergence of personal income across U.S. regions: 1880 income and 1880–2000 income growth. The negative relation between income growth and initial income, shown for the U.S. states in figure 11.2, applies in figure 11.3 to averages over the four main census regions.

are both estimated with substantial error. Hence, even within regions, poor states tended to grow slower than rich states during the 1920s. The joint estimate for the nine subperiods is now 0.0164 (0.0021), similar to that for the basic regression.

Aggregate shocks that affect groups of states differentially, such as shifts in the relative prices of agricultural products or oil, might explain the instability of the estimated coefficients. Following Barro and Sala-i-Martin (1991, 1992a, 1992b), the third column of table 11.1 adds an additional variable to the regression as an attempt to hold these aggregate shocks constant. The variable, denoted by S_{it} (for structure), is calculated as

$$S_{it} = \sum_{j=1}^{9} \omega_{ij,t-T} \cdot [\log(y_{jt}/y_{j,t-T})/T] \tag{11.8}$$

where $\omega_{ij,t-T}$ is the weight of sector j in state i's personal income at time $t-T$ and y_{jt} is the national average of personal income per worker in sector j at time t. The nine sectors used are agriculture, mining, construction, manufacturing, trade, finance and real estate, transportation, services, and government. We think of S_{it} as a proxy for the effects reflected in the term $\varphi_i S_t$ in equation (11.4).

The structural variable reveals how much a state would grow if each of its sectors grew at the national average rate. For example, suppose that economy i specializes in the production of cars and that the aggregate car sector does not grow over the period between $t - T$ and t. The low value of S_{it} for this region indicates that it should not grow very fast because the car industry has suffered from the shock.

Note from equation (11.8) that S_{it} depends on the contemporaneous growth rates of national averages and on lagged values of state i's sectoral shares. For this reason, the variable can be reasonably treated as exogenous to the current growth experience of state i.

Because of lack of data, we can include the structural variable only for the periods after 1929. For the periods before 1929, we obtain a rough measure of S_{it} by using the share of agriculture in the state's total income.

Column three includes structural variables, as well as regional dummies, in the growth regressions. (The coefficients on the regional and structural variables are allowed to differ for each period.) One contrast with the previous results is that the estimated β coefficient for the 1920s becomes positive and close to 0.02. The coefficients for the 1980s and 1990s are also positive but their size continues to be small. The joint estimate of β for the nine subperiods is 0.0212 (0.0023).

The main conclusion is that the U.S. states tend to converge at a speed of about 2 percent per year. Averages for the four census regions converge at a rate that is similar to that for states within regions. If we hold constant measures of structural shocks, we cannot reject the hypothesis that the speed of convergence is stable over time, although the estimates for the last two decades are insignificantly different from zero.

11.2.2 Measurement Error

The existence of temporary measurement error in income tends to introduce an upward bias in the estimate of β; that is, the elimination of measurement error over time can generate the appearance of convergence.[7] One reason for measurement error is that each state's nominal income is deflated by a national price index, because accurate indexes do not exist at the state level.

One way to handle measurement error is to use earlier lags of the log of income as instruments in the regressions. If measurement error is temporary (and the error term is not serially correlated), the earlier lags of the log of income would be satisfactory instruments for the log of income at the start of each period. If we reestimate column 1 of table 11.1 with the previous lag of the log of income used as an instrument, we get a joint estimate

7. The same property holds for short-term business fluctuations. We may want to design a model in which these temporary fluctuations of output are distinguished from the kinds of transitional dynamics that appear in growth models.

of β of 0.0176 (0.0019). This panel uses nine subperiods starting in 1900 because the observation for 1880–1900 is lost. The OLS estimate of β for the same nine subperiods is 0.0165 (0.0018). Hence, the use of instruments generates a minor change in the estimate of β, which suggests that measurement error does not explain the significantly negative relation between growth and the initial level of income.

When we estimate the subperiods separately, we again find only a small difference between the instrumental-variable (IV) and OLS estimates. The largest change applies to 1950–60, for which the IV estimate is 0.0139 (0.0040), compared with the OLS value of 0.0193 (0.0039).

The results for columns 2 and 3 of table 11.1 are similar. Our conclusion is that measurement error is unlikely to be a key element in the results.

11.2.3 σ Convergence

Figure 11.4 shows the cross-sectional standard deviation for the log of per capita personal income net of transfers for 47 or 48 U.S. states or territories from 1880 to 2000. The dispersion declined from 0.54 in 1880 to 0.33 in 1920 but then rose to 0.40 in 1930. This

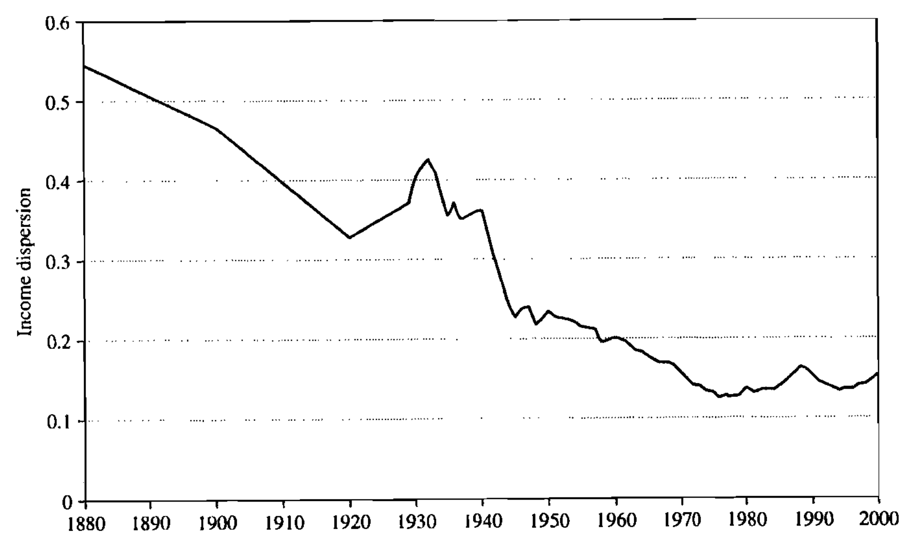

Figure 11.4
Dispersion of personal income across U.S. states, 1880–2000. The figure shows the cross-sectional standard deviation of the log of per capita personal income for 47 or 48 U.S. states or territories from 1880 to 2000. This measure of dispersion declined from 1880 to 1920, rose in the 1920s, fell from 1930 to the mid-1970s, rose through 1988, declined again through 1992, and then remained fairly flat.

rise reflects the adverse shock to agriculture during the 1920s; the agricultural states were relatively poor in 1920 and suffered a further reduction in income with the fall in agricultural prices.

After reaching a peak in 1932, the dispersion fell to 0.36 in 1940, 0.24 in 1950, 0.20 in 1960, and 0.16 in 1970. The long-run decline stopped in the mid-1970s, with a low point of 0.14 in 1976. After that, σ_t rose to a peak of 0.16 in 1988. Dispersion fell to 0.14 in the early 1990s, then remained relatively flat.

11.3 Convergence Across Japanese Prefectures

11.3.1 β Convergence

Barro and Sala-i-Martin (1992b) analyze the pattern of β convergence for per capita income across 47 Japanese prefectures (see the appendix, section 11.12, for the sources and definitions). Table 11.2 reports nonlinear estimates of the convergence coefficient, β, for the period 1930–90. The setup of table 11.2 parallels that of table 11.1.

The first row of table 11.2 pertains to regressions for the whole period, 1930–90. The basic equation in column 1 includes only the log of initial income as a regressor. The estimated β coefficient is 0.0279 (0.0033), with an R^2 of 0.92. The good fit can be appreciated in figure 11.5. The strong negative correlation between the growth rate from 1930 to 1990 and the log of per capita income in 1930 confirms the existence of β convergence across the Japanese prefectures.

The estimated β coefficient is essentially the same in column 2, which incorporates dummies for the seven Japanese districts as explanatory variables. This finding suggests that the speed of convergence for prefectures within districts is similar to that across districts. This idea can be checked by running a regression that uses the seven data points for the growth and level of the average per capita income of districts. The negative relation between the growth rate from 1930 to 1990 and the log of per capita income in 1930 is displayed in figure 11.6. The β coefficient estimated from these observations (not reported in the table) is 0.0261 (0.0079). Hence, we confirm that the speed of convergence across districts is about the same as that within districts.

The second and third rows of table 11.2 break the full sample into two long subperiods, 1930–55 and 1955–90. For the basic equation, the speed of convergence for the first subperiod is larger than that for the second, 0.0358 (0.0035) versus 0.0191 (0.0035). The same relation holds for the second column, which adds the district dummies as explanatory variables. (Different coefficients on the dummies are estimated for the two subperiods.) Hence, we conclude that the speed of convergence after 1955 was substantially slower than that between 1930 and 1955. The lack of sectoral data for the early period does not, how-

Table 11.2
Regressions for Personal Income Across Japanese Prefectures

	(1) Basic Equation		(2) Equations with District Dummies		(3) Equations with Structural Variables and District Dummies	
Period	$\hat{\beta}$	$R^2[\hat{\sigma}]$	$\hat{\beta}$	$R^2[\hat{\sigma}]$	$\hat{\beta}$	$R^2[\hat{\sigma}]$
1930–90	0.0279 (0.0033)	0.92 [0.0019]	0.0276 (0.0024)	0.97 [0.0012]	—	—
1930–55	0.0358 (0.0035)	0.86 [0.0045]	0.0380 (0.0037)	0.90 [0.0038]	—	—
1955–90	0.0191 (0.0035)	0.59 [0.0027]	0.0222 (0.0035)	0.81 [0.0020]	—	—
1955–60	−0.0152 (0.0079)	0.07 [0.0133]	−0.0023 (0.0082)	0.44 [0.0111]	0.0047 (0.0118)	0.46 [0.0112]
1960–65	0.0296 (0.0072)	0.30 [0.0108]	0.0360 (0.0079)	0.55 [0.0093]	0.0414 (0.0096)	0.56 [0.0093]
1965–70	−0.0010 (0.0062)	0.00 [0.0097]	0.0127 (0.0067)	0.47 [0.0076]	0.0382 (0.0091)	0.62 [0.0065]
1970–75	0.0967 (0.0100)	0.78 [0.0095]	0.0625 (0.0092)	0.87 [0.0078]	0.0661 (0.0118)	0.87 [0.0079]
1975–80	0.0338 (0.0100)	0.23 [0.0087]	0.0455 (0.0119)	0.37 [0.0085]	0.0469 (0.0145)	0.37 [0.0086]
1980–85	−0.0115 (0.0077)	0.04 [0.0075]	0.0076 (0.0089)	0.37 [0.0066]	0.0102 (0.0094)	0.37 [0.0067]
1985–90	0.0007 (0.0067)	0.00 [0.0067]	0.0086 (0.0082)	0.28 [0.0061]	0.0085 (0.0085)	0.28 [0.0062]
Joint, 7 subperiods	0.0125 (0.0032)	—	0.0232 (0.0034)	—	0.0312 (0.0040)	—
Likelihood-ratio statistic (p value)	94.6 (0.000)	—	40.6 (0.000)	—	26.4 (0.002)	—

Note: See the appendix (section 11.12) for a discussion of the data on Japanese prefectures, and see the note to table 11.1 for the form of the regressions. The variable $y_{i,t-T}$ is per capita income in prefecture i at the beginning of the period divided by the overall CPI. All samples have 47 observations. The likelihood-ratio statistic refers to a test of the equality of the coefficients of the log of initial income over the seven subperiods. The p value comes from a χ^2 distribution with six degrees of freedom.

ever, allow us to investigate the cause of this difference. We therefore restrict the rest of the analysis to the post-1955 period.

The next seven rows of table 11.2 break the sample into five-year subperiods starting in 1955. For three of the subperiods, the sign of the estimated β coefficient in the basic equation is opposite to the one expected. The speed of convergence is positive and significant for the periods 1960–65, 1970–75, and 1975–80. The joint estimate for the seven subperiods

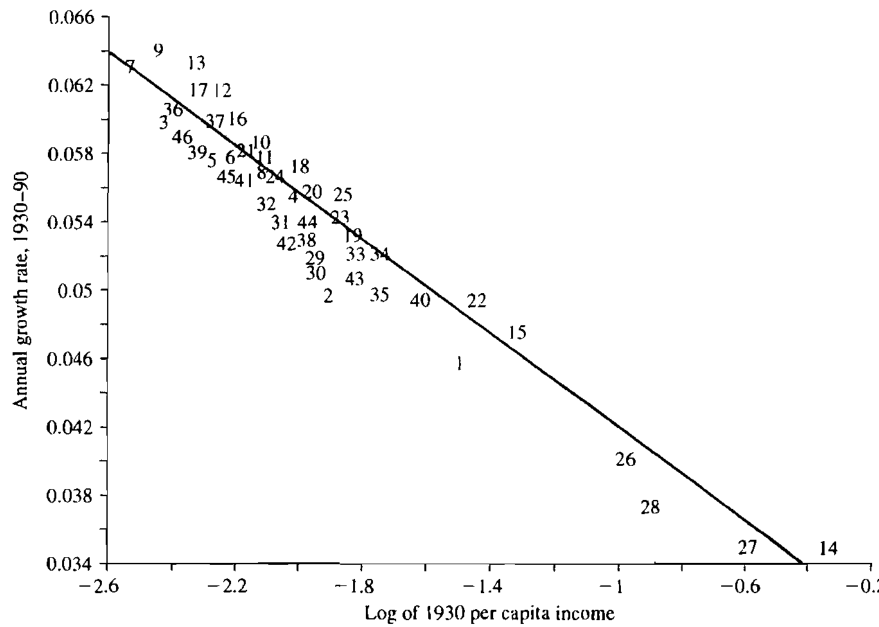

Figure 11.5
Convergence of personal income across Japanese prefectures: 1930 income and 1930–90 income growth. The growth rate of prefectural per capita income for 1930–90, shown on the vertical axis, is negatively related to the log of per capita income in 1930, shown on the horizontal axis. Thus absolute β convergence exists for the Japanese prefectures. The numbers shown identify each prefecture; see table 11.10.

is 0.0125 (0.0032). A test for the equality of coefficients over time is strongly rejected; the p value is 0.000.

The results with district dummies in column 2 allow for different coefficients on the dummies in each subperiod. In this case, only the estimated β coefficient for 1955–60 has the wrong sign, and it is not significant. The joint estimate is 0.0232 (0.0034). However, we still reject the equality of coefficients; the p value is again 0.000.

Column 3 adds a measure of the structural variable, S_{it}, defined in equation (11.8). This variable is analogous to the one constructed for the U.S. states. The coefficients on the structural variable are allowed to differ for each subperiod. In contrast with the previous two columns, none of the subperiods has the wrong sign when the sectoral variable is included. The joint estimate for the seven subperiods is 0.0312 (0.0040). We still reject the hypothesis of coefficient stability over time: the p value is now 0.002.

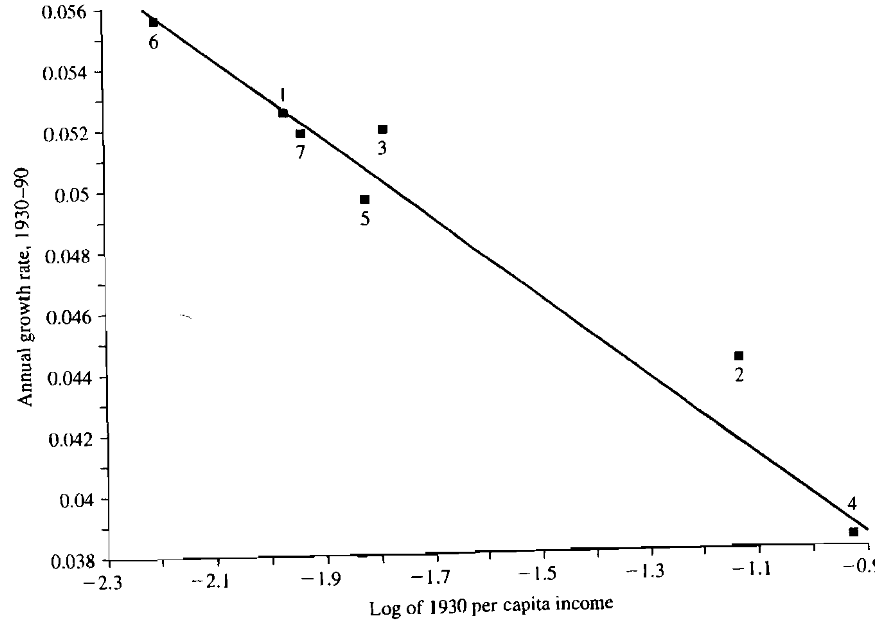

Figure 11.6
Convergence of personal income across Japanese districts: 1930 income and 1930–90 income growth. The negative relation between income growth and initial income, shown for Japanese prefectures in figure 11.5, applies also in figure 11.6 to averages for the seven major districts.

One source of instability in the estimated β coefficients is that Tokyo is an outlier in the 1980s: Tokyo was by far the richest prefecture in its district in 1980 and had the largest growth rate from 1980 to 1990, an outcome not captured by the structural variable that we have included. If we add a dummy for Tokyo for the 1980s, we get estimated β coefficients of 0.0218 (0.0112) for 1980–85 and 0.0203 (0.0096) for 1985–90. With this dummy included, the test of equality of coefficients now rejects with a p value of 0.010.

Another source of instability is the period 1970–75, for which the estimated β coefficient of 0.0661 (0.0118) is substantially higher than the others. A likely explanation for this high estimated value of β is that the oil shock of 1973 had an especially adverse impact on the richer industrial areas. The structural variable is supposed to hold constant this type of shock, but the construct that we have been able to measure does not seem to capture this effect.

As with the U.S. states, we reestimated the equations for Japanese prefectures with earlier lags of income used as instruments. The conclusion again is that the estimates are not materially affected. For example, in column 3 of table 11.2, the joint estimate of β falls from 0.0312 (0.0040) to 0.0282 (0.0042) when the instruments are used.

11.3.2 σ Convergence Across Prefectures

We want now to assess the extent to which there has been σ convergence across prefectures in Japan. We calculate the unweighted cross-sectional standard deviation for the log of per capita income, σ_t, for the 47 prefectures from 1930 to 1990. Figure 11.7 shows that the dispersion of personal income increased from 0.47 in 1930 to 0.63 in 1940. One explanation of this phenomenon is the explosion of military spending during the period. The average growth rates for districts 1 (Hokkaido–Tohoku) and 7 (Kyushu), which are mainly agricultural, were −2.4 percent and −1.7 percent per year, respectively. In contrast, the industrial regions of Tokyo, Osaka, and Aichi grew at 3.7, 3.1, and 1.7 percent per year, respectively.

The cross-prefectural dispersion decreased dramatically after World War II: it fell to 0.29 in 1950, 0.25 in 1960, 0.23 in 1970, and hit a minimum of 0.12 in 1978. The dispersion then increased slightly: σ_t rose to 0.13 in 1980, 0.14 in 1985, and 0.15 in 1987, but has been relatively stable since 1987. Thus the pattern is similar to that for the U.S. states.

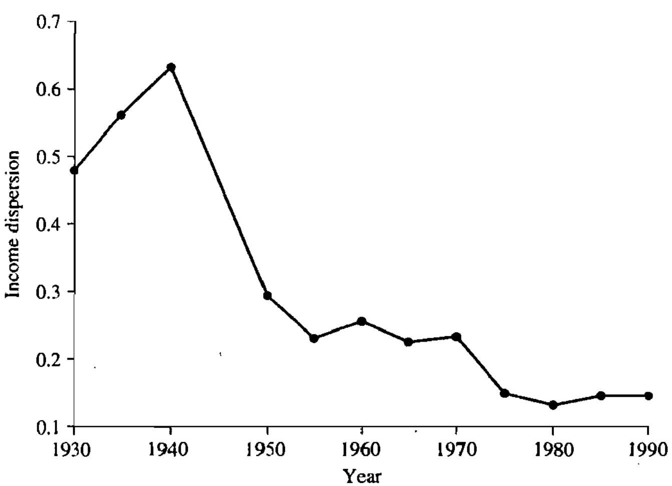

Figure 11.7
Dispersion of personal income across Japanese prefectures, 1930–90. The figure shows the cross-sectional standard deviation of the log of per capita personal income for 47 Japanese prefectures from 1930 to 1990. This measure of dispersion fell from the end of World War II until 1980.

11.4 Convergence Across European Regions

11.4.1 β Convergence

Barro and Sala-i-Martin (1991) analyzed convergence for 90 regions in eight European countries: 11 in Germany, 11 in the United Kingdom, 20 in Italy, 21 in France, 4 in the Netherlands, 3 in Belgium, 3 in Denmark, and 17 in Spain. The data, described in the appendix (section 11.12), correspond to GDP per capita for the first seven countries and to income per capita for Spain.

Table 11.3 shows the estimates of β in the form of equation (11.6) for the period 1950–90. The regressions include country dummies for each period to proxy for differences in the steady-state values of x_i and $\hat{y}_i^*$ in equation (11.6) and for countrywide fixed effects in the error terms. The country dummies, which are not reported in table 11.3, have substantial explanatory power. The first four rows of column 1 show the results for four decades. The estimates of β are reasonably stable over time; they range from 0.010 (0.004) for the 1980s to 0.023 (0.009) for the 1960s. The joint estimate for the four decades is 0.019 (0.002). The

Table 11.3
Convergence Across European Regions

	(1) Equations with Country Dummies		(2) Equations with Sectoral Shares and Country Dummies	
Period	$\hat{\beta}$	$R^2[\hat{\sigma}]$	$\hat{\beta}$	$R^2[\hat{\sigma}]$
1950–60	0.018 (0.006)	0.83 [0.0099]	0.034 (0.009)	0.84 [0.0094]
1960–70	0.023 (0.009)	0.97 [0.0065]	0.020 (0.006)	0.97 [0.0064]
1970–80	0.020 (0.009)	0.99 [0.0079]	0.022 (0.007)	0.99 [0.0077]
1980–90	0.010 (0.004)	0.97 [0.0066]	0.007 (0.005)	0.97 [0.0064]
Joint, 4 subperiods	0.019 (0.002)	— —	0.018 (0.003)	— —
Likelihood-ratio statistic (p value)	4.9 (0.179)		8.6 (0.034)	

Note: See the appendix (section 11.12) for a discussion of the data on European regions, and see the note to table 11.1 for the form of the regressions. The variable $y_{i,t-T}$ is an index of the per capita GDP (income for Spain) in region i at the beginning of the interval. All samples have 90 observations. The likelihood-ratio statistic refers to a test of the equality of the coefficients of the log of initial per capita GDP or income over the four subperiods. The p value comes from a χ^2 distribution with three degrees of freedom.

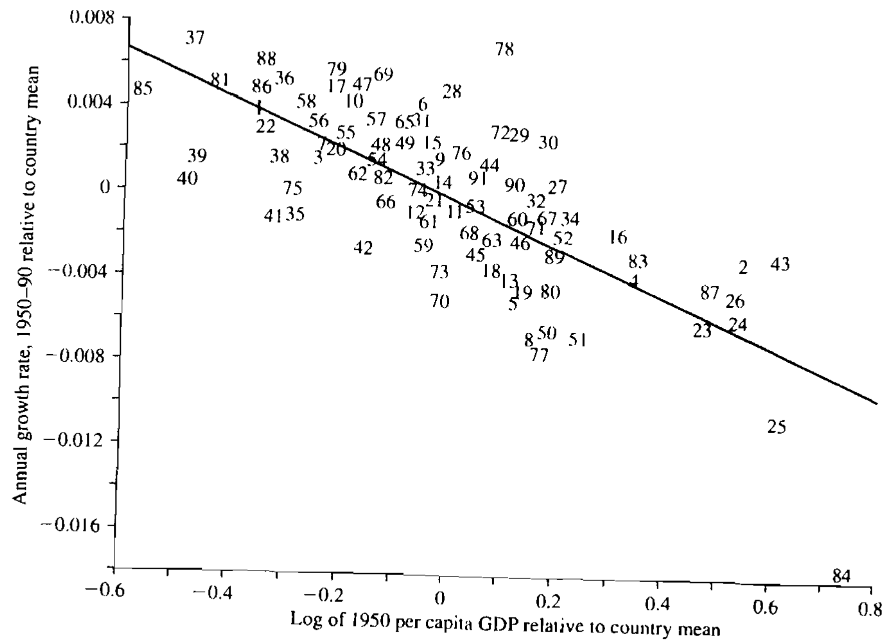

Figure 11.8
Growth rate from 1950 to 1990 versus 1950 per capita GDP for 90 regions in Europe. The growth rate of a region's per capita GDP for 1950–90, shown on the vertical axis, is negatively related to the log of per capita GDP in 1950, shown on the horizontal axis. The growth rate and level of per capita GDP are measured relative to the country means. Hence, this figure shows that absolute β convergence exists for the regions within Germany, the United Kingdom, Italy, France, the Netherlands, Belgium, Denmark, and Spain. The numbers shown identify the regions; see table 11.9.

hypothesis of constant β over time cannot be rejected at conventional levels of significance; the p value is 0.18.

Figure 11.8 shows for the 90 regions the relation of the growth rate of per capita GDP (income for Spain) from 1950 to 1990 (1955 to 1987 for Spain) to the log of per capita GDP or income at the start of the period. The variables are measured relative to the means of the respective countries. The figure shows the negative relation that is familiar from the U.S. states and Japanese prefectures. The correlation between the growth rate and the log of initial per capita GDP or income in figure 11.8 is −0.72. Since the underlying numbers are expressed relative to own-country means, the relation in figure 11.8 pertains to β convergence within countries, rather than between countries. The graph therefore corresponds to the estimates that include country dummies in column 1 of table 11.3.

Column 2 adds the share of agriculture and industry in total employment or GDP at the start of each subperiod.[8] These share variables are as close as we can come with our present data for the European regions to measuring the structural variable, S_{it}, that appears in equation (11.8). The results allow for period-specific coefficients for the sectoral shares.

The joint estimate of β for the four subperiods is now 0.018 (0.003). The test of the hypothesis of stability of β across periods yields a p value of 0.034. Thus, in contrast to our findings for the United States and Japan, the inclusion of the share variables makes the β coefficients appear less stable over time. Probably, a better measure of structural composition would yield more satisfactory results.

We have also estimated the joint system for Europe with individual β coefficients for the five large countries (Germany, the United Kingdom, Italy, France, and Spain). This system corresponds to the four-period regression shown in column 2 of table 11.3, except that the coefficient β is allowed to vary over the countries (but not over the subperiods). This system contains country dummies (with different coefficients for each subperiod) and share variables (with coefficients that vary over the subperiods but not across the countries). The resulting estimates of β are as follows: Germany (11 regions), 0.0224 (0.0067); United Kingdom (11 regions), 0.0277 (0.0104); Italy (20 regions), 0.0155 (0.0037); France (21 regions), 0.0121 (0.0061); and Spain (17 regions), 0.0182 (0.0048). Note that the individual point estimates are all close to 2 percent per year; they range from 1.2 percent per year for France to 2.8 percent per year for the United Kingdom.

A test for equality of the β coefficients across the five countries yields a p value of 0.55. Hence, we cannot reject the hypothesis that the speed of regional convergence within the five European countries is the same.

We also reestimated the European equations with earlier lags of per capita GDP or income used as instruments. This procedure necessitated the elimination of the first subperiod; hence, we include only the three decades from 1960 to 1990. The use of instruments had little impact on the results that included only country dummies, corresponding to column 1 of table 11.3. The joint estimate of β goes from 0.0187 (0.0022) in the OLS case (with only three subperiods included) to 0.0165 (0.0023). If the agricultural and industrial share variables are added, however, the joint estimate of β goes from 0.0153 (0.0034) to 0.0073 (0.0038). We think that the sharp drop in the estimated β coefficient in this case reflects inadequacies in the share variables as measures of structural shifts.

8. The share figures for the first three subperiods are based on employment. The values for 1980–90 are based on GDP.

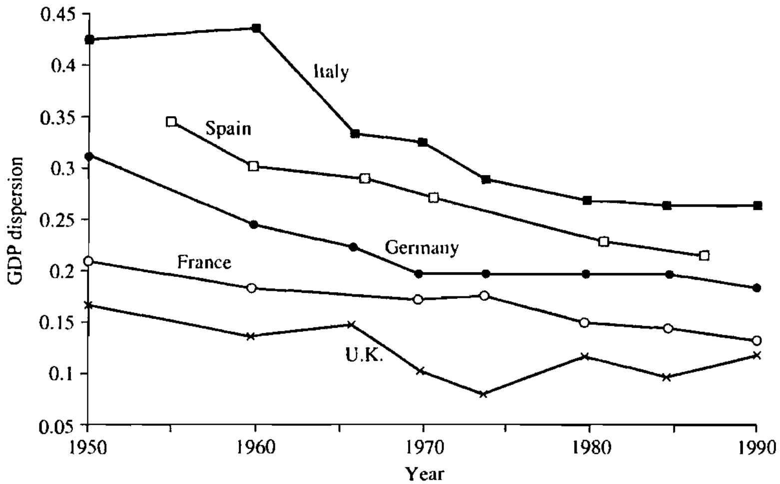

Figure 11.9
Dispersion of per capita GDP within five European countries. The figure shows the cross-sectional standard deviation of the log of per capita GDP from 1950 to 1990 for 11 regions in Germany, 11 in the United Kingdom, 20 in Italy, 21 in France, and 17 in Spain. This measure of dispersion fell in most cases since 1950 but has been roughly stable in Germany and the United Kingdom since 1970.

11.4.2 σ Convergence

Figure 11.9 shows the behavior of σ_t for the regions within the five large countries: Germany, the United Kingdom, Italy, France, and Spain. The countries are always ranked in descending order of dispersion as Italy, Spain, Germany, France, and the United Kingdom. The overall pattern shows declines in σ_t over time for each country, although little net change occurs since 1970 for Germany and the United Kingdom. The rise in σ_t from 1974 to 1980 for the United Kingdom—the only oil producer in the European sample—likely reflects the effect of oil shocks. In 1990 the values of σ_t are 0.27 for Italy, 0.22 for Spain (for 1987), 0.19 for Germany, 0.14 for France, and 0.12 for the United Kingdom.

11.5 Convergence Across Other Regions Around the World

Many researchers have recently studied the patterns of convergence across regions in various countries around the world. Coulombe and Lee (1993) find that the speed of convergence across regions in Canada is not too different from the 2 percent per year we found for the U.S. states, Japanese prefectures, and European regions. Persson (1997) finds similar results

for 24 Swedish counties for the period 1911–93. Cashin and Sahay (1995) find strong evidence of absolute convergence across Indian states between 1961 and 1991. Other regional studies in the recent literature include O'Leary (2000) for Ireland; Petrakos and Saratsis (2000) for Greece; Hossain (2000) for Bangladesh; Utrera and Koroch (1998) for Argentina; Magalhaes, Hewings, and Azzoni (2000) for Brazil; Cashin (1995) for Australasia; Yao and Weeks (2000) for China; Cashin and Loayza (1995) for South Pacific countries; Gezici and Hewings (2001) for Turkey; and Sanchez-Robles and Villaverde (2001) for Spain.

11.6 Migration Across the U.S. States

This section considers the empirical determinants of net migration among the U.S. states. The analysis in section 9.1.3 suggests that m_{it}, the annual rate of net migration into region i between years $t - T$ and t, can be described by a function of the form

$$m_{it} = f(y_{i,t-T}, \theta_i, \pi_{i,t-T}; \text{variables that depend on } t \text{ but not } i) \tag{11.9}$$

where $y_{i,t-T}$ is per capita income at the beginning of the period, θ_i is a vector of fixed amenities (such as climate and geography), and $\pi_{i,t-T}$ is the population density in region i at the beginning of the period.[9] The set of variables that depends on t but not on i includes any elements that influence per capita incomes and population densities in other economies. Also included are effects like technological progress in heating and air conditioning—these changes alter people's attitudes about weather and population density.

Per capita income—a proxy for wage rates—would have a positive effect on migration, whereas population density would have a negative effect. The functional form that we implement empirically is

$$m_{it} = a + b \cdot \log(y_{i,t-T}) + c_1\theta_i + c_2\pi_{i,t-T} + c_3 \cdot (\pi_{i,t-T})^2 + v_{it} \tag{11.10}$$

where v_{it} is an error term, $b > 0$, and the form allows for a quadratic in population density, $\pi_{i,t-T}$. The marginal effect of $\pi_{i,t-T}$ on m_{it} is negative if $c_2 + 2c_3 < 0$.

Although there is an extensive literature about variables to include as amenities, θ_i, the present analysis includes only the log of average heating-degree days, denoted $\log(\text{heat}_i)$, which is a disamenity so that $c_1 < 0$. The variable $\log(\text{heat}_i)$ has a good deal of explanatory power for net migration across the U.S. states. We considered alternative measures of the weather, but they did not fit as well. It would be useful to include migration for retirement, a mechanism that likely explains outliers such as Florida. However, these kinds of

9. Some amenities, such as government policies with respect to tax rates and regulations, would vary over time. We do not deal with these types of variables in the present analysis.

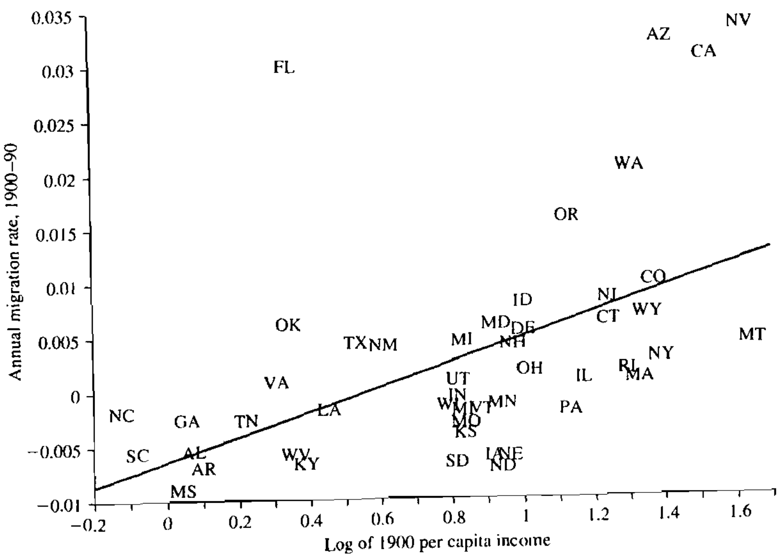

Figure 11.10
Migration and initial state income, 1900–90. The average net migration rate for 48 U.S. states or territories from 1900 to 1990, shown on the vertical axis, is positively related to the log of initial per capita income, shown on the horizontal axis. Florida, Arizona, California, and Nevada have notably higher net migration rates than the values predicted by their initial levels of income.

modifications probably would not change the basic findings that we now present about the relation between net migration and state per capita income.

The data on net migration for the U.S. states start in 1900 and are available for every census year except 1910 and 1930—see Barro and Sala-i-Martin (1991). We calculate the 10-year annual migration rates into a state by dividing the number of net migrants between dates $t - T$ and t by the state's population at date $t - T$.

Figure 11.10 shows the simple long-term relation between the migration rate and the log of initial income per capita.[10] The horizontal axis plots the log of state per capita income in 1900. The positive association is evident (correlation = 0.51). The main outlier is Florida, which has a lower than average initial income per capita and a very high net migration rate of 3 percent per year.

10. The variable on the vertical axis is the average annual in-migration rate for each state from 1900 to 1987. The variable is the average for each subperiod weighted by the length of the interval.

Table 11.4
Regressions for Net Migration into U.S. States, 1900–89

Period	Log of Per Capita Income	Heating Degree Days	Population Density	Square of Population Density	$R^2[\hat{\sigma}]$
1900–20	0.0335	−0.0066	−0.0433	0.0307	0.70
	(0.0075)	(0.0037)	(0.0079)	(0.0095)	[0.0111]
1920–30	0.0363	−0.0124	−0.0433	0.0307	0.61
	(0.0078)	(0.0027)	(0.0079)	(0.0095)	[0.0079]
1930–40	0.0191	−0.0048	−0.0433	0.0307	0.71
	(0.0037)	(0.0014)	(0.0079)	(0.0095)	[0.0041]
1940–50	0.0261	−0.0135	−0.0433	0.0307	0.82
	(0.0055)	(0.0022)	(0.0079)	(0.0095)	[0.0065]
1950–60	0.0438	−0.0205	−0.0433	0.0307	0.70
	(0.0086)	(0.0031)	(0.0079)	(0.0095)	[0.0091]
1960–70	0.0435	−0.0056	−0.0433	0.0307	0.70
	(0.0083)	(0.0025)	(0.0079)	(0.0095)	[0.0069]
1970–80	0.0240	−0.0077	−0.0433	0.0307	0.73
	(0.0091)	(0.0024)	(0.0079)	(0.0095)	[0.0072]
1980–89	0.0163	−0.0066	−0.0433	0.0307	0.72
	(0.0061)	(0.0019)	(0.0079)	(0.0095)	[0.0053]
Joint, 8 subperiods	0.0260	individual	−0.0427	0.0300	—
	(0.0023)	coefficients	(0.0079)	(0.0097)	—

Note: The likelihood-ratio statistic for a test of the equality of the income coefficients over the eight subperiods is 17.1, with a p value of 0.017 (from a χ^2 distribution with seven degrees of freedom). The regressions use iterative, weighted least squares and take the form

$$m_{it} = a_t + b_t \cdot \log(y_{i,t-T}) + c_{1t} \cdot \text{Heat}_i + c_2 \cdot \pi_{i,t-T} + c_3 \cdot \pi_{i,t-T}^2 + c_{4t} \cdot \text{Region}_i + c_{5t} \cdot S_{it}$$

where m_{it} is the net flow of migrants into state i between years $t - T$ and t, expressed as a ratio to the population at $t - T$; Heat_i is heating degree days; $\pi_{i,t-T}$ is population density (thousands of persons per square mile); Region_i is a set of dummies for the four main census regions; and S_{it} is the structural variable described in the text. The estimates of a_t, c_{4t}, and c_{5t} are not shown. The data are discussed in the appendix (section 11.12). All samples have 48 observations. Standard errors are in parentheses.

Table 11.4 shows regression results in the form of equation (11.10) for net migration into U.S. states. The results reported are for eight subperiods starting with 1900–20. The regressions include period-specific coefficients for $\log(y_{i,t-T})$ and for the log of heating-degree days. (The hypothesis of stability over the subperiods in the coefficients of $\log[\text{heat}_i]$ is rejected at the 5 percent level, although the estimated coefficients on $\log[y_{i,t-T}]$ change little if only a single coefficient is estimated for the heat variable.) Since the hypothesis that the coefficients for the population-density variables are stable over time is accepted at the 5 percent level, we estimate equation (11.10) with one coefficient for the density and one for the square of the density. The regressions also include period-specific coefficients for regional dummies and structural-share variables. (The estimated coefficients for the regional and structural variables are sometimes significant but play a minor role overall.)

The estimated coefficients for log(heat$_i$) in table 11.4 are all negative and most are significantly different from 0; other things equal, people prefer warmer states. The jointly estimated coefficients for density are −0.043 (0.008) on the linear term and 0.030 (0.010) on the squared term. These point estimates imply that the marginal effect of population density on migration is negative for all states, except for the three with the highest densities: New Jersey, Rhode Island since 1960, and Massachusetts since 1970.

The coefficient on the log of initial per capita income is significantly positive for all subperiods. The joint estimate is 0.0260 (0.0023). The estimated response of migration to the log of initial level is, however, not stable over time: the p value for the rejection of this hypothesis is 0.017. The main sources of instability are the unusually large coefficients on income in the 1950s and 1960s; the coefficients in these two subperiods are 0.0438 (0.0086) and 0.0435 (0.0083), respectively.

Although highly significant, the jointly estimated coefficient on initial income, 0.026, is small in an economic sense. The coefficient means that, other things equal, a 10 percent differential in income per capita raises net in-migration only by enough to raise the area's rate of population growth by 0.26 percent per year. Our previous results suggest that differences in per capita income tend themselves to vanish at a slow speed, roughly 2 percent per year. The combination of the results for migration with those for income convergence suggests that net migration rates would be highly persistent over time. The data confirm this idea: the correlation between the average migration rate for 1900–40 with that for 1940–89 is 0.70.

11.7 Migration Across Japanese Prefectures

Before we analyze migration across Japanese prefectures and implement equation (11.10) for Japan, we should mention that there is a substantial difference between the typical Japanese prefecture and the typical U.S. state in terms of area. The average size of a Japanese prefecture is 6394 square kilometers,[11] roughly half the size of Connecticut. The largest prefecture, Hokkaido, is 83,520 km^2, or roughly the size of South Carolina. The second largest prefecture, Iwate, has an area of 15,277 km^2, a bit larger than Connecticut and a bit smaller than New Jersey. In comparison, the average U.S. state has an area of 163,031 km^2, and the area of the largest state in the continental United States, Texas, is

11. This figure excludes Hokkaido, which is about five times as large as any of the other prefectures. The average size including Hokkaido is 8036 km^2, two-thirds the size of Connecticut.

691,030 km^2. California, with an area of 411,049 km^2, is slightly larger than all of Japan (377,682 km^2).

The contrast in size means that Japanese prefectures resemble metropolitan areas more than states, so that daytime commuting across prefectures can be significant. Urban economists, such as Henderson (1988), think that people like to live in cities for two reasons. First, there are demand or consumption externalities. That is, cities provide amenities, such as theaters and museums, features that can be supplied only if there is a sufficient scale of demand. Second, there are production externalities, which tend to generate high wages in big cities. An offsetting force is that people want to live away from crowded cities because they tend to be associated with crime, less friendly neighborhoods, and (in equilibrium) high land and housing prices (see Roback, 1982). Thus the decision to migrate to a city involves a trade-off. This trade-off can be avoided if people live in a suburb and commute to the central city. People are especially willing to pay high commuting costs when densities in the central city are extremely high.

To deal with these issues empirically, we would like to have a measure of the density of the neighboring prefectures. Conceptually, we could construct such a measure by weighting the neighbors' densities by their distance in some way. In practice, however, we observe that there are two main areas in Japan that have an abnormally high population density, Tokyo and Osaka. In 1990, Tokyo's density was 5470 people/km^2 and Osaka's was 4674 people/km^2, compared to an average for the other prefectures of 624 people/km^2.[12] Hence, the problems that we have mentioned are likely to arise in these two regions only. We can confirm this idea by considering the ratio of daytime to nighttime population, a measure of the extent of commuting.[13] A ratio smaller than one indicates that there are people who live in that prefecture but work in another, and a ratio larger than one indicates the opposite. The ratio is close to one for all prefectures except for the ones around Tokyo and Osaka: Tokyo's ratio is 1.184 and Osaka's is 1.053. The ratios for the Tokyo region are 0.872 for Saitama, 0.876 for Chiba, and 0.910 for Kanagawa. For the Osaka region, the ratios are 0.955 for Hyogo, 0.871 for Nara, and 0.986 for Wakayama.[14]

We constructed a variable called *neighbor's density* by assigning the prefectures of the Tokyo area (Tokyo and its immediate neighbors, Saitama, Chiba, and Kanagawa) and the Osaka area (Osaka and its immediate neighbors, Hyogo, Nara, and Wakayama) the average density of their immediate neighbors. For other prefectures, the variable equals its

12. In comparison, the U.S. state with the largest density in 1990 was New Jersey with 390 people/km^2.

13. The source of these data is the Statistics Bureau, Management and Coordination Agency.

14. There seems to be some commuting across prefectures in the areas surrounding Kyoto and Aichi, but the magnitudes are much smaller: Aichi's ratio is 1.016 (and its neighboring prefecture, Gifu, has a ratio of 0.977) and Kyoto's is 1.011.

own population density. We expect to find a positive relation between migration and this neighbor variable and a negative relation between migration and own density. This relation would indicate that people do not like to live in dense areas (they have to pay the congestion costs) but like to be close to these areas (so that they get the benefits of a big city).

The functional form that we estimate is

$$m_{it} = a + b \cdot \log(y_{i,t-T}) + c_1\theta_i + c_2\pi_{i,t-T} + c_3\pi^{ne}_{i,t-T} + v_{it} \tag{11.11}$$

where v_{it} is an error term, and $\pi^{ne}_{i,t-T}$ is the population density of the surrounding prefectures. To calculate the amenity (weather) variable, we squared the difference between the maximum and average temperatures, added the square of the difference between the minimum and average temperatures, and then took the square root. Hence, this variable measures extreme temperature. A variable similar to the one used for the United States (heating degree days) was unavailable. We experimented with other weather variables, such as maximum and minimum temperatures and average snowfall over the year. These alternative variables did not fit as well.

Figure 11.11 shows the relation between the average annual migration rate for 1955–87 and the log of income per capita in 1955. The clear positive association (simple correlation of 0.58) suggests that net migration reacts positively to income differentials. An interesting point is that the three outliers at the top of the figure are Chiba, Saitama, and Kanagawa, the prefectures surrounding Tokyo.

Table 11.5 shows the results of estimating migration equations of the form of equation (11.10). The first row refers to the average migration rate for the whole period, 1955–90. The coefficient on the log of initial income per capita is 0.0126 (0.0061). As expected, net migration is negatively associated with own density (−0.0049 [0.0022]) and positively associated with neighbor's density (0.0190 [0.0034]). The extreme temperature variable is insignificant.

The next seven rows in table 11.5 show results for the 5-year subperiods beginning with 1955–60. The estimated coefficient on initial income is significantly positive for all subperiods, except for 1975–80, for which the coefficient is positive, but insignificant. The joint estimate is 0.0188 (0.0019), which implies that, other things equal, a 10 percent increase in a prefecture's per capita income raises net in-migration by enough to raise that prefecture's rate of population growth by 0.19 percentage points per year. This result is close to that found for the U.S. states. A test of the stability of the income coefficients over time is rejected with a p value of 0.006.

The own-density variable is significantly negative, except for the first subperiod, and the neighbors' density variable is positive for all subperiods (significantly so for four of the seven subperiods). The extreme weather variable is negative, but only marginally significant.

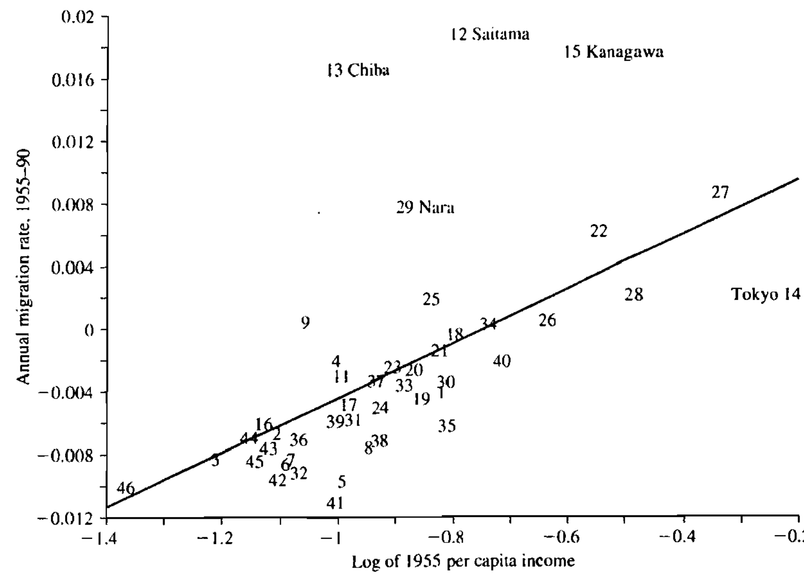

Figure 11.11
Migration and initial prefectural income, 1955–90. The average net migration rate for 47 Japanese prefectures from 1955 to 1990, shown on the vertical axis, is positively related to the log of 1955 per capita income, shown on the horizontal axis. The three prefectures surrounding Tokyo—Chiba, Saitama, and Kanagawa—had substantially higher net migration rates than the values predicted by their initial levels of income.

Thus weather does not seem to play an important role in the process of internal migration in Japan.

To summarize, some main findings are that the rate of net in-migration to a prefecture is negatively related to own density and positively related to the density of neighbors. Holding other things constant, migration is positively associated with initial per capita income. A notable result is the similarity of the coefficients on income for the United States and Japan, 0.026 from the joint estimation for the U.S. states and 0.019 from the joint estimation for Japanese prefectures.

Recall that differences in per capita income tend to dissipate at a slow rate, something like 2.5 to 3 percent per year for the Japanese prefectures. Putting this result together with those for migration, the implication is that net migration rates would be highly persistent over time. The data confirm this idea: the correlation between the average migration rate for 1955–70 with that for 1970–90 is 0.60.

Table 11.5
Regressions for Net Migration into Japanese Prefectures, 1955–90

Period	Log of Per Capita Income	Extreme Temperature	Own Population Density	Neighbors' Population Density	$R^2[\hat{\sigma}]$
1955–90	0.0126	0.00014	−0.0049	0.0190	0.62
	(0.0061)	(0.00062)	(0.0022)	(0.0034)	[0.0061]
1955–60	0.0216	−0.00014	0.0060	0.0025	0.85
	(0.0036)	(0.00012)	(0.0013)	(0.0019)	[0.0038]
1960–65	0.0317	−0.00014	−0.0019	0.0147	0.74
	(0.0058)	(0.00012)	(0.0020)	(0.0031)	[0.0071]
1965–70	0.0344	−0.00014	−0.0065	0.0142	0.71
	(0.0070)	(0.00012)	(0.0017)	(0.0025)	[0.0066]
1970–75	0.0194	−0.00014	−0.0064	0.0114	0.53
	(0.0060)	(0.00012)	(0.0015)	(0.0023)	[0.0070]
1975–80	0.0060	−0.00014	−0.0037	0.0052	0.32
	(0.0067)	(0.00012)	(0.0011)	(0.0014)	[0.0043]
1980–85	0.0101	−0.00014	−0.0023	0.0037	0.39
	(0.0044)	(0.00012)	(0.0006)	(0.0086)	[0.0030]
1985–90	0.0148	−0.00014	−0.0026	0.0046	0.56
	(0.0040)	(0.00012)	(0.0006)	(0.0084)	[0.0029]
Joint, 7	0.0188	−0.00040	individual	individual	—
subperiods	(0.0019)	(0.00015)	coefficients	coefficients	—

Note: The likelihood-ratio statistic for the hypothesis that the income coefficients are the same is 18.0, with a p value of 0.006. The regressions use iterative, weighted least squares to estimate equations of the form

$$m_{it} = a_t + b \cdot \log(y_{i,t-T}) + c_1 \cdot \text{Temp}_i + c_{2t} \cdot \pi_{i,t-T} + c_{3t} \cdot \pi^{ne}_{i,t-T} + c_{4t} \cdot \text{District}_i + c_{5t} \cdot S_{it}$$

where m_{it} is the net flow of migrants into prefecture i between years $t-T$ and t, expressed as a ratio to the population at time $t-T$; Temp_i is a measure of extreme temperature, calculated as deviations of maximum and minimum temperatures from the average temperature; $\pi_{i,t-T}$ is population density (thousands of persons per square kilometer); $\pi^{ne}_{i,t-T}$ is the population density of the neighboring prefectures (see the text); District_i is a set of dummy variables for the district; and S_{it} is the structural variable described in the text. All samples have 47 observations. (See the note to table 11.4 for additional information.)

11.8 Migration Across European Regions

We now estimate the sensitivity of the net migration rate to income across the regions of the five large European countries: Germany, the United Kingdom, Italy, France, and Spain. The dependent variable is the average net migration rate for each of the four decades starting in 1950. We are missing observations for the United Kingdom in the 1950s and 1980s and for France in the 1980s.

We estimate a system of regressions similar to those for the United States and Japan. The explanatory variables are the logarithm of per capita GDP or income at the beginning of

the decade, population density at the beginning of the decade, sectoral variables (shares in employment or GDP of agriculture and industry at the start of each decade), a temperature variable, and country dummies. We estimate a system of equations for the five countries, with the density and temperature variables restricted to have the same coefficients over time and across countries but with the coefficients of the other variables allowed to vary over time and across countries.

Table 11.6 reports the estimated coefficients on the log of initial per capita GDP or income. The first column contains the estimates for the 1950s, the second for the 1960s, and so on. The last column restricts the coefficients to be the same over the decades. The first row is for Germany, the second for the United Kingdom, the third for Italy, the fourth for France, and the fifth for Spain. The last row restricts the coefficients to be the same for the five countries.

Table 11.6
Regressions for Net Migration into European Regions, 1950–90, Coefficients on the Log of Per Capita GDP

	1950s	1960s	1970s	1980s	Total
Germany	0.0311	0.0074	0.0040	0.0024	0.0076
	(0.0121)	(0.0088)	(0.0038)	(0.0086)	(0.0014)
United Kingdom	—	0.0049	−0.0069	—	−0.0041
		(0.0011)	(0.0013)		(0.0023)
Italy	0.0182	0.0208	0.0089	0.0309	0.0117
	(0.0041)	(0.0027)	(0.0020)	(0.0106)	(0.0018)
France	0.0090	−0.0008	0.0097	—	0.0100
	(0.0056)	(0.0095)	(0.0041)		(0.0036)
Spain	0.0126	0.0135	0.0117	0.0031	0.0034
	(0.0068)	(0.0112)	(0.0063)	(0.0070)	(0.0021)
Overall	0.0107	0.0072	0.0046	0.0141	0.0064
	(0.0038)	(0.0040)	(0.0024)	(0.0070)	(0.0021)

Note: The regressions take the form

$$m_{ijt} = a_{jt} + b_{jt} \cdot \log(y_{ij,t-T}) + c_1 \cdot \text{Temp}_{ij} + c_2 \cdot \pi_{ij,t-T} + c_3 \cdot (\text{Country dummy}) + c_{4jt} \cdot \text{AG}_{ij,t-T} + c_{5jt} \cdot \text{IN}_{ij,t-T}$$

where m_{ijt} is the net flow of migrants into region i of country j between years $t-T$ and t, expressed as a ratio to the population at time $t-T$; Temp_{ij} is the average maximum temperature; $\pi_{ij,t-T}$ is population density (thousands of persons per square kilometer); $\text{AG}_{ij,t-T}$ is the share of employment or GDP (for the 1980s) in agriculture; and $\text{IN}_{ij,t-T}$ is the corresponding share in industry. All estimation is by the iterative, seemingly unrelated procedure. The table reports only the estimates of the coefficients b_{jt}. The numbers in the first five rows and first four columns apply when each country has a different coefficient for each period. The last column restricts the coefficients to be the same over time for each country. The last row restricts the coefficients to be the same across countries for each decade. The number in the intersection of the last row and column applies when all countries and time periods have a single coefficient.

In contrast with the results for the United States and Japan, the coefficients on the log of per capita GDP or income are not precisely estimated for the European countries. For Germany, the estimated coefficient for the 1950s is positive and significant, 0.031 (0.012), whereas those for the other three decades are insignificant. The estimated income coefficients for Italy are significantly positive, but many of those for the United Kingdom, France, and Spain are insignificant.

If we restrict the coefficients to be the same over time but allow them to vary across countries, the estimated values are 0.0076 (0.0014) for Germany, −0.0041 (0.0023) for the United Kingdom, 0.0117 (0.0018) for Italy, 0.0100 (0.0036) for France, and 0.0034 (0.0021) for Spain. If we restrict the coefficients to be the same across countries but allow them to vary over time, the estimated values are 0.0107 (0.0038) for the 1950s, 0.0072 (0.0040) for the 1960s, 0.0046 (0.0024) for the 1970s, and 0.0141 (0.0070) for the 1980s. Finally, if we restrict the coefficients to be the same across countries *and* over time, we get the estimate 0.0064 (0.0021). Although this estimate is significantly positive, the size of the coefficient is much smaller than the comparable values for the United States (0.026) and Japan (0.019). The main finding, therefore, is that the migration rate for European regions is positively related to per capita GDP or income, but the magnitude of the relation is weak, and the coefficients cannot be estimated with great precision.

11.9 Migration and Convergence

We found in chapter 9 that the migration of workers with low human capital from poor to rich economies tended to speed up the convergence of per capita income and product. The convergence coefficients estimated in growth regressions would include this effect from migration. In this section we attempt to estimate the effect of migration on convergence by including the net migration rate as an explanatory variable in the growth regressions. If migration is an important source of convergence—and if we can treat the migration rate as exogenous with respect to the error term in the growth equation—the estimated convergence coefficient, β, should become smaller when migration is held constant.

We enter the contemporaneous net migration rate in growth regressions in table 11.7. The first row reports the estimated speed of convergence, β, for the U.S. states. The sample period, 1920–90, is divided into seven ten-year subperiods. The regression includes period-specific coefficients for constant terms, dummies for the four major census regions, and the structural variable discussed before. The coefficient on the log of initial per capita income is constrained to be the same for each subperiod. This setup parallels the joint estimation shown in table 11.1, column 3, except for the elimination of the two early subperiods.

Column 1 of the table reports the estimate of β when the migration rate is not included in

Table 11.7
Migration and Convergence

	(1) Migration Excluded	(2) Migration Included (OLS)		(3) Migration Included (IV)	
	β	β	Migration	β	Migration
United States, 1920–90	0.0196 (0.0025)	0.0231 (0.0028)	0.0931 (0.0305)	0.0174 (0.0033)	−0.006 (0.048)
Japan, 1955–90	0.0312 (0.0040)	0.0340 (0.0044)	0.0907 (0.0041)	0.0311 (0.0042)	−0.108 (0.112)
Germany, 1950–90	0.0243 (0.0088)	0.0240 (0.0091)	−0.014 (0.235)	0.0181 (0.0093)	−0.542 (0.429)
United Kingdom, 1960–80[a]	0.0176 (0.0132)	0.0220 (0.0203)	0.116 (0.395)	0.0261 (0.0267)	0.222 (0.570)
Italy, 1950–90	0.0206 (0.0058)	0.0244 (0.0070)	0.166 (0.156)	0.0180 (0.0098)	−0.121 (0.370)
France, 1950–80[b]	0.0224 (0.0265)	0.0172 (0.0063)	−0.038 (0.126)	0.0177 (0.0065)	−0.084 (0.178)
Spain, 1950–90	0.0245 (0.0102)	0.0295 (0.0096)	−0.124 (0.102)	0.0268 (0.0119)	−0.068 (0.203)

Note: The regressions for the growth rates of per capita income or GDP are analogous to the joint estimations shown in table 11.1, column 3, for the U.S. states; table 11.2, column 3, for the Japanese prefectures; and table 11.3, column 2, for the European regions (except that the five large European countries are treated separately here). The β coefficients refer to the log of initial per capita income or GDP, and the migration coefficients refer to the net migration rate. In column 1 the migration rate is not included as a regressor. In column 2 the migration rate is added, and the estimation is by OLS. In column 3 instrumental estimation is used. The instruments are the regressors included in the migration equations, as reported in table 11.4 for the United States, table 11.5 for Japan, and table 11.6 for Europe.
[a] Two subperiods.
[b] Three subperiods.

the regressions. The speed of convergence is 0.0196 (0.0025), close to the familiar 2 percent per year. Column 2 adds the net migration rate as a regressor. (The coefficient on this variable is constrained to be the same for each subperiod.) The estimated coefficient on the migration rate is positive and significant, 0.093 (0.030), and the estimate of β, 0.0231 (0.0028), is actually somewhat higher than that shown in column 1. Thus, contrary to expectations, the estimate of β does not diminish when the net migration rate is held constant.

The results are likely influenced by the endogeneity of the net migration rate. Specifically, states with more favorable growth prospects (owing to factors not held constant by the included explanatory variables) are likely to have higher per capita growth rates *and* higher net migration rates. We attempt to isolate exogenous shifts in migration by using as instruments the explanatory variables used to explain the net migration rate in table 11.4. These variables include population density and the log of heating degree days. (The assumption is that these determinants of migration do not enter directly into the growth equation.) The results, contained in column 3 of table 11.7, show an insignificant coefficient on the migration rate, −0.006 (0.048), and an estimated β coefficient, 0.0174 (0.0033), that is slightly lower than that in column 1. These results suggest that migration does not account for a large part of β convergence for the U.S. states.

The second row of table 11.7 applies the same procedure to Japan. The first column reports the joint estimate of β over seven five-year periods when the migration rate is excluded as a regressor. The estimate of β, 0.0312 (0.0040), is the same as that in column 3 of table 11.2. When the migration rate is added in column 2 of table 11.7, the estimated coefficient on migration is positive and similar to that found for the United States, 0.0907 (0.0041), and the estimate of β increases to 0.0340 (0.0044). In column 3, which includes instruments for migration, the estimated coefficient on migration is insignificant, −0.11 (0.11), and the estimate of β, 0.0311 (0.0042), is essentially the same as that in column 1. Hence, as for the U.S. states, migration does not appear to be a major element in β convergence for the Japanese prefectures.

The last five rows of table 11.7 apply an analogous procedure to the five large European countries. The main findings are similar to those for the United States and Japan in that the estimated β coefficients do not change a great deal when migration rates are held constant. One surprising result is that the net migration rates are insignificant in the OLS regressions for the European regions, whereas the usual endogeneity story suggests positive coefficients. It may be that the regional net migration rates are not well measured for the European countries, a possibility that would also account for the difficulties in the estimated migration equations in these cases.

A second prediction from the migration theory in chapter 9 is that economies with higher sensitivity of net migration to per capita income will have higher convergence coefficients, β. To check this possibility, we plot in figure 11.12 the estimated β coefficients against the estimated coefficients of the log of per capita GDP or income from the migration equations. The figure has seven data points, corresponding to the United States, Japan, Germany, the United Kingdom, Italy, France, and Spain. The figure shows a weak positive relation between the two coefficients; the correlation is 0.27.[15] The imprecision with which the coefficients in the migration equations are estimated for the European countries suggests that this relation should be interpreted with caution. See Braun (1993) for further discussion of this approach.

15. The β coefficients for France and the United Kingdom are those estimated over the same subperiods for which the migration data are available. The β coefficient estimated over the full sample is lower for France and higher for the United Kingdom. If we use these alternative estimates of β, the correlation with the coefficient from the migration equations is slightly higher, 0.32.

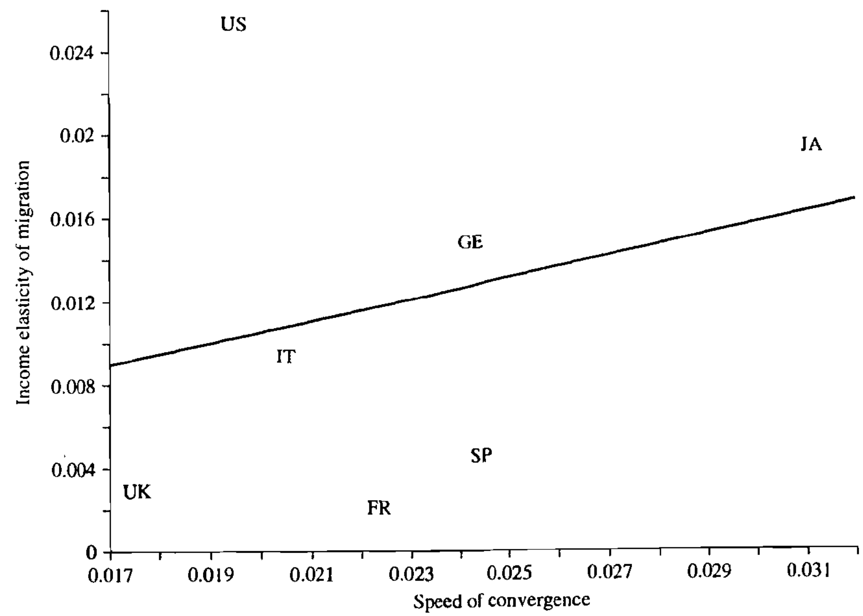

Figure 11.12
Income Coefficient of Migration and Speed of Convergence. The vertical axis shows the estimated coefficient on the log of per capita income or GDP from migration regressions. The horizontal axis has the estimated β convergence coefficient from growth regressions. The seven data points—for the United States, Japan, Germany, the United Kingdom, Italy, France, and Spain—exhibit a positive relation, as predicted by the theory of migration and growth.

11.10 β Convergence in Panel Data with Fixed Effects

Following Islam (1995), a number of researchers have attempted to estimate the speed of convergence using panel data sets and variants of fixed-effects estimation. Caselli, Esquivel, and Laffort (1996), for example, use panel data for a cross section of countries, while Canova and Marcet (1995) use regional data. One claimed advantage of panel data over cross sections is that one does not need to hold constant the steady state because it can be implicitly estimated using fixed effects. The main result is that estimates of the speed of convergence from panel data with fixed effects tend to be much larger than the 2 percent-per-year number estimated from cross sections or panels without fixed effects. Speeds of convergence in the range of 12 to 20 percent per year are not uncommon in this literature.

One potential problem with the fixed-effects approach is that, in order to work, one needs to include many time-series observations. This procedure can be carried out only by shortening the time periods within which the growth rate is computed. In other words, the dependent variable tends to be the yearly growth rate or the growth rate over two to five years. The problem with such short time spans is that the growth rates tend to capture short-term adjustments around the trend rather than long-term convergence. In particular, the existence of business cycles tends to bias upward the estimates of speeds of convergence. In this context, Shioji (1997) provides evidence that, once one corrects for the measurement error introduced by business cycles, the estimated speed of convergence from panels with fixed effects is still close to 2 percent per year.

11.11 Conclusions

We studied the behavior of the U.S. states since 1880, the prefectures of Japan since 1930, and the regions of eight European countries since 1950. The results indicate that absolute β convergence is the norm for these regional economies. That is, poor regions of these countries tend to grow faster per capita than rich ones. The convergence is absolute because it applies when no explanatory variables other than the initial level of per capita product or income are held constant.

We can interpret the results as consistent with the neoclassical growth model described in chapters 1 and 2 if regions within a country have roughly similar tastes, technologies, and political institutions. This relative homogeneity generates similar steady-state positions. The observed convergence effect is, however, also consistent with the models of technological diffusion described in chapter 8.

One surprising result is the similarity of the speed of β convergence across data sets. The estimates of β are around 2–3 percent per year in the various contexts. This slow speed of convergence implies that it takes 25–35 years to eliminate one-half of an initial gap in per capita incomes. This behavior deviates from the quantitative predictions of the neoclassical growth model if the capital share is close to one-third. The empirical evidence is, however, consistent with the theory if the capital share is around three-quarters.

The analysis of migration indicates that the rate of net migration tends to respond positively to the initial level of per capita product or income, once a set of other explanatory variables is held constant. This relation is clear for the U.S. states and the Japanese prefectures but is weaker for the regions of five large European countries. We also check whether the presence of β convergence in the regional data can be explained by the behavior of net migration. The evidence here is not definitive but suggests that migration plays only a minor role in the convergence story.

11.12 Appendix on Regional Data Sets

We describe data for the U.S. states, regions of eight European countries (Germany, the United Kingdom, Italy, France, the Netherlands, Belgium, Denmark, and Spain), and prefectures of Japan. Data for regions of other countries, such as Argentina, Brazil, China, India, Mexico, and the USSR, are also available. Additional information is available by city and county; see, for example, Ades and Glaeser (1995).

11.12.1 Data for U.S. States

Table 11.8 shows a sampling of the data for the U.S. states (shown on the U.S. map in figure 11.13). Figures on nominal personal income and nominal per capita personal income are available by state since 1929 from the U.S. Commerce Department (Bureau of Economic Analysis, 2002; updates appear in issues of *U.S. Survey of Current Business*). The concept of personal income used in these regional accounts corresponds to that employed in the national accounts. The numbers are reported annually, but values prior to 1965 are based on interpolations of estimates constructed at approximately five-year intervals. Data are reported with and without transfer payments. Figures on gross state product are available annually since 1963 (from issues of *U.S. Survey of Current Business*).

Reliable data on price levels are unavailable by state, although some information exists for cities. We have computed real income by dividing the nominal figures on personal income by the national values of the consumer price index (1982–84 = 1.0). (We used the figures from *Citibase* for all items except shelter since 1947. Before 1947, we used the overall index from U.S. Department of Commerce, 1975, series E135.) As long as the same index is used at each date for each state, the particular index chosen does not affect the relative levels and growth rates across the states.

Earlier income figures are reported by Easterlin (1960a, 1960b) for 1920 (48 states), 1900 (48 states or territories), 1880 (47 states or territories, with Oklahoma excluded), and 1840 (29 states or territories). These data are exclusive of transfer payments, and the figures for 1840 do not cover all components of personal income. Estimates of the consumer price index for all items (U.S. Department of Commerce, 1975, series E135) are used to deflate these earlier values.

For the census years since 1930, labor earnings (including those from self-employment) can be broken down into nine sectors: agriculture; mining; construction; total manufacturing; transportation and public utilities; wholesale and retail trade; finance, insurance, and real estate; services; and government and government enterprises. For periods before 1930, information is available on the fraction of income originating in agriculture.

Table 11.8
Data for U.S. States

State		Real Per Capita Income, 1900 ($1000s, 1982–84 base)	Real Per Capita Income, 2000 ($1000s, 1982–84 base)	Growth Rate of Real Per Capita Income	Population, 1900 (millions)	Population, 1990 (millions)	Growth Rate of Population, 1900–90	Net Migrants, 1900–89 (millions)
AL	Alabama	1.00	12.95	0.0256	1.829	4.046	0.0088	−1.32
AZ	Arizona	3.69	13.79	0.0132	0.093	3.681	0.0409	2.03
AR	Arkansas	1.03	12.11	0.0246	1.312	2.353	0.0065	−1.14
CA	California	4.20	17.78	0.0144	1.403	29.956	0.0340	16.59
CO	Colorado	3.66	17.90	0.0159	0.529	3.302	0.0203	1.11
CT	Connecticut	3.19	22.55	0.0196	0.908	3.290	0.0143	0.76
DE	Delaware	2.52	17.15	0.0192	0.185	0.669	0.0143	0.18
FL	Florida	1.29	15.36	0.0248	0.529	13.044	0.0356	9.37
GA	Georgia	0.98	15.33	0.0275	2.222	6.504	0.0120	−0.28
ID	Idaho	2.54	13.04	0.0164	0.154	1.011	0.0209	0.04
IL	Illinois	2.99	17.57	0.0177	4.822	11.443	0.0096	−0.17
IN	Indiana	2.09	14.81	0.0196	2.516	5.554	0.0088	−0.30
IA	Iowa	2.33	14.55	0.0183	2.232	2.780	0.0024	−1.41
KS	Kansas	2.15	15.12	0.0195	1.470	2.480	0.0058	−0.65
KY	Kentucky	1.38	13.27	0.0226	2.147	3.690	0.0060	−1.54
LA	Louisiana	1.47	12.71	0.0216	1.382	4.211	0.0124	−0.52
ME	Maine	2.16	14.02	0.0187	0.694	1.231	0.0064	−0.11
MD	Maryland	2.34	18.55	0.0207	1.188	4.802	0.0155	1.26
MA	Massachusetts	3.49	20.81	0.0179	2.850	6.020	0.0083	0.14
MI	Michigan	2.13	16.04	0.0202	2.421	9.314	0.0150	0.62
MN	Minnesota	2.38	17.61	0.0200	1.737	4.390	0.0103	−0.34
MS	Mississippi	0.97	11.51	0.0247	1.551	2.574	0.0056	−1.62
MO	Missouri	2.16	15.00	0.0194	3.107	5.127	0.0056	−0.83
MT	Montana	4.77	12.44	0.0096	0.226	0.799	0.0140	−0.07
NE	Nebraska	2.43	15.26	0.0184	1.066	1.580	0.0044	−0.71
NV	Nevada	4.54	16.31	0.0128	0.035	1.224	0.0395	0.79
NH	New Hampshire	2.46	18.23	0.0200	0.412	1.111	0.0110	0.31
NJ	New Jersey	3.19	20.48	0.0186	1.884	7.735	0.0157	2.20
NM	New Mexico	1.70	12.08	0.0196	0.180	1.520	0.0237	0.16
NY	New York	3.71	19.04	0.0164	7.269	18.002	0.0101	1.13
NC	North Carolina	0.82	14.81	0.0289	1.894	6.653	0.0140	−0.30
ND	North Dakota	2.40	13.67	0.0174	0.312	0.637	0.0079	−0.49
OH	Ohio	2.55	15.40	0.0180	4.158	10.859	0.0107	0.14
OK	Oklahoma	1.31	13.01	0.0230	0.670	3.146	0.0172	−0.19
OR	Oregon	2.85	15.26	0.0168	0.395	2.861	0.0220	1.27
PA	Pennsylvania	2.88	16.30	0.0173	6.302	11.893	0.0071	−1.99
RI	Rhode Island	3.36	16.09	0.0157	0.429	1.005	0.0095	0.05
SC	South Carolina	0.86	13.22	0.0273	1.340	3.498	0.0107	−0.75
SD	South Dakota	2.11	14.34	0.0192	0.381	0.696	0.0067	−0.43
TN	Tennessee	1.16	14.28	0.0251	2.021	4.887	0.0098	−0.46
TX	Texas	1.58	15.30	0.0227	3.049	17.055	0.0191	3.33
UT	Utah	2.11	12.89	0.0181	0.272	1.729	0.0206	0.06
VT	Vermont	2.19	14.85	0.0191	0.344	0.565	0.0055	−0.05
VA	Virginia	1.27	17.14	0.0260	1.854	6.213	0.0134	0.61
WA	Washington	3.40	17.18	0.0162	0.496	4.909	0.0255	2.16
WV	West Virginia	1.35	12.01	0.0219	0.959	1.790	0.0069	−1.10
WI	Wisconsin	2.05	15.49	0.0202	2.058	4.906	0.0097	−0.33
WY	Wyoming	3.57	15.14	0.0144	0.089	0.452	0.0181	0.03

Notes: The two-letter abbreviation (zip code) for each of the 48 states is shown before the state name.
The U.S. Census regional classifications are as follows:
Northeast: ME, NH, VT, MA, RI, CT, NY, NJ, PA.
South: DE, MD, VA, WV, NC, SC, GA, FL, KY, TN, AL, MS, AR, LA, OK, TX.
Midwest: MN, IA, MO, ND, SD, NE, KS, OH, IN, IL, MI, WI.
West: MT, ID, WY, CO, NM, AZ, UT, NV, WA, OR, CA.

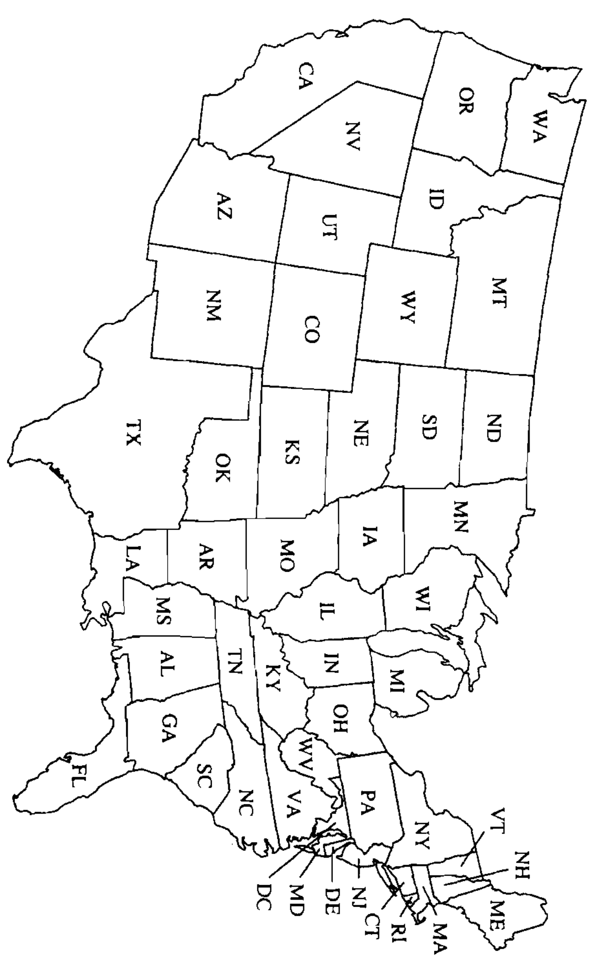

Figure 11.13
Map of the U.S. states.

Population density is the ratio of population to total area (land plus water); the data on area are in U.S. Department of Commerce, Bureau of the Census (1990). Net migration flows can be computed from census figures by taking the change in population over a period, subtracting the number of births, and adding the number of deaths.

11.12.2 Data for European Regions

Table 11.9 has a sampling of the data for regions of European countries (shown on the map in figure 11.14). We have data on GDP, population, and related variables for regions of eight European countries—Germany (11 regions), the United Kingdom (11), Italy (20), France (21), the Netherlands (4), Belgium (3), Denmark (3), and Spain (17).

For the countries other than Spain, the data on GDP and population for 1950, 1960, and 1970 are from Molle, Van Holst, and Smits (1980). Figures for 1966 (missing France and Denmark), 1970 (missing Denmark), 1974, 1980, 1985, and 1990 (missing Denmark) are from *Eurostat*. For Spain, data on regional income and GDP are provided for various years from 1955 to 1987 by the Banco de Bilbao (various issues). The figures on population are from INE, *Anuario Estatistico de España* (various issues). The data applied originally to 50 provinces and have been aggregated to 17 regions.

Table 11.9
Data for European Regions

Region	Real Per Capita GDP, 1950 Proportionate Deviation from Country Mean[a]	Real Per Capita GDP, 1990 Proportionate Deviation from Country Mean[b]	Growth Rate of Real Per Capita GDP Deviation from Country Mean[c]	Population, 1950[d] (millions)	Population, 1990[e] (millions)	Growth Rate of Population[f]	Net Migrants, Various Periods[g] (millions)
Germany							
1. Schleswig-Holstein	−0.36	−0.20	0.0039	2.595	2.615	0.0002	0.31
2. Hamburg	0.54	0.42	−0.0029	1.606	1.641	0.0005	0.13
3. Niedersachsen	−0.25	−0.18	0.0019	6.797	7.342	0.0019	0.21
4. Bremen	0.34	0.20	−0.0034	0.559	0.679	0.0049	0.10
5. Nordrhein Westfalia	0.12	−0.08	−0.0049	13.207	17.248	0.0067	2.05
6. Hessen	−0.06	0.12	0.0044	4.324	5.718	0.0070	1.19
7. Rheinland-Pfalz	−0.25	−0.15	0.0023	3.005	3.735	0.0054	0.25
8. Saarland	0.17	−0.10	−0.0067	0.955	1.071	0.0029	0.00
9. Baden-Württemberg	−0.03	0.02	0.0014	6.430	9.729	0.0104	1.78
10. Bayern	−0.19	−0.01	0.0045	9.185	11.337	0.0053	1.52
11. Berlin (West)	−0.02	−0.04	−0.0005	2.147	2.118	−0.0003	0.26
United Kingdom							
12. North	−0.07	−0.07	−0.0008	3.133	3.075	−0.0005	−0.24
13. Yorkshire-Humberside	0.11	−0.01	−0.0039	4.494	4.952	0.0024	−0.16
14. East Midlands	−0.02	0.04	0.0005	2.909	4.019	0.0081	0.21
15. East Anglia	−0.04	0.10	0.0027	1.381	2.059	0.0100	0.34
16. South-East	0.30	0.27	−0.0016	15.174	17.458	0.0035	−0.45
17. South-West	−0.22	0.03	0.0056	3.238	4.667	0.0091	0.66
18. North-West	0.08	−0.02	−0.0034	6.424	6.389	−0.0001	−0.48
19. West Midlands	0.14	−0.01	−0.0045	4.422	5.219	0.0041	−0.20
20. Wales	−0.24	−0.10	0.0025	2.584	2.881	0.0027	0.08
21. Scotland	−0.03	0.00	−0.0002	5.096	5.102	0.0000	−0.45
22. Northern Ireland	−0.35	−0.22	0.0031	1.371	1.589	0.0037	−0.20
Italy							
23. Piemonte	0.47	0.23	−0.0066	3.504	4.357	0.0054	0.87
24. Valle d'Aosta	0.53	0.31	−0.0057	0.095	0.116	0.0050	0.02
25. Liguria	0.61	0.18	−0.0106	1.555	1.723	0.0026	0.30
26. Lombardia	0.52	0.34	−0.0045	6.433	8.928	0.0082	1.25

Table continued

Table 11.9
(Continued)

Region	Real Per Capita GDP, 1950 Proportionate Deviation from Country Mean[a]	Real Per Capita GDP, 1990 Proportionate Deviation from Country Mean[b]	Growth Rate of Real Per Capita GDP Deviation from Country Mean[c]	Population, 1950[d] (millions)	Population, 1990[e] (millions)	Growth Rate of Population[f]	Net Migrants, Various Periods[g] (millions)
27. Trentino–Alto Adige	0.19	0.22	0.0007	0.735	0.889	0.0048	−0.03
28. Veneto	−0.01	0.19	0.0050	3.841	4.392	0.0034	−0.35
29. Fruili-Venezia-Giulia	0.12	0.24	0.0030	1.200	1.202	0.0000	−0.58
30. Emilia-Romagna	0.17	0.28	0.0027	3.509	3.925	0.0028	0.19
31. Marche	−0.06	0.08	0.0036	1.352	1.433	0.0015	−0.13
32. Toscana	0.16	0.13	−0.0006	3.152	3.562	0.0031	0.29
33. Umbria	−0.04	0.03	0.0016	0.806	0.822	0.0005	−0.07
34. Lazio	0.21	0.17	−0.0008	3.322	5.181	0.0111	0.62
35. Campania	−0.29	−0.33	−0.0011	4.276	5.831	0.0078	−0.88
36. Abruzzi	−0.32	−0.10	0.0054	1.238	1.269	0.0006	−0.27
37. Molise	−0.49	−0.20	0.0071	0.398	0.336	−0.0042	−0.14
38. Puglia	−0.33	−0.26	0.0017	3.181	4.076	0.0062	−0.77
39. Basilicata	−0.47	−0.41	0.0016	0.617	0.624	0.0003	−0.25
40. Calabria	−0.48	−0.46	0.0005	1.987	2.153	0.0020	−0.79
41. Sicilia	−0.32	−0.37	−0.0012	4.422	5.185	0.0040	−1.08
42. Sardegna	−0.16	−0.27	−0.0027	1.259	1.661	0.0069	−0.23
France							
43. Region Parisienne	0.61	0.50	−0.0026	7.009	10.227	0.0094	1.02
44. Champagne-Ardenne	0.05	0.11	0.0015	1.110	1.341	0.0047	−0.06
45. Picarde	0.05	−0.05	−0.0026	1.355	1.804	0.0072	0.04
46. Haute Normandie	0.13	0.05	−0.0020	1.232	1.731	0.0085	0.03
47. Centre	−0.18	0.02	0.0049	1.758	2.363	0.0074	0.30
48. Basse Normandie	−0.14	−0.04	0.0024	1.145	1.385	0.0048	−0.10
49. Bourgogne	−0.11	−0.01	0.0025	1.376	1.602	0.0038	0.10
50. Nord–Pas de Calais	0.17	−0.09	−0.0067	3.309	3.945	0.0044	−0.39
51. Lorraine	0.24	−0.03	−0.0067	1.874	2.293	0.0050	−0.22
52. Alsace	0.19	0.14	−0.0014	1.196	1.619	0.0075	0.15
53. Franche-Comte	0.05	0.03	−0.0005	0.841	1.092	0.0065	0.02
54. Pays de la Loire	−0.11	−0.03	0.0020	2.293	3.048	0.0071	0.03
55. Bretagne	−0.20	−0.08	0.0030	2.358	2.784	0.0042	0.03
56. Poitou-Charente	−0.25	−0.11	0.0035	1.379	1.588	0.0035	−0.03
57. Aquitaine	−0.15	0.00	0.0036	2.206	2.787	0.0058	0.35
58. Midi-Pyrénées	−0.27	−0.10	0.0043	1.982	2.423	0.0050	0.29
59. Limousin	−0.05	−0.14	−0.0023	0.760	0.719	−0.0014	0.04
60. Rhône-Alpes	0.12	0.09	−0.0009	3.580	5.338	0.0100	0.77
61. Auvergne	−0.06	−0.09	−0.0009	1.261	1.314	0.0010	0.03
62. Languedoc-Roussillon	−0.18	−0.14	0.0008	1.453	2.119	0.0094	0.48
63/64. Provence–Alpes–Côtes d'Azur–Corse	0.08	−0.01	−0.0021	2.533	4.499	0.0144	1.52
Netherlands							
65. Noord	−0.10	0.04	0.0035	1.215	1.596	0.0068	—
66. Oost	−0.12	−0.13	−0.0003	1.788	3.050	0.0134	—
67. West	0.18	0.12	−0.0015	5.155	6.996	0.0076	—
68. Zuid	0.04	−0.03	−0.0016	2.007	3.306	0.0125	—
Belgium							
69. Vlaanderen	−0.14	0.09	0.0057	3.963	4.486	0.0030	—
70. Wallonie	−0.01	−0.21	−0.0049	2.841	3.251	0.0034	—
71. Brabant	0.15	0.12	−0.0008	1.849	2.248	0.0049	—
Denmark							
72. Sjalland-Lolland-Falster-Bornholm	0.08	0.19	0.0031	1.984	1.718	−0.0040	—
73. Fyn	−0.02	−0.14	−0.0034	0.396	0.586	0.0109	—
74. Jylland	−0.06	−0.05	0.0003	1.902	2.817	0.0109	—

Table continued

Table 11.9
(Continued)

Region	Real Per Capita GDP, 1950 Proportionate Deviation from Country Mean[a]	Real Per Capita GDP, 1990 Proportionate Deviation from Country Mean[b]	Growth Rate of Real Per Capita GDP Deviation from Country Mean[c]	Population, 1950[d] (millions)	Population, 1990[e] (millions)	Growth Rate of Population[f]	Net Migrants, Various Periods[g] (millions)
Spain							
75. Andalucia	−0.29	−0.29	0.0002	5.621	6.920	0.0053	−1.67
76. Aragon	0.01	0.08	0.0022	1.095	1.213	0.0026	−0.12
77. Asturias	0.17	−0.06	−0.0074	0.893	1.126	0.0059	−0.02
78. Balears	0.08	0.34	0.0080	0.423	0.682	0.0122	0.12
79. Canaries	−0.22	−0.03	0.0059	0.800	1.485	0.0158	0.02
80. Cantabria	0.18	0.05	−0.0043	0.406	0.527	0.0067	−0.04
81. Castilla–La Mancha	−0.43	−0.26	0.0052	2.028	1.714	−0.0043	−0.91
82. Castilla-Leon	−0.13	−0.11	0.0007	2.864	2.626	−0.0022	−0.97
83. Catalunya	0.34	0.25	−0.0029	3.271	6.008	0.0156	1.42
84. Euskadi (Basque)	0.74	0.11	−0.0197	1.075	2.129	0.0175	0.43
85. Extremadura	−0.58	−0.43	0.0047	1.366	1.129	−0.0049	−0.70
86. Galicia	−0.36	−0.20	0.0050	2.604	2.804	0.0019	−0.41
87. Madrid	0.48	0.34	−0.0042	1.956	4.876	0.0234	1.40
88. Murcia	−0.35	−0.15	0.0062	0.759	1.027	0.0078	−0.16
89. Navarra	0.19	0.13	−0.0019	0.384	0.521	0.0078	0.00
90. La Rioja	0.11	0.14	0.0008	0.230	0.260	0.0032	−0.03
91. Valencia	0.05	0.10	0.0014	2.316	3.787	0.0126	0.54

[a]Difference of logarithm of per capita GDP in 1950 from country mean in 1950. Values for Spain are for 1955.
[b]Difference of logarithm of per capita GDP in 1990 from country mean in 1990. Values for Denmark are for 1985 and for Spain are for 1987.
[c]Difference of annual growth rate of per capita GDP from 1950 to 1990 from country mean growth rate. Values for Denmark are for 1950–85 and for Spain are for 1955–87.
[d]Values for Spain are for 1951.
[e]Values for Denmark are for 1986.
[f]Annual growth rate of population from 1950 to 1990. Values for Denmark are for 1950–86 and for Spain are for 1951–90.
[g]Time periods are 1954–88 for Germany, 1961–85 for the United Kingdom, 1951–87 for Italy, 1954–82 for France, and 1951–87 for Spain.
Note: The numbers for the regions correspond to those used for the map in figure 11.4.

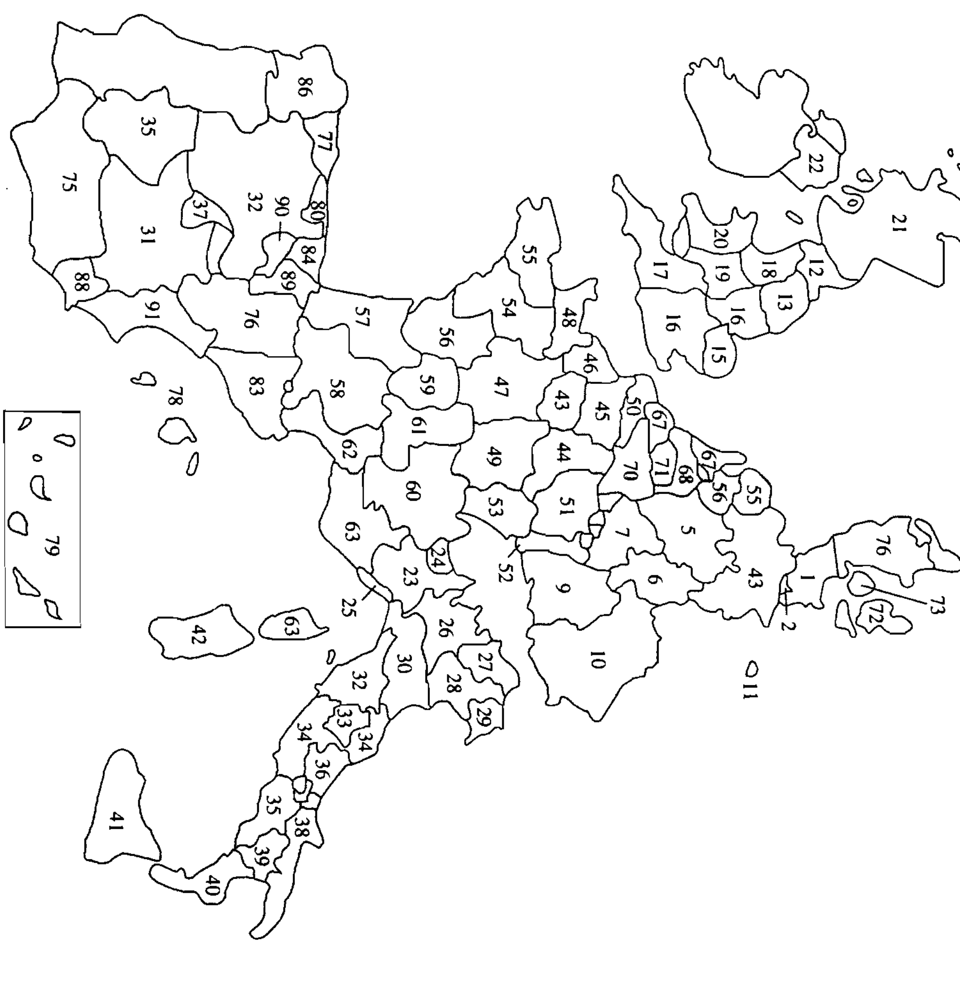

Figure 11.14
Map of European regions.

Ve do not have regional price data. In addition, the figures on GDP are sometimes pro-
ɛd in an index form that are not comparable across countries. We have therefore focused regional GDP figures that are expressed as deviations from means for the respective ntries.

'or the countries other than Spain, Molle, Van Holst, and Smits (1980) provide a break-
'n of employment into three sectors—agriculture, industry, and services—for 1950, 0, and 1970. For the other years, *Eurostat* provides a division of GDP into the same e sectors. For Spain, the breakdown of GDP into these three components for the various 's is available from Banco de Bilbao (various issues).

et migration flows are computed for the five larger countries from information on pop-
on, births, and deaths. The national sources are as follows: Germany: Statistischen desamtes, *Statistisches Jahrbuch für die Bundesrepublik Deutschland,* various years. ed Kingdom: *Population Trends 51,* Spring 1988. France: INSEE, *Statistiques et Indi-urs des Regions Francaises,* 1978; INSEE, *Donnes de Demographie Regionale 1982,*). Italy: ISTAT, *Sommario Storice di Statistiche Sulla Populazzione: Anni 1951–1987,*). Spain: INE, *Anuario Estatistico de España,* various issues.

2.3 Data for Japanese Prefectures

for Japanese prefectures are in table 11.10 (a prefectural map is shown in figure 11.15). figures on income are collected since 1955 by the Economic Planning Agency (EPA) pan. The accounts are constructed in accordance with the "1983 standardized system efectural accounts," so that all figures are comparable. The aggregate of the income ɜs from the 47 prefectures coincides theoretically with Japan's national income. The ıre collected annually and published in the *Annual Report on Prefectural Accounts.* For , we obtained income data by prefecture from *National Economy Studies Association.* o not have price data by prefecture and therefore use national price indexes to deflate region's income.

ta on population are from the Statistics Bureau at the Management and Coordination cy. The principal source of these figures is the quinquennial population census taken ; Statistics Bureau.

gration data are collected by the Statistics Bureau. These figures are derived from the *Resident Registers* and the *Statistical Survey on Legal Migrants.* These data exclude ıs without Japanese nationality.

Table 11.10
Data for Japanese Prefectures

Prefecture	Real Per Capita Income, 1955[a] (million yen, 1985 base)	Real Per Capita Income, 1990 (million yen, 1985 base)	Growth Rate of Real Per Capita Income[b]	Population, 1955 (millions)	Population, 1990 (millions)	Growth Rate of Population	Net Migrants, 1955–90[c] (millions)
1. Hokkaido	0.441	2.396	0.0484	4.784	5.644	0.0030	−0.76
2. Aomori	0.326	2.045	0.0525	1.391	1.483	0.0012	−0.36
3. Iwate	0.298	2.093	0.0557	1.437	1.417	−0.0003	−0.41
4. Miyagi	0.367	2.453	0.0543	1.748	2.249	0.0046	−0.11
5. Akita	0.371	2.137	0.0500	1.362	1.227	−0.0019	−0.44
6. Yamagata	0.337	2.206	0.0537	1.370	1.258	−0.0016	−0.38
7. Fukushima	0.339	2.413	0.0561	2.120	2.104	−0.0001	−0.57
8. Niigata	0.388	2.398	0.0520	2.501	2.475	−0.0002	−0.63
9. Ibaraki	0.348	2.648	0.0580	2.099	2.845	0.0055	0.09
10. Tochigi	0.518	2.788	0.0561	1.571	1.935	0.0038	−0.13
11. Gumma	0.369	2.640	0.0562	1.624	1.966	0.0035	−0.15
12. Saitama	0.460	2.825	0.0519	2.279	6.405	0.0188	2.41
13. Chiba	0.368	2.880	0.0588	2.225	5.555	0.0166	1.93
14. Tokyo	0.811	4.238	0.0472	8.016	11.855	0.0071	0.10
15. Kanagawa	0.564	2.960	0.0474	2.901	7.980	0.0184	2.58
16. Yamanashi	0.321	2.557	0.0593	0.819	0.853	0.0007	−0.16
17. Nagano	0.374	2.633	0.0558	2.050	2.157	0.0009	−0.33
18. Shizuoka	0.452	2.883	0.0530	2.638	3.671	0.0060	−0.02
19. Toyama	0.426	2.616	0.0518	1.028	1.120	0.0016	−0.16
20. Ishikawa	0.412	2.608	0.0527	0.964	1.165	0.0034	−0.09
21. Gifu	0.441	2.551	0.0502	1.599	2.067	0.0047	−0.07
22. Aichi	0.579	2.971	0.0467	3.779	6.690	0.0104	0.86
23. Mie	0.406	2.621	0.0533	1.505	1.793	0.0032	−0.11
24. Fukui	0.395	2.429	0.0519	0.758	0.824	0.0015	−0.13
25. Shiga	0.434	2.794	0.0532	0.857	1.222	0.0065	0.09
26. Kyoto	0.531	2.664	0.0461	1.928	2.603	0.0054	0.02
27. Osaka	0.709	3.190	0.0430	4.586	8.735	0.0117	1.27

Table continued

Table 11.10
(Continued)

Prefecture	Real Per Capita Income, 1955[a] (million yen, 1985 base)	Real Per Capita Income, 1990 (million yen, 1985 base)	Growth Rate of Real Per Capita Income[b]	Population, 1955 (millions)	Population, 1990 (millions)	Growth Rate of Population	Net Migrants, 1955–90[c] (millions)
28. Hyogo	0.618	2.668	0.0418	3.660	5.405	0.0071	0.29
29. Nara	0.418	2.190	0.0473	0.777	1.375	0.0104	0.30
30. Wakayama	0.438	2.109	0.0449	1.012	1.074	0.0011	−0.15
31. Tottori	0.373	2.193	0.0506	0.615	0.616	0.0000	−0.12
32. Shimane	0.336	2.121	0.0527	0.931	0.781	−0.0032	−0.26
33. Okayama	0.413	2.555	0.0521	1.716	1.926	0.0021	−0.16
34. Hiroshima	0.478	2.678	0.0492	2.180	2.850	0.0049	0.00
35. Yamaguchi	0.445	2.299	0.0469	1.619	1.573	−0.0005	−0.34
36. Tokushima	0.344	2.297	0.0542	0.898	0.832	−0.0014	−0.20
37. Kagawa	0.394	2.524	0.0531	0.951	1.023	0.0013	−0.11
38. Ehime	0.397	2.157	0.0483	1.563	1.515	−0.0006	−0.37
39. Kochi	0.367	2.025	0.0484	0.917	0.825	−0.0019	−0.18
40. Fukuoka	0.490	2.502	0.0466	3.867	4.811	0.0040	−0.28
41. Saga	0.368	2.131	0.0502	0.982	0.878	−0.0020	−0.34
42. Nagasaki	0.369	2.027	0.0487	1.795	1.563	−0.0025	−0.65
43. Kumamoto	0.326	2.294	0.0558	1.898	1.840	−0.0006	−0.47
44. Oita	0.316	2.218	0.0556	1.298	1.237	−0.0009	−0.30
45. Miyazaki	0.317	2.078	0.0537	1.155	1.169	0.0002	−0.28
46. Kagoshima	0.255	2.019	0.0591	2.084	1.798	−0.0027	−0.68
47. Okinawa	0.282	1.880	0.0542	0.801	1.222	0.0077	−0.01

[a]Value for Tochigi is for 1960.
[b]Value for Tochigi is for 1960–90.
[c]Value for Okinawa is for 1965–90.
Notes: The numbers for the prefectures correspond to those used for the map in figure 11.15. The district classifications are as follows: District 1 (Hokkaido-Tohoku), prefectures 1–8. District 2 (Kanto-Koshin), prefectures 9–17. District 3 (Chubu), prefectures 18–24. District 4 (Kinki), prefectures 25–30. District 5 (Chugoku), prefectures 31–35. District 6 (Shikoku), prefectures 36–39. District 7 (Kyushu), prefectures 40–47.

Figure 11.15
Map of Japanese prefectures.