Industrial Specialization and the Asymmetry of Shocks Across Regions

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Abstract

Economic integration, through greater capital market integration, will induce higher regional specialization in production, rendering regional shocks less symmetric. To support this claim empirically, we develop a utility based measure of shock asymmetry and calculate it for each U.S. state. We regress it (using both ordinary least squares and instrumental variables) on a state-by-state 1-digit industrial specialization index and a 2-digit manufacturing specialization index, controlling for relevant economic and demographic variables. The main empirical result is that both specialization indices are positively and significantly correlated with the degree of shock asymmetry in both ordinary least squares and instrumental variables regressions.

This finding, combined with the causal relation running from inter-regional capital market integration to regional specialization in production found in Kalemli-Ozcan, Sorensen, and Yosha (1999), points to the following chain of events: Economic integration fosters the development of institutions that facilitate inter-regional risk sharing. Equipped with better insurance against asymmetric shocks, regions can afford to increase their specialization in production which, in turn, renders shocks more asymmetric. This mechanism counter-balances the effect suggested by Frankel and Rose (1998)--that economic integration among regions (or countries) will induce more trade among them rendering regional shocks more symmetric. Which effect will dominate is an open empirical question.

1 Introduction

It has recently been argued by Frankel and Rose (1998) that economic integration among regions (or countries) will induce more trade among them rendering regional shocks more symmetric. They further mention inter-regional spillovers of demand shocks and knowledge and technology spillovers (Coe and Helpman 1995) as additional mechanisms that may render regional shocks more symmetric following economic integration. Our goal is to draw attention to the following, counter-balancing, effect: Economic integration, through greater capital market integration, will induce higher regional specialization in production, rendering regional shocks *less* symmetric.

To establish empirically, for a group of integrated regions, the chain of causality implied by this argument, four main building blocks are needed: (1) a measure of shock asymmetry for each region (how "different" a region's shocks are relative to the average); (2) a measure of specialization in production for each region (how "different" a region's production patterns are relative to the average); (3) a positive correlation between these measures; and (4) a causal relation running from inter-regional capital market integration to regional specialization in production.

Kalemli-Ozcan, Sørensen, and Yosha (1999) have provided the second and fourth components. They calculated an index of specialization for regions (or countries) belonging to several groups (e.g., U.S. states, OECD countries), estimated the degree of capital market integration (a measure of risk sharing) within each of these groups, and regressed the specialization index on the degree of risk sharing, controlling for relevant economic characteristics and using variables such as shareholder rights as instruments for the amount of inter-regional risk sharing. They found a positive and significant relation between the degree of specialization of individual members of a group of regions and the amount of risk that is shared within the group, concluding that risk sharing—facilitated by a favorable legal environment and a developed financial system—is a direct causal determinant of industrial specialization.

Here, we develop a utility based measure of shock asymmetry that measures, for each region, the increase in per capita discounted expected utility that would be achieved by moving from financial autarky (each region consumes the value of its gross product) to full insurance (each region consumes a fixed fraction of aggregate gross product). We calculate this metric for each U.S. state and regress it on the state-by-state 1-digit industrial specialization index and the 2-digit manufacturing specialization index, controlling for relevant economic and demographic variables.

The main empirical result is that both specialization indices are positively and significantly correlated with the degree of shock asymmetry. This finding, combined with those reported in Kalemli-Ozcan, Sørensen, and Yosha (1999), points to the following chain of events: Economic integration fosters the development of institutions that facilitate inter-regional risk sharing. Equipped with better insurance against asymmetric shocks, regions can afford to increase their specialization in production which, in turn, renders shocks more asymmetric.

Academic research on the asymmetry of shocks to regions and nations dates back at least to Cohen and Wyplosz (1989) and Weber (1991) who studied country level output growth rate correlations for European countries, and to Stockman (1988) who distinguished between country-specific and industry-specific shocks. The latter paper inspired numerous studies, e.g., Kollman (1995), Fatas (1997), and Hess and Shin (1998). Bayoumi and Eichengreen (1993) focused on demand versus supply shocks and used a vector autoregression procedure to study them, whereas De Grauwe and Vanhaverbeke (1993) distinguished between region-specific and country-specific shocks. See Clark and Shin (1998) for a comprehensive survey of this, by now quite large, body of research.

This literature has generated a debate: Some studies seem to suggest that economic integration will result in less symmetric shocks (De Grauwe and Vanhaverbeke 1993) or that the degree of asymmetry will not change (Forni and Reichlin 1997), while others conclude that economic integration will result in more symmetric shocks (Clark and van Wincoop 1999). These studies typically either attempt to identify the full stochastic process for, e.g., regional output (as in Forni and Reichlin) or concentrate directly on the determinants of output correlations (as in Clark and van Wincoop). The approach taken here—computing the welfare gains of moving from autarky to full risk sharing—relies on identifying assumptions, but does not require identification of the full stochastic process for regional output. A major advantage of this approach is that the welfare gains measure provides a simple and intuitive economic interpretation, that complements the insight gained from studying output correlations.

Our goal is to highlight and illustrate empirically the following economic mechanism—greater capital market integration will induce higher regional specialization in production, rendering regional shocks less symmetric. Frankel and Rose (1998) suggest another mechanism—economic integration will induce more trade rendering regional shocks more symmetric. Which mechanism will turn out to have a stronger influence is an empirical question that we relegate to future work.

In the next section we review conceptual issues that are relevant for the effect of capital market integration and the asymmetry of regional shocks. In Section 3 we develop the measure of shock asymmetry, in Section 4 we present the specialization indices that we will use, and in Section 5 we describe our data and present the empirical results. Section 6 concludes the paper.

2 Capital Market Integration, Industrial Specialization, and the Asymmetry of Regional Shocks

The idea that financial globalization will induce higher specialization in production is not new. It is rooted in a critique of traditional trade theory, by Brainard and Cooper (1968), Kemp and Liviatan (1973), and Ruffin (1974). They argued that in the presence of production risk and with no markets for insuring this risk, countries that specialize in the production of a small number of goods may suffer a loss in economic welfare due to the high variance of GDP. Helpman and Razin (1978a, 1978b) pointed out that the inclination to specialize will be restored if there is international trade in both goods and financial assets, namely, when international financial markets as well as goods markets are integrated. Regions and countries that are insured against asymmetric shocks, through diversification of ownership achieved via capital markets, can afford to have a specialized production structure.

The idea that insurance induces specialization has made an impact in the economic growth and development literature.[1] Most closely related to the topic of this paper is Obstfeld (1994a). In his model, countries choose the investment mix in risky (high return) projects and safe (low return) projects. International capital market integration provides insurance, inducing countries to shift investment towards high return projects, promoting faster growth.

Kalemli-Ozcan, Sørensen, and Yosha (1999) have taken up the common empirical implication of the theoretical literature described above, i.e., that cross-regional insurance will induce higher regional specialization in production. For various groups of regions or countries (e.g., U.S. states, Japanese prefectures, European Community countries), they calculated a measure of the degree of insurance among members of the group, and for each member they computed an index of industrial specialization in manufacturing production. They regressed the region-by-region specialization indices on the degree of insurance (risk sharing) within each group of regions controlling for other potential determinants of industrial specialization. To address the possibility of endogeneity bias, they used instrumental variables, which are exogenous to the degree of specialization but are likely to be correlated with the extent of observed inter-regional risk sharing. These include quantitative indicators of the "legal environment" that are likely to have an impact on the amount of cross-regional ownership of assets, for example, the degree of protection of investor rights (La Porta et al. 1997, 1998). They further used the GDP share of the financial sector—an indicator of "financial depth"—as an alternative instrument.

They found a significant positive correlation between regional specialization in manufacturing and inter-regional insurance. Their instrumental variables regressions provide evidence of a causal link running from risk sharing (income insurance), facilitated by a developed and reliable financial system, to specialization in production.

What are the implications of these findings for the asymmetry of shocks in a future European Monetary Union, for example? It is a well established empirical fact that, today,

[1] See, e.g., Greenwood and Jovanovic (1990), Saint-Paul (1992), Acemoglu and Zilibotti (1997), and Feeney (1997).

there is little risk sharing between countries.[2] Capital market integration, an inevitable consequence of economic integration, is bound to change this state of affairs. First, there is some indication that a change is already taking place in Europe. Recently, Liebermann (1999) has replicated the Sørensen and Yosha (1998) study, extending the sample period to include the 1990s. She finds significantly higher cross-country insurance during the period 1992–1997 for a sample of fourteen European countries, with ten percent of idiosyncratic shocks to countries' GDP absorbed via cross-country ownership of assets. European capital markets seem to be gradually integrating. Second, the high degree of cross-regional ownership in the U.S., documented by Asdrubali, Sorensen, and Yosha (1996), suggests that, *ceteris paribus,* economic and monetary unification will indeed induce a greater geographical spread of ownership across Europe.

As a consequence, we should expect industrial specialization to increase. Individual entrepreneurs will be less reluctant to put more eggs in the same basket, and will specialize more in the production of goods and services in which they have the highest comparative advantage. This is due to the fact that a greater fraction of their (or their investors') income will be derived from other sources, such as internationally diversified investment funds, and to the fact that they will more easily be able to sell chunks of their enterprises to foreign investors, since they themselves will be seeking to diversify their portfolios internationally. Producers will also find it less risky to exploit economies of scale, and increase the production of some products reducing the number of products they produce. Finally, it is likely that governments will insist less on subsidizing diversity within national borders.

We expect the main impact to occur in manufacturing, where corporate ownership is most prevalent, and entry and exit to and from sub-industries is relatively fast. At the 1-digit level, production patterns are determined to a large extent by exogenous circumstances, most notably the existence of natural resources such as oil, minerals, or fertile land. But even at the 1-digit level, cross-border insurance should have an impact on spe-

[2]See, e.g., French and Poterba (1991) and Tesar and Werner (1995) who document "home bias" in portfolio holdings, Backus, Kehoe, and Kydland (1992) who compare cross-country GDP correlations and consumption correlations, and Sørensen and Yosha (1998) and Arreaza (1998) who carry out cross-country variance decompositions of shocks to GDP for EC/OECD and Latin American countries respectively. All these studies point to negligible risk sharing through cross-country ownership of assets.

cialization, at least at the margin. To illustrate, with insurance against asymmetric shocks, it would be less risky for the Italian Riviera regions to further specialize in tourism, for the Danes to further specialize in agricultural production, and for countries like France to reduce subsidies to farmers.

If regions specialize more, the opportunities to insure against shocks *within* regions are reduced. Therefore, higher specialization in production, at the 1-digit level as well as in manufacturing, should render GDP shocks less symmetric. To test this empirical implication of our analysis, we turn, yet again, to the U.S. experience. We exploit the great diversity of U.S. states and check empirically whether more specialized states, at the 1-digit level and in manufacturing, are subject to less symmetric shocks to their gross product. To carry out the test, we need, first, to develop a measure of regional shock asymmetry, a methodological issue to which we now turn.

3 A Utility Based Measure of Shock Asymmetry

Our metric builds on the following counter-factual thought experiment. Consider a group of regions inhabited by risk averse agents (consumers) who derive utility from consumption. These regions constitute a "stochastic endowment economy" in the sense that the gross product of regions is regarded by consumers as exogenous and stochastic. Securities markets in this economy are complete, permitting cross-regional insurance. Thus, consumers smooth income and consumption through trade in securities. For each region in the group, we compute the increase in per capita discounted expected utility that would be achieved by moving from autarky (each region consumes its gross product) to full insurance (each region consumes a fixed fraction of aggregate gross product). This is our region-by-region measure of shock asymmetry.

The derivation of the metric is closely related to the calculation of welfare gains from risk sharing (Obstfeld 1994b, van Wincoop 1994). We will discuss the relation to this literature as we proceed, and compare our empirical findings for U.S. states with van Wincoop's findings for OECD countries.

We turn to the calculation of the metric. Let the regions be indexed by i. Consumers within region i are identical ex-ante as well as ex-post: All have the same utility function and are subject to the same realization of uncertainty, namely, they produce the same stochastic gross product. Our metric thus focuses on shock asymmetry between regions, ignoring potential asymmetry within regions.

Let consumers have a logarithmic utility function,[3] and suppose that securities markets are complete. The representative consumer of region i chooses a consumption plan in period $t = 0$, solving the problem

$$\begin{aligned} &\max_{\{c^i_{\omega_t}\}} \int_0^\infty e^{-\delta t}\, \Sigma_{\omega_t} \pi_{\omega_t} \log c^i_{\omega_t}\, dt \\ \text{s.t.}\quad &\int_0^\infty \Sigma_{\omega_t} p_{\omega_t} c^i_{\omega_t}\, dt \;\leq\; \int_0^\infty \Sigma_{\omega_t} p_{\omega_t}\, gdp^i_{\omega_t}\, dt, \end{aligned} \tag{1}$$

where $c^i_{\omega_t}$ and $gdp^i_{\omega_t}$ are consumption and gross output, resp., in region i in state of nature ω_t which occurs with probability π_{ω_t}. p_{ω_t} is the price in period 0 of a period t state ω_t contingent unit of consumption, and δ is the common intertemporal subjective discount rate. Since in period 0 securities markets are complete, each consumer faces a single budget constraint.

The first order condition with respect to $c^i_{\omega_t}$ is

$$e^{-\delta t}\; \frac{\pi_{\omega_t}}{c^i_{\omega_t}} - \lambda^i\, p_{\omega_t} = 0, \tag{2}$$

where λ^i is a Lagrange multiplier. Market clearing implies that for all ω_t

$$\Sigma_i\, n^i c^i_{\omega_t} = \Sigma_i\, n^i\, gdp^i_{\omega_t}, \tag{3}$$

where n^i is the population of region i. We normalize prices as follows:

$$\int_0^\infty \Sigma_{\omega_t} p_{\omega_t} dt = 1. \tag{4}$$

[3] For the characterization of full risk sharing, the assumption of logarithmic utility is stronger than necessary (see, e.g., Huang and Litzenberger 1988), but for the ensuing derivation of the shock asymmetry metric it is necessary. For simplicity, we make it up-front.

Assuming that consumers' endowments are bounded, (4) implies that the integrals in the budget constraint in (1) are well defined.

From (2) and (4) we obtain[4]

$$p_{\omega_t} = \text{constant} \times e^{-\delta t} \frac{\pi_{\omega_t}}{\Sigma_i n^i c^i_{\omega_t}} . \tag{5}$$

Eliminating p_{ω_t} using (2) and (5), using the market clearing condition (3), and letting $gdp_t = \Sigma_i n^i gdp^i_{\omega_t} / \Sigma_i n^i$, we get

$$c^i_{\omega_t} = k^i gdp_t . \tag{6}$$

Thus, under full risk sharing, each region consumes, every period and regardless of the realization of the shocks, a fixed fraction of the aggregate gross product. The constant k^i represents the strength of region i's claim in the inter-regional risk sharing arrangement.

To compute k^i, multiply and divide by π_{ω_t} inside the summation operator on both sides of the budget constraint in (1) (which binds at an optimum), use (2) to substitute for $p_{\omega_t}/\pi_{\omega_t}$, substitute $k^i gdp_t$ for $c^i_{\omega_t}$, and rearrange, to obtain

$$k^i = \delta \int_0^\infty e^{-\delta t} E_0 \frac{gdp^i_t}{gdp_t} dt . \tag{7}$$

The formula has a simple interpretation: The strength of region i in the risk sharing arrangement (the share of aggregate gross product that region i consumes) is proportional to its discounted expected share in aggregate gross product.

The analysis so far, including the characterization of full risk sharing in equation (6), has been independent of the nature of the joint stochastic process governing the gross product of the regions. To compute the shock asymmetry metric, we must make distributional assumptions. Let the natural logarithm of the per capita gross product of the group of regions and the per capita gross product of each region be random walks with linear trend drift. Suppose that, conditional on gdp^i_0 and gdp_0, the joint distribution of the log-differences

[4] Solve for $c^i_{\omega_t}$ in (2), multiply both sides by n^i, sum over i, solve for p_{ω_t}, sum over ω_t, integrate both sides over t, solve for $\Sigma_i(n^i/\lambda^i)$ using (4) and substitute the result into the expression for p_{ω_t}, obtaining (5), where the constant is $1/\int_0^\infty e^{-\delta t}\Sigma_{\omega_t}\pi_{\omega_t} \, [1/\Sigma_i n^i c^i_{\omega_t}] \, dt$.

of these processes is stationary and normal: $\Delta \log gdp_t \sim N(\mu, \sigma^2)$, $\Delta \log gdp_t^i \sim N(\mu^i, \sigma_i^2)$, and $\text{cov}(\Delta \log gsp_t^i, \Delta \log gdp_t) = \text{cov}^i$ for all t. This assumption involves an approximation since the aggregate GDP cannot, in general, be strictly log-normally distributed if each region's GDP is log-normally distributed.

With these distributional assumptions, the constant k^i can be expressed in the following even simpler and economically intuitive manner. Let $y_t = (\log gdp_t^i - \log gdp_0^i) - (\log gdp_t - \log gdp_0)$. Then, $E\, y_t = (\mu^i - \mu)\, t$ and $\text{var}\, y_t = \text{var}(\Delta \log gdp_t - \Delta \log gdp_t^i)\, t = (\sigma^2 + \sigma_i^2 - 2\,\text{cov}^i)\, t$. Recalling that for $z \sim N(\eta, \phi^2)$, $E e^{az} = e^{a\eta + \frac{1}{2}a^2\phi^2}$, we have

$$\begin{aligned} k^i &= \delta \int_0^\infty e^{-\delta t}\, E_0 \frac{e^{\log gdp_t^i}}{e^{\log gdp_t}}\, dt \\ &= e^{\log gdp_0^i - \log gdp_0}\, \delta \int_0^\infty e^{-\delta t}\, E_0\, e^{y_t}\, dt \\ &= e^{\log gdp_0^i - \log gdp_0}\, \delta \int_0^\infty e^{-\delta t} e^{(\mu^i - \mu + \frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 \,-\, \text{cov}^i)\, t}\, dt \\ &= \left(\frac{gdp_0^i}{gdp_0}\right) \left(\frac{\delta}{\delta \,-\, (\mu^i - \mu + \frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 \,-\, \text{cov}^i)}\right) . \end{aligned} \tag{8}$$

The constant k^i, region i's claim to output in the risk sharing arrangement, is higher for regions with a larger initial share in aggregate output, and for regions with a lower covariance between $\Delta \log gdp_t^i$ and $\Delta \log gdp_t$, reflecting a higher insurance value of region i for the other regions. The higher the variance of region i's gross product, other things equal, the more it can contribute to smoothing shocks in other regions; the higher the variance of the aggregate gross product of the regions, keeping the variance of region i's gross product constant, the more other regions would be willing to "pay" region i for joining the risk sharing arrangement.[5]

As a technical note, the k_i coefficients do not sum to unity due to the distributional approximation made (that aggregate GDP is log-normally distributed). The size of the bias depends on the estimated parameters σ^2, σ_i^2, cov^i (the bias is zero if the output processes of all regions are perfectly correlated), and on the value of δ chosen. For our chosen value

[5] Of course, σ^2, the variance of the growth rate of aggregate GDP, cannot change without *any* of the σ_i^2's changing. The distributional approximation regarding aggregate GDP thus allows us to treat σ^2 as a parameter (that can be estimated from aggregate GDP data) rather than as a complicated function of the region-by-region σ_i^2's.

of $\delta = 0.02$, and our sample of U.S. states, the bias is negligible with $\Sigma_i k^i \approx 1.01$.[6]

The term $\mu^i - \mu$, the deviation of region's i trend growth from average trend growth, reflects inter-temporal consumption smoothing considerations. A high trend growth of region i, relative to other regions, is reflected in a high consumption share, due to the high future share in aggregate output relative to the low initial share in aggregate output. In what follows, we will disentangle the gains from intertemporal smoothing and the gains from insurance (this can be done thanks to the logarithmic utility assumption).

We turn to the shock asymmetry index. The discounted expected utility gain to region i of moving from no to full risk sharing is[7]

$$\begin{aligned}
& \int_0^\infty e^{-\delta t}\, E_0 \,\log[k^i gdp_t]\, dt - \int_0^\infty e^{-\delta t}\, E_0 \,\log gdp_t^i\, dt \\
= \;& \int_0^\infty e^{-\delta t} \log \frac{\delta}{\delta - (\mu^i - \mu + \frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 - \operatorname{cov}^i)}\, dt + \int_0^\infty e^{-\delta t} (\mu - \mu^i)\, t\, dt \\
= \;& -\int_0^\infty e^{-\delta t} \log \left(1 - \tfrac{1}{\delta}(\mu^i - \mu + \tfrac{1}{2}\sigma^2 + \tfrac{1}{2}\sigma_i^2 - \operatorname{cov}^i)\right) dt + \tfrac{1}{\delta}(\mu - \mu^i) \qquad (9) \\
\approx \;& \int_0^\infty e^{-\delta t}\, \tfrac{1}{\delta}(\mu^i - \mu + \tfrac{1}{2}\sigma^2 + \tfrac{1}{2}\sigma_i^2 - \operatorname{cov}^i)\, dt - \tfrac{1}{\delta}(\mu^i - \mu) \\
= \;& \int_0^\infty e^{-\delta t}\, \tfrac{1}{\delta}(\tfrac{1}{2}\sigma^2 + \tfrac{1}{2}\sigma_i^2 - \operatorname{cov}^i)\, dt + \tfrac{1}{\delta^2}(\mu^i - \mu) - \tfrac{1}{\delta}(\mu^i - \mu)\,.
\end{aligned}$$

The third term in the last line of (9) is the discounted expected utility gain or loss from initially being a lender or a borrower. A low trend growth of region i relative to other regions entails a utility gain reflecting the compensation for initially being a "net lender" to other regions. A high trend growth relative to the average entails a utility loss reflecting the "payment" to other regions for initially being a "net borrower."

The second term in the last line of (9) originates from the denominator of the expression for k^i (see the last line of (8)). A high trend growth of region i relative to other regions entails a high consumption share for this region, and therefore, a high utility gain from risk sharing. This term is an order of magnitude larger than the third (off-setting) term discussed in the previous paragraph.

In what follows, we will ignore both these terms since we want to focus on the gains

[6] For $\delta = 0.01$, the bias is larger.

[7] The second to last step uses the approximation $\log(1 + x) \approx x$.

from "pure" risk sharing—the first term in the last line of (9). The logarithmic utility specification allows us to study (and estimate) these gains without confounding them with gains from intertemporal substitution.

The utility based shock asymmetry metric

The first term in (9) is the discounted expected utility gain of moving from no risk sharing to perfect risk sharing. Integrating, we obtain $\frac{1}{\delta^2}\left(\frac{1}{2}\,\sigma^2 + \frac{1}{2}\,\sigma_i^2 - \,\mathrm{cov}^i\right)$. We prefer, however, to express the gains from risk sharing using the term inside the integral in the last line of (9),

$$\frac{1}{\delta}\,\left(\frac{1}{2}\,\sigma^2 \,+\, \frac{1}{2}\,\sigma_i^2 \,-\, \mathrm{cov}^i\right)\,. \tag{10}$$

It constitutes a permanent increase to the natural logarithm of region's i gross product, or in other words, a permanent increase in the region's GDP growth rate.[8] We regard it as a reasonable and intuitive region-by-region metric of shock asymmetry: The more a region can gain from sharing *idiosyncratic* risk with other regions in a group, the more *asymmetric* are its shocks relative to the group.[9]

In any empirical implementation, the parameters σ^2, σ_i^2, and cov^i are estimated using regional and aggregate output data. A natural measure of output is Consumer Price Index (CPI) deflated gross product. We stress the logic of deflating by the CPI rather than by a GDP-deflator: Since our metric is utility based, we want measured output to reflect consumption in autarky (with no risk sharing regions consume the value of their GDP). Thus, we want to translate GDP to the amount of consumption that it can buy which is obtained by deflating using the CPI.[10]

[8] To express the increase in the region's GDP growth rate in percent, multiply by 100. When we display our empirical results, this is the convention we adopt.

[9] Our metric can be thought of as measuring potential welfare gains from sharing risk within a group.

[10] To illustrate, consider Alaska, and suppose that it produces *only* oil. Suppose now that physical production of oil remains fixed from period t to period $t+1$ but that the price of oil doubles, whereas the CPI is unchanged. Deflating by the GDP-deflator would yield no change in Alaska's autarkic consumption, whereas deflating by the CPI would yield a doubling of autarkic consumption, which makes more sense since Alaskans became "richer" as a consequence of the oil price increase. In sum, when using a utility based metric of shock asymmetry, output must be measured in consumption-equivalent terms.

Discussion

Our metric may under-estimate gains from insurance for two reasons. First, we use logarithmic utility with a coefficient of relative risk aversion equal to unity whereas, typically, it is assumed, whenever CRRA utility is used, that this coefficient is larger. Second, as illustrated by Obstfeld (1994b), with preferences that allow for separate parameters for risk aversion and intertemporal elasticity of substitution, welfare gains estimates are typically higher than with CRRA utility.

Another issue is the stochastic process governing shocks to the gross product of regions. Obstfeld (1994b) has pointed out that the welfare gains from risk sharing are substantial because shocks (even small shocks) have a large cumulative effect over longer horizons. If gross product were not highly persistent, the welfare gains from risk sharing would be small. Indeed, the random walk assumption is important for the above derivation of the shock asymmetry metric (as is the case in van Wincoop's 1994 estimation of welfare gains from risk sharing). We assume that the growth rate (the log-difference) of the gross product of regions (U.S. states in our case) is a random walk with drift. This results in over-estimation of welfare gains if the actual growth rate of the gross state product of U.S. states is stationary, and in under-estimation of the gains if the actual growth rate is more persistent than a random walk.

We performed Augmented Dickey-Fuller tests for a unit root in the gross product of U.S. states (state by state), and were never able to reject a unit root. These tests, based on relatively short samples, have low power against near unit root alternatives, and indeed the question of whether typical macroeconomic series contain unit roots is still an open question. Nevertheless, as shown in the appendix to Obstfeld (1992), welfare gains are substantial when shocks to gross product show high persistence, whether or not the process contains an exact random walk.

Finally, the approximation that aggregate GDP is log-normally distributed may introduce bias (of unknown direction) through the calculation of the k^i's, but as was mentioned above, for our data and using $\delta = 0.02$, the bias is negligible.

The simplicity and transparency of the metric renders it appealing in our view. In any event, in this paper we focus on the *relative* size (across regions) of the welfare gains from risk sharing, interpreting the region-by-region gains as a metric of shock asymmetry, and using it to test whether higher specialization in production is associated with a greater asymmetry. Therefore, pinning down the absolute level of the welfare gains from risk sharing is not crucial for our purpose.

4 The Specialization in Production Measure

We measure specialization in production as in Kalemli-Ozcan, Sørensen, and Yosha (1999). Each index is computed (for each region) for the relevant sample years and averaged over time. The 1-digit specialization index for region i is

$$\mathrm{SPEC}_1^i = \sum_{s=1}^{S} \left(\frac{\mathrm{GDP}_i^s}{\mathrm{GDP}_i} - \frac{1}{J-1} \sum_{j \neq i} \frac{\mathrm{GDP}_j^s}{\mathrm{GDP}_j} \right)^2 ,$$

where GDP_i^s is the GDP of (1-digit) sector s in region i, GDP_i is the total GDP of this region, S is the number of sectors, and J is the number of regions in the group. The index represents the distance between the vector of sector shares in region i's GDP, $\mathrm{GDP}_i^s \,/\, \mathrm{GDP}_i$, and the vector of average sector shares across the regions other than i. It measures the extent to which region i differs, in terms of industrial composition, from the other regions. Similarly, the manufacturing (2-digit) specialization index for region i is

$$\mathrm{SPEC}_{1M}^i = \sum_{s=1}^{S} \left(\frac{\mathrm{GDP}_i^s}{\mathrm{GDP}_i^M} - \frac{1}{J-1} \sum_{j \neq i} \frac{\mathrm{GDP}_j^s}{\mathrm{GDP}_j^M} \right)^2 ,$$

where GDP_i^s is the GDP of manufacturing sector s in region i, and GDP_i^M is the total manufacturing GDP of this region.

Alternatively, we use the specialization measures

$$\mathrm{SPEC}_2^i = \sum_{s=1}^{S} \left| \frac{\mathrm{GDP}_i^s}{\mathrm{GDP}_i} - \frac{1}{J-1} \sum_{j \neq i} \frac{\mathrm{GDP}_j^s}{\mathrm{GDP}_j} \right| ,$$

and

$$\mathrm{SPEC}^{i}_{2M} = \sum_{s=1}^{S} \left| \frac{\mathrm{GDP}^{s}_{i}}{\mathrm{GDP}^{M}_{i}} - \frac{1}{J-1} \sum_{j \neq i} \frac{\mathrm{GDP}^{s}_{j}}{\mathrm{GDP}^{M}_{j}} \right| ,$$

for 1-digit and manufacturing specialization, respectively. This alternative index puts less weight on single very specialized sectors.

5 Empirical Findings

Data Used

We use data for state level gross state product from the Bureau of Economic Analysis (BEA). (Washington D.C. is very atypical and is omitted.) The sample period for gross state product by sector (used for computing specialization indices) is 1977–1994, while for total gross product (used for computing the shock asymmetry metric) it is 1963–1994.[11] We transform all gross product magnitudes to per capita terms using population by state data, also obtained from the BEA. We denote by GSP per capita gross state product and by GDP per capita U.S. gross domestic product. We use data for ISIC 1-digit industries and utilize BEA data for 21 manufacturing sub-sectors, which we aggregate to 9 ISIC 2-digit levels.

Percent (of total population) high school graduates, percent Bachelor's degree holders, percent advanced degree holders, and college enrollment (all for 1990) are from the Statistical Abstract of the United States, 1997. Share of black population in total population for year 1990, elementary and secondary school enrollment rate averaged over 1980–1994, share of high school graduates in total population averaged over 1980–1994, share of population aged between 25–64 averaged over 1977–1994 and total land mass are also from the 1997 Statistical Abstract.

[11] The BEA official gross state product series starts in 1977 and we have combined this series with older series. The BEA advises against using the older data for sectoral level gross state product.

The shock asymmetry index, the specialization index, and descriptive statistics

The first column of Table 1 displays the variance of the GSP growth rate in percent (the variance of $100 * \Delta \log \text{GSP}$) for each U.S. state. The second column displays, for each U.S. state, the covariance of percent GSP-growth with percent U.S. GDP-growth (the covariance of $100 * \Delta \log \text{GSP}$ and $100 * \Delta \log \text{GDP}$). The third column is our measure of shock asymmetry (the expression in equation (10) multiplied by 100) which equals $\frac{1}{100 * \delta}$ times [one half the variance of $100 * \Delta \log \text{GDP}$ + one half the first column − the second column], where $\delta = 0.02$ and the variance of $100 * \Delta \log \text{GDP}$ is 8.39.

The average across states of the shock asymmetry index weighted by population is 1.29. It is interpreted as the average permanent percentage increase in GSP that would be obtained by moving from autarky to full risk sharing. It is of the same order of magnitude as the welfare gain measure estimated by van Wincoop (1994) for OECD countries. This average welfare gain from inter-state risk sharing is quite large, but we reiterate that estimating the level of welfare gains is difficult since the estimate strongly depends on the degree of persistence of shocks to GSP and on the chosen discount factor. For instance, decreasing the discount factor to 0.01 (the value chosen by van Wincoop 1994) would double the value of the shock asymmetry index. Discount factors are usually estimated very imprecisely in econometric work, and measures of persistence are well known to be extremely sensitive to model specification. Nevertheless, the *relative* size across states of the shock asymmetry index, which is all that matters for our further analysis, is independent of the discount factor and unlikely to be very sensitive to the persistence of GSP shocks.

Alaska's asymmetry index is far above that of any other state, reflecting the high variability of Alaska's CPI-deflated GSP and its negative correlation with U.S. GDP. Alaska is the only state for which (CPI-deflated) GSP is negatively correlated with U.S. GDP. The five states with the highest shock asymmetry indices are Alaska, Louisiana, North Dakota, South Dakota, and Wyoming. It is apparent from Table 1 that these states are relatively small in terms of population, and that Wyoming and, in particular, Alaska have very large levels of GSP (i.e., high levels of per capita output).

A glance at the share of various 1-digit subsectors in GSP, reported in Table 2, reveals that the high asymmetry states often are oil states, with Alaska and Wyoming both deriving more than 20 percent of GSP from oil extraction and Oklahoma just about 20 percent.

The index of specialization at the 1-digit level is displayed in the first column of Table 2. (The numerical value of the index is hard to interpret, although a value of 0 means that the state has sector shares identical to the average sector shares of the remaining U.S. states.) Alaska and Wyoming are very specialized and Nevada is quite specialized at the 1-digit level. Specialization at the 2-digit manufacturing level is reported in column two of Table 2. (These numbers are identical to those used by Kalemli-Ozcan, Sørensen, and Yosha (1999) for the U.S.) Some states with a small manufacturing sector, like Alaska, Montana, and Hawaii, have a highly specialized manufacturing sector, but manufacturing is also very specialized in Delaware, Louisiana, and West Virginia.

Regression analysis: Ordinary least squares

Table 3 reports the central results of our paper, namely, ordinary least squares (OLS) regressions of the asymmetry index on the $\textsc{spec}_1$ and $\textsc{spec}_{1M}$ specialization measures. As small states, oil states, and agricultural states may exhibit very asymmetric GSP shocks, due to few opportunities for within-state diversification and an atypical endowment structure, we control for population and the GSP shares of oil and agriculture as well as the endowment of human capital (proxied by the percentage of college enrollment in the population). The share of, for instance, services may also be correlated with asymmetry, but it is less likely to be exogenous to state level asymmetry and is therefore not included as a regressor.

The regressions are weighted by log-population, and the dependent variable is the logarithm of the asymmetry index. The log-asymmetry index is less dominated by outliers like Alaska and Wyoming relatively to the plain index. Similarly, the specialization indices are log-transformed.

The main result is that specialization is indeed a significant determinant of asymmetry. The manufacturing index is significant (at the 5 percent level) across all specifications in Table 3. The coefficient of the 1-digit specialization index is positive and its point estimate is quite robust to choice of specification. It is significant in all columns but column 2. It is slightly surprising that the 1-digit specialization index is not significant in column 2, but as can be seen from a comparison with column 1 (where the GSP share of oil is left out), this seems to be due to a strong correlation of 1-digit specialization with the share of oil extraction in GSP (the strong relation of the GSP oil share and specialization is evident from Table 1). However, when the human capital endowment is controlled for, both specialization indices are significant. Size—as measured by population—is not significant at the 5 percent level, but has the expected sign, and the coefficient is robust across specifications.

In Table 4 we experiment further with regression specifications. Including GSP (per capita output) as a regressor has no significant impact on the results. The alternative measure of specialization, SPEC_2, yields a significant coefficient for manufacturing specialization and a positive but not significant coefficient for 1-digit specialization. (If we leave out the share of oil in GSP, 1-digit specialization becomes significant also for SPEC_2.) Overall our OLS regressions indicate that specialization in production is a determinant of shock asymmetry.

Regression analysis: Instrumental variables

We cannot rule out the possibility that specialization is affected by shock asymmetry. As an example, imagine that the agricultural output of a state has a particularly high variance (relative to other states) due to special soil or weather conditions. Since its agricultural production is very variable, the state is likely to decrease agricultural production, thus affecting the specialization index (downwards if the state was specialized in agriculture to begin with, and upwards if not).

To get a feel for the magnitude of this potential endogeneity problem, we performed instrumental variables regressions, using instruments that are less likely to be affected by variation in sectoral output. In particular, we use the share of oil and mining in GSP, indicators of human capital, land mass, and population density. We find the results encouraging. The order of magnitude of the coefficients of the specialization indices is in general larger than in the OLS regressions, but the standard errors are, not surprisingly, also larger. The index of manufacturing specialization is robustly significant, while the 1-

digit specialization index typically reaches P-values of about 10 percent. Population is not significant but retains a sensible negative coefficient. All in all, the instrumental variables regressions support the notion that there is a direct effect from industrial specialization to asymmetry of output shocks.

6 Conclusion

We demonstrated that U.S. states with a relatively high degree of industrial specialization exhibit, on average, output shocks that are less correlated with aggregate U.S. output. We argued that this constitutes evidence in support of a mechanism that may (partly or fully) offset the one described by Frankel and Rose (1998). The mechanism we have in mind, is one where economic agents choose to specialize after having spread the risk of specialization in the nation-wide capital market, so that increased variability of output will not have a large effect on the variability of income.

This should not be taken as an argument against economic integration. On the contrary, it is an argument in support of integration which will lead, true, to more asymmetric output shocks, but not necessarily to more asymmetric *income* shocks. These may actually become more symmetric, despite the greater asymmetry of output shocks, as a consequence of extensive cross-country ownership of productive assets.

References

Acemoglu, Daron and Fabrizio Zilibotti (1997), "Was Prometheus Unbound by Chance? Risk, Diversification, and Growth," Journal of Political Economy 105, 709–751.

Arreaza, Adriana (1998), "Consumption Smoothing, Capital Flows, and Fiscal Policy in Latin American Countries," mimeo., Brown University.

Asdrubali, Pierfederico, Bent E. Sørensen, and Oved Yosha (1996), "Channels of Interstate Risk Sharing: United States 1963–90," Quarterly Journal of Economics 111, 1081–1110.

Backus, David, Patrick Kehoe, and Finn Kydland (1992), "International Real Business Cycles," Journal of Political Economy 100, 745–775.

Bayoumi, Tamim and Barry Eichengreen (1993), "Shocking Aspects of European Monetary Integration," in: F. Torres and F. Giavazzi, eds., Adjustment and Growth in the European Monetary Union (Cambridge University Press, New York).

Brainard, William C. and Richard N. Cooper (1968), "Uncertainty and Diversification of International Trade," Food Research Institute Studies in Agricultural Economics, Trade, and Development 8, 257–285.

Clark, Todd E. and Kwanho Shin (1998), "The Sources of Fluctuations Within and Across Countries," forthcoming in: G. Hess and E. van Wincoop, eds., Intranational Macroeconomics (Cambridge University Press, New York).

Clark, Todd E. and Eric van Wincoop (1999), "Borders and Business Cycles," mimeo., Federal Reserve Bank of Kansas City and Federal Reserve Bank of New York.

Coe, David and Elhanan Helpman (1995), "International R&D Spillovers," European Economic Review 39, 859–887.

Cohen, Daniel and Charles Wyplosz (1989), "The European Monetary Union: An Agnostic Evaluation," in: R. Bryant, D. Currie, J. Frenkel, P. Masson, and R. Portes, eds., Macroeconomic Policies in an Interdependent World (Brookings, Washington DC).

De Grauwe, Paul and Wim Vanhaverbeke (1993), "Is Europe an Optimum Currency Area? Evidence from Regional Data," in: P. Masson and M. Taylor, eds., Policy Issues in the Operation of Currency Unions (Cambridge University Press, New York).

Fatas, Antonio (1997), "EMU: Countries or Regions? Lessons from the EMS Experience," European Economic Review 41, 743–751.

Feeney, JoAnne (1997), "International Risk Sharing, Learning by Doing, and Growth," mimeo.

Forni, Mario, and Lucrezia Reichlin (1997), "National Policies and Local Economies: Europe and the United States," CEPR Discussion Paper no. 1632.

Frankel, Jeffrey, and Andrew Rose (1998), "The Endogeneity of the Optimum Currency Area Criterion," Economic Journal 108, 1009–1025.

French, Kenneth and Jim Poterba (1991), "Investor Diversification and International Equity Markets," American Economic Review: Papers and Proceedings 81, 222–226.

Greenwood, Jeremy and Boyan Jovanovic (1990), "Financial Development, Growth, and the Distribution of Income," Journal of Political Economy 98, 1076–1107.

Helpman, Elhanan and Assaf Razin (1978a), "Uncertainty and International Trade in the Presence of Stock Markets," Review of Economic Studies 45, 239–250.

Helpman, Elhanan and Assaf Razin (1978b), A Theory of International Trade under Uncertainty, (Academic Press, New York).

Hess, Gregory D. and Kwanho Shin (1998), "Intranational Business Cycles in the United States," Journal of International Economics 44, 289–313.

Huang, Chi-fu and Robert H. Litzenberger (1988) Foundations for Financial Economics (Elsevier Publishers, New York).

Kalemli-Ozcan, Sebnem, Bent E. Sørensen, and Oved Yosha (1999), "Risk Sharing and Industrial Specialization: Regional and International Evidence," Brown University Working Paper, 99-16.

Kemp, Murray C. and Nissan Liviatan (1973), "Production and Trade Patterns under Uncertainty," The Economic Record 49, 215–227.

Kollman, Robert (1995), "The Correlations of Productivity Growth across Regions and Industries in the United States," Economics Letters 47, 437–443.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert Vishny (1997), "Legal Determinants of External Finance," Journal of Finance 52, 1131–1150.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert Vishny (1998), "Law and Finance," Journal of Political Economy 106, 1113–1155.

Liebermann, Joelle (1999), "Channels of Risk Sharing in the European Union," M.A. thesis, ECARE, Brussels.

Obstfeld, Maurice (1992), "Evaluating Risky Consumption Paths: The Role of Intertemporal Substitutability," NBER Technical Paper no. 120.

Obstfeld, Maurice (1994a), "Risk-Taking, Global Diversification, and Growth," American Economic Review 84, 1310–1329.

Obstfeld, Maurice (1994b), "Evaluating Risky Consumption Paths: The Role of Intertemporal Substitutability," European Economic Review 38, 1471–86.

Ruffin, Roy (1974), "Comparative Advantage Under Uncertainty," Journal of International Economics 4, 261–273.

Saint-Paul, Gilles (1992), "Technological Choice, Financial Markets and Economic Development," European Economic Review 36, 763–781.

Sørensen, Bent E. and Oved Yosha (1998), "International Risk Sharing and European Monetary Unification," Journal of International Economics 45, 211–238.

Stockman, Alan C. (1988), "Sectoral and National Aggregate Disturbances to Industrial Output in Seven European Countries," Journal of Monetary Economics 21, 387–409.

Tesar, Linda, and Ingrid Werner (1995), "Home Bias and High Turnover," Journal of International Money and Finance 14, 467–492.

van Wincoop, Eric (1994), "Welfare Gains from International Risk Sharing," Journal of Monetary Economics 34, 175–200.

Weber, Axel (1991), "EMU and Asymmetries and Adjustment Problems in EMS—Some Empirical Evidence," European Economy 1, 187–207.

Table 1:
Asymmetry Index and Size Indicators

States	(1) Variance (GSP)	(2) Covariance (GSP,GDP)	(3) Asymmetry Index	(4) Population	(5) GSP per Capita
Alabama	11.57	9.05	0.46	3.99	12.60
Alaska	171.19	−9.42	49.60	0.50	37.09
Arizona	16.70	9.41	1.56	3.25	14.11
Arkansas	15.97	10.37	0.91	2.33	11.93
California	8.35	7.57	0.40	26.97	18.36
Colorado	5.06	5.05	0.84	3.18	16.84
Connecticut	10.81	7.99	0.80	3.20	19.54
Delaware	18.57	8.61	2.43	0.64	19.96
Florida	11.17	8.38	0.70	11.52	13.98
Georgia	14.65	10.46	0.53	6.06	15.10
Hawaii	10.18	4.16	2.56	1.05	18.97
Idaho	18.71	8.90	2.33	0.99	12.84
Illinois	11.09	9.19	0.27	11.47	17.16
Indiana	21.54	12.58	1.19	5.52	14.30
Iowa	23.61	11.30	2.35	2.84	14.67
Kansas	10.06	7.47	0.88	2.43	15.35
Kentucky	11.43	8.80	0.55	3.69	13.37
Louisiana	23.58	3.27	6.36	4.27	16.89
Maine	13.25	8.68	1.07	1.18	12.85
Maryland	9.41	7.99	0.46	4.53	16.03
Massachusetts	12.21	8.38	0.96	5.89	17.87
Michigan	35.57	15.27	3.36	9.23	15.22
Minnesota	15.12	10.15	0.80	4.24	16.38
Mississippi	15.24	10.00	0.90	2.57	11.05
Missouri	15.75	10.54	0.76	5.03	14.90
Montana	15.66	6.69	2.67	0.81	13.26
Nebraska	18.44	9.73	1.84	1.58	15.21
Nevada	10.78	7.66	0.96	1.02	18.68
New Hampshire	17.00	9.81	1.44	1.02	15.16
New Jersey	9.77	7.77	0.65	7.59	18.34
New Mexico	9.27	1.46	3.68	1.44	14.45
New York	8.87	7.57	0.53	17.85	18.88
North Carolina	14.41	10.13	0.63	6.31	14.85
North Dakota	72.82	10.35	15.13	0.65	14.32
Ohio	15.02	10.81	0.45	10.83	15.18
Oklahoma	14.85	3.55	4.04	3.15	14.28
Oregon	17.72	10.74	1.16	2.74	14.64
Pennsylvania	9.47	8.39	0.27	11.88	14.69
Rhode Island	10.58	8.10	0.69	0.98	14.50
South Carolina	15.38	10.66	0.61	3.33	12.80
South Dakota	35.85	11.56	5.28	0.70	13.46
Tennessee	16.63	10.94	0.79	4.76	13.88
Texas	12.19	4.17	3.06	16.01	17.31
Utah	6.59	5.39	1.05	1.63	13.41
Vermont	15.10	9.55	1.10	0.54	13.65
Virginia	8.91	7.63	0.51	5.83	16.30
Washington	11.76	8.15	0.96	4.52	16.52
West Virginia	8.60	5.43	1.53	1.88	11.88
Wisconsin	11.39	9.17	0.36	4.80	14.84
Wyoming	34.70	0.82	10.36	0.47	23.48

Notes: Column 1 is $10^4 * \sigma_i^2$, where $\sigma_i^2 = \mathrm{var}(\Delta \log \mathrm{GSP}^i)$ [in other words, it is $\mathrm{var}(100 * \Delta \log \mathrm{GSP}^i)$].
Column 2 is $10^4 * \mathrm{cov}^i$, where $\mathrm{cov}^i = \mathrm{cov}\,(\Delta \log \mathrm{GSP}^i, \Delta \log \mathrm{GDP})$.
Column 3 is $10^2 * \frac{1}{\delta}\,(\frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 - \mathrm{cov}^i)$, where $\delta = 0.02$ and $\sigma^2 = 0.000839$.
Population is in millions. GSP per capita is in thousands of 1983 dollars.
The first three columns are calculated for the sample 1963–1994. The last two columns display average values for 1977–1994.

Table 2:

Specialization Indices and Sectoral GSP Shares

States	(1) 1-digit Specialization Index	(2) 2-digit(Manuf.) Specialization Index	(3) Agriculture GSP Share	(4) Oil-extraction GSP Share	(5) Manufacturing GSP Share
Alabama	0.63	3.69	2.37	0.88	24.03
Alaska	13.10	22.60	1.55	30.56	3.98
Arizona	0.59	7.89	2.40	0.02	13.60
Arkansas	0.81	1.11	5.67	1.59	24.71
California	0.64	3.23	2.33	1.12	16.29
Colorado	0.53	2.42	2.31	2.38	13.01
Connecticut	1.40	7.37	0.66	0.02	23.82
Delaware	3.16	21.88	1.49	0.03	28.05
Florida	1.47	1.13	2.61	0.29	10.13
Georgia	0.36	5.40	1.96	0.01	20.31
Hawaii	4.14	20.61	1.95	0.00	4.38
Idaho	0.61	9.42	8.93	0.04	17.20
Illinois	0.49	1.24	1.88	0.20	21.51
Indiana	2.26	3.08	2.52	0.06	32.18
Iowa	1.14	2.49	9.27	0.00	24.51
Kansas	0.25	1.30	5.24	3.06	18.66
Kentucky	1.12	1.54	3.60	0.36	27.18
Louisiana	3.38	19.57	1.37	19.03	15.38
Maine	0.40	9.07	2.54	0.01	21.44
Maryland	1.42	1.11	1.05	0.00	11.84
Massachusetts	1.20	7.16	0.67	0.00	21.81
Michigan	2.12	10.63	1.30	0.53	31.77
Minnesota	0.36	2.89	4.52	0.03	21.86
Mississippi	0.68	2.15	3.93	3.02	22.99
Missouri	0.44	1.46	2.70	0.01	22.43
Montana	1.91	22.61	6.68	4.38	8.21
Nebraska	1.11	3.78	10.31	0.19	14.29
Nevada	6.07	1.69	0.93	0.25	4.62
New Hampshire	1.12	5.46	0.83	0.00	25.17
New Jersey	0.76	4.61	0.55	0.00	20.41
New Mexico	3.63	4.25	2.36	12.30	7.15
New York	1.74	1.89	0.58	0.06	16.05
North Carolina	2.26	6.87	2.57	0.00	32.09
North Dakota	3.41	3.06	11.51	7.80	5.90
Ohio	1.79	2.91	1.36	0.40	30.70
Oklahoma	1.26	3.13	3.04	11.67	15.62
Oregon	0.31	12.15	3.47	0.01	21.39
Pennsylvania	0.59	1.14	1.17	0.15	23.51
Rhode Island	1.00	2.47	0.94	0.02	23.87
South Carolina	1.49	8.87	1.64	0.00	27.97
South Dakota	2.34	4.73	13.65	0.17	10.02
Tennessee	0.81	1.03	1.88	0.09	25.78
Texas	0.96	3.28	1.78	11.61	15.99
Utah	0.44	2.13	1.57	2.54	14.71
Vermont	0.40	6.29	3.29	0.00	22.17
Virginia	0.85	3.16	1.22	0.02	17.55
Washington	0.36	2.79	3.23	0.01	17.11
West Virginia	1.60	15.37	0.84	1.42	18.05
Wisconsin	1.62	3.03	3.94	0.00	29.96
Wyoming	14.35	19.32	2.57	23.19	3.97

Notes: Specialization indices are defined in the text.
Any 1-digit sectoral share is the average (over the sample period) of the GSP share of that sector.
The sample period for all columns is 1977–1994.

Table 3: Determinants of GSP Shock Asymmetry

	(1)	(2)	(3)	(4)
Dependent variable:	Asym. Index	Asym. Index	Asym. Index	Asym. Index
Regressors:				
1-digit specialization	0.37	0.18	0.23	0.45
(SPEC_1 index)	(2.82)	(1.79)	(2.34)	(3.61)
Manuf. specialization	0.42	0.31	0.29	0.36
(SPEC_{1M} index)	(3.38)	(3.50)	(3.35)	(3.11)
log Population	–0.16	–0.16	–0.15	–0.16
	(1.36)	(1.83)	(1.85)	(1.42)
Agriculture GSP Share	10.92	10.77	9.64	8.69
	(2.33)	(3.23)	(2.94)	(1.98)
Oil-extraction GSP Share	–	10.01	9.09	–
	–	(6.71)	(5.98)	–
Human Capital	–	–	0.04	0.07
	–	–	(1.94)	(2.99)

Notes: Any 1-digit sectoral share is the average (over the period 1977–1994) of the GSP share of that sector.
The Human Capital variable is the percentage of college enrollments in the population in 1990.
The specialization indices are defined in the text.
All variables in all regressions are weighted by log-population.
t-values in parentheses.

Table 4: Determinants of Asymmetry: Sensitivity Analysis

Dependent variable:	(1) Asym. Index	(2) Asym. Index	(3) Asym. Index	(4) Asym. Index
Regressors:				
1-digit specialization	0.18	0.25	–	–
(SPEC$_1$ index)	(1.77)	(2.42)	–	–
Manuf. specialization	0.32	0.30	–	–
(SPEC$_{1M}$ index)	(3.45)	(3.38)	–	–
1-digit specialization	–	–	0.91	1.21
(SPEC$_2$ Index)	–	–	(0.96)	(1.29)
Manuf. specialization	–	–	1.58	1.55
(SPEC$_{2M}$ index)	–	–	(3.25)	(3.25)
log Population	–0.15	–0.14	–0.12	–0.12
	(1.74)	(1.64)	(1.32)	(1.27)
Agriculture GSP Share	10.69	9.05	10.90	9.95
	(3.11)	(2.66)	(3.10)	(2.86)
Oil-extraction GSP Share	10.06	9.30	10.50	9.97
	(6.42)	(5.97)	(6.73)	(6.08)
GDP per capita	–0.03	–0.21	–	–
	(0.11)	(0.70)	–	–
Human Capital	–	0.04	–	0.04
	–	(2.05)	–	(1.70)

Notes: Any 1-digit sectoral share is the average (over the period 1977–94) of the share of the GSP of the relevant sector in total GSP of each region.
The Human Capital variable is the percentage of college enrollments in the population in 1990.
GSP per capita for each state is the average over the period 1977–94.
The specialization indices are defined in the text.
All variables in all regressions are weighted by log of population.
t-values in parentheses.

Table 5: Determinants of Asymmetry: IV Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation:	OLS	IV	IV	IV	IV	IV	IV	IV
Dependent variable:	Asym. Index	Asym. Index	Asym. Index	Asym. Index	Asym. Index	Asym. Index	Asym. Index	Asym. Index
Regressors:								
1-digit specialization	0.34	0.48	0.41	0.48	0.41	0.51	0.47	0.52
(SPEC$_1$ index)	(2.41)	(1.58)	(1.15)	(1.57)	(1.56)	(1.77)	(1.53)	(1.80)
Manuf. specialization	0.37	0.93	1.20	0.93	0.76	0.84	0.96	0.83
(SPEC$_{1M}$ index)	(2.80)	(2.13)	(2.19)	(2.12)	(2.09)	(2.14)	(2.26)	(2.13)
log Population	−0.30	−0.11	−0.03	−0.11	−0.17	−0.13	−0.10	−0.13
	(2.63)	(0.58)	(0.13)	(0.58)	(1.05)	(0.77)	(0.53)	(0.76)

Notes: The instruments for column (2) are: Average share of oil-extraction in GSP (1977–1994), average share of mining in GSP (1977–1994), land mass, average log-population density (1977–1994), percent of high school graduates (1990), percent of Bachelor's degree holders (1990), percent of advanced degree holders (1990), and percent of college enrollment in the population (1990). Column (3) uses the same instruments as column (2) with the exclusion of the mining share. Column (4) uses the same instruments as column (2) with the exclusion of land mass. Column (5) uses the same instruments as column (2) and also uses share of black population in total population (1990), average elementary and secondary school enrollment rate (1980–1994), average share of high school graduates in the population (1980–1994), average share of population aged 25–64 (1977–1994). Column (6) uses the same instruments as column (5) with the exclusion of average share of 25–64 year-olds. Column (7) uses the same instruments as column (6) with the exclusion of the share of black population. Column (8) uses the same instruments as column (6) with the exclusion of percent of high school graduates (1990).
The specialization indices are defined in the text.
All variables in all regressions are weighted by log of population.
t-values in parentheses.