Risk Sharing and Industrial Specialization: Regional and International Evidence*

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Abstract

We provide empirical evidence that risk sharing enhances specialization in production. We calculate an index of regional specialization for European Community (EC) and non-EC OECD countries, U.S. states, Canadian provinces, Japanese prefectures, and regions of Italy, Spain, and the United Kingdom. Then, we estimate the degree of risk sharing within each of these groups of regions. Finally, we perform a regression of the specialization index on the degree of risk sharing, controlling for relevant economic variables. We find a positive relation between the degree of specialization and the amount of risk sharing within a group. Instrumental variables regressions indicate that risk sharing is a causal determinant of specialization.

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1 Introduction

That countries gain from specialization is a widely accepted economic tenet. Gains from specialization arise from technological differences (Ricardo), factor endowments (Heckscher-Ohlin), or increasing returns to scale.[1] These theories have traditionally been formulated in non-stochastic environments but in the presence of production risk and with no markets for insuring it, countries may decide not to specialize since producing few goods may entail a loss in economic welfare due to the high variance of gross domestic product (GDP); see Brainard and Cooper (1968), Kemp and Liviatan (1973), and Ruffin (1974).

Insurance of production risk may take many forms. Common examples are explicit insurance against adverse outcomes (such as natural disasters) and forward markets where commodities are sold at a fixed price for future delivery; but the main mechanism for spreading risk among regions and countries is geographical diversification of income sources achieved via capital markets. If inter-regional and international capital markets are well integrated, regions and countries can insure against idiosyncratic shocks and thereby "afford" to specialize. Comparative advantage is then exploited better—whether it is due to technology, factor endowments, or economies of scale. Indeed, Helpman and Razin (1978a, 1978b) showed that country specialization will be higher when there is international trade in both securities and goods. Their analysis covers the Ricardian case (without insurance, countries may not specialize in goods they can produce at low unit cost) and the Heckscher-Ohlin case (without insurance, countries will not specialize as much in goods that are intensive in the factors in which they are abundant); a simple example provided in the next section illustrates that their proposition also applies to the case where trade is driven by increasing returns to scale.[2]

Insurance induced specialization may have non-trivial consequences for economic growth. Greenwood and Jovanovic (1990), Saint-Paul (1992), Obstfeld (1994a), Acemoglu and Zilibotti (1997), and Feeney (1999) construct models where capital market integration induces more specialization and risk taking and, thereby, enhances economic growth.[3] Yet, no ev-

[1] See, e.g., Krugman (1979) and Helpman (1981, 1984).

[2] Further work on this topic includes Anderson (1981), Grossman and Razin (1984, 1985), Helpman (1988), and Feeney (1994).

[3] In Obstfeld (1994a) the basic premise is that countries choose the investment mix in risky projects with high average returns and safe, low return, projects. International asset trade allows them to hold a diversified portfolio and to shift investment towards high return projects. Acemoglu and Zilibotti (1997) stress that developing countries have fewer opportunities to diversify production and tend to specialize in safe technologies. In Greenwood and Jovanovic (1990), financial intermediaries pool risks and help achieve higher and safer

idence has been brought to bear on the importance of inter-regional (and inter-country) insurance for industrial specialization. Hufbauer and Chilas (1974) and Krugman (1991) observe that U.S. states are more specialized than OECD countries and interpret this as evidence that barriers to trade are greater across countries than across U.S. states, but neither performs a systematic empirical study of the determinants of regional specialization—a task we undertake here.[4]

The theoretical models described above point to the following empirical strategy: for various groups of regions or countries (e.g., U.S. states, Japanese prefectures, European Community countries) calculate the degree of insurance among members of the group and compute an index of industrial specialization for each member. Then, to test the common empirical prediction of the above theories, check whether a high degree of insurance (risk sharing) within a group is associated with high regional specialization within the group, when other potential determinants of specialization are controlled for.

In all the theoretical models cited above, the extent of diversification of income sources is taken as given. It is, however, wise to allow the degree of inter-regional risk sharing to be affected—at least to some extent—by the degree of specialization in production. To determine the direction of causality, one can search for instrumental variables which are exogenous to the degree of specialization but are likely to be correlated with the extent of inter-regional risk sharing. We use two kinds of instrumental variables: the share of the financial sector in GDP—an indicator of "financial depth"—and indicators of the degree of shareholder protection (better protection facilitates asset ownership across regions).[5] Our results are robust to the use of these instruments indicating that causality runs from risk sharing to specialization.

The basic logic of our approach is best illustrated by the striking difference in patterns of

returns on investment. In Saint-Paul (1992), the basic trade-off is between the gains from specialization due to comparative advantage in production and a lower variance of output, while Feeney (1999) develops the idea that in the presence of learning by doing in production, an increase in specialization entails higher growth during a transition period.

[4] It is well documented that there is a positive empirical relation between "financial depth" and economic growth; see King and Levine (1993), Levine and Zervos (1998), and Rajan and Zingales (1998). These studies do not focus on specific mechanisms through which financial intermediation and capital market integration promote growth. One such mechanism is higher specialization in production facilitated by better spreading of production risk.

[5] La Porta et al. (1997) provide evidence that indicates that shareholder protection is a determinant of national stock market capitalization (the premier institution for nationwide risk sharing). La Porta et al. (1998) argue that shareholder protection is determined by the "legal environment" which itself is historically determined.

risk sharing and specialization in "federations" (where data are available by region) versus groups of countries. It is, by now, a well established empirical regularity that there is little risk sharing between countries.[6] In contrast, there is substantial inter-regional risk sharing within federations.[7] If risk sharing is important for specialization one would expect regions within federations to be more specialized than countries. Our empirical work confirms this hypothesis.

The finding survives when we perform a regression analysis with the 158 regions and countries in our sample, controlling for characteristics such as geographical distance and population density. Finally, the positive relation between risk sharing and specialization also survives when we perform the regressions only with regions within federations (eliminating groups of countries from the sample). This confirms that the differences in specialization patterns are not entirely driven by higher barriers to international versus intranational trade and factor mobility.

Constructing measures of industrial specialization in production is standard but measuring the amount of risk sharing among regions or countries is not. For example, we may want to measure the extent to which regions insure their income or, alternatively, the extent to which they insure their consumption. We discuss relevant conceptual and empirical aspects of this issue at the end of the next section. In the empirical analysis, we use both types of measures with similar results.

In the next section, we spell out a simple framework that highlights the effect of risk sharing on specialization. In Section 3, we describe our measures of specialization and risk sharing. The empirical results are presented in Section 4 and Section 5 concludes. The data are described in detail in the Appendix.

[6]See French and Poterba (1991) and Tesar and Werner (1995) who document the "home bias" puzzle, 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 movements in GDP for EC/OECD and Latin American countries, respectively.

[7]See Asdrubali, Sørensen, and Yosha (1996) for U.S. states, Alberola and Asdrubali (1998) for regions of Spain, and Dedola, Usai, and Vannini (1998) for regions of Italy and the United Kingdom. In this paper, we further document considerable risk sharing among provinces within Canada and among prefectures within Japan. Related work on inter-regional risk sharing includes Crucini (1999), Athanasoulis and van Wincoop (1998), del Negro (1998), and Hess and Shin (1998).

2 Conceptual Issues

Insurance and specialization in the presence of increasing returns

The theoretical foundations for the effect of risk sharing on industrial specialization are well established so we do not present a detailed model. It is, nevertheless, helpful to reformulate the theory in simple words to set the stage for the empirical analysis. We present a variant of the theory that relates risk sharing to specialization where production technology exhibits increasing returns to scale. This variant is new, although it is a straightforward adaptation of existing models.

Consider a "risk sharing group" consisting of several regions of equal size.[8] The regions can be thought of as states within a country, countries within the OECD, and so forth. Consumers in each region are risk averse. There is one consumption good that can be produced with inelastically supplied labor and no fixed costs, using any of several ex-ante identical technologies which exhibit increasing returns to scale and are subject to imperfectly correlated productivity shocks. For each region, the choice of how many technologies to use depends on the trade-off between the desire to take advantage of increasing returns in production and the gains from diversifying the productivity shocks across technologies.[9]

For simplicity, assume that there are as many technologies as regions. Suppose that income insurance is available through inter-regional holdings of claims to output and that insurance markets are complete. Then, each region will specialize in one technology in order to fully exploit the economies of scale in production and, furthermore, each region will specialize in a different technology so that the gains from diversification are maximized within the risk sharing group. The resulting allocation of income (and consumption) is efficient, i.e., perfect risk sharing is achieved in the sense that all idiosyncratic risk is eliminated within the group.

Alternatively, if only partial inter-regional insurance is possible, the more insurance the fewer technologies each region will use. At the margin, the diversification (self-insurance) benefit from an additional technology will offset the cost of forgone benefits from increasing returns in production. Obtaining such a result formally requires a specific model and an explicit definition of what is meant by partial insurance. Since our focus is empirical, we

[8]The basic logic does not rely on this or on most other simplifying assumptions that we make in this section.

[9]In Krugman (1991), the basic trade-off is between the desire to take advantage of increasing returns in production and the reduced transport costs if many goods are produced locally.

choose not to engage in such modeling. Our goal in this section is to illustrate the relevance of the Helpman and Razin (1978a, 1978b) analysis for the increasing returns case (with no comparative advantage due to differences in technology or endowments). It should be apparent that the one good multi-technology setting is equivalent to a multi-good setting where regions specialize in the production of particular goods rather than in the use of specific technologies.[10] Since the basic trade-off between diversification and specialization has been modeled extensively in the literature, we believe that there is no need to elaborate further on this intuition.[11]

Income insurance versus consumption smoothing

There are two central mechanisms for smoothing regional output fluctuations. First, residents of a region can hold claims (directly or through intermediaries) to the output in other regions. The dividend, interest, and rental revenue from these claims will insure income as long as output across regions is imperfectly correlated. Second, a region's residents can adjust their wealth portfolios in response to income fluctuations by buying and selling assets and by borrowing and lending on inter-regional credit markets.

The first mechanism—ex-ante inter-regional insurance—is effective for smoothing both permanent and transitory shocks. To illustrate, if in some year Florida's GDP is drastically reduced due to a natural disaster, personal income in Florida will not fall by as much as output if many residents receive interest and dividend income from out-of-state investment funds and savings accounts. This is true regardless of the persistence of the shock to Florida's GDP. The second mechanism—ex-post adjustment of asset portfolios—can smooth only transitory shocks. This is a well understood implication of permanent income theory: facing an income shock, inhabitants of a region will adjust their stock of wealth in order to maintain their level

[10]The multi-good setting (with many more goods than regions and preference for variety) probably provides a more realistic explanation of why regions are rarely fully specialized.

[11]In the above example, there are as many technologies as regions. If insurance markets are complete, full regional specialization in production is equivalent to full localization (or concentration) of production—each technology is used in exactly one region. This suggests that the specialization patterns of regions and the regional concentration of production are strongly related. Yet, as the following example illustrates, these are distinct concepts. Suppose that there are more technologies than regions (the more realistic case). If risk aversion is sufficiently strong then, even if inter-regional insurance is feasible, regions will use more than one technology as long as the added gains from diversification exceed forgone benefits from economies of scale. Production may, thus, be fully concentrated with every technology being used in exactly one region without full specialization in production since each region uses more than one technology. In this paper, we focus solely on the issue of regional specialization in production on which the above cited theoretical studies bear.

of consumption only if the income shock is perceived as transitory.

In practice, macroeconomic shocks contain transitory and persistent components that are hard to identify empirically, so both types of mechanisms may be relevant for specialization decisions. Indeed, regions and countries smooth shocks through *both* ex-ante insurance of income and ex-post adjustment of saving.[12] In the empirical analysis, we use a measure of income insurance via capital markets[13] and, alternatively, a measure of overall consumption insurance. It is not a priori clear which measure should be more closely related to specialization in production. This depends on statistical properties of the data—such as persistence—which are hard to estimate, and on how production decisions are made. These are often made by managers and entrepreneurs who may be better able to raise funds outside their own region or country if capital markets are well developed. However, households' educational and occupational choices are also important in shaping patterns of industrial specialization and it is not obvious if households on average rely more on consumption smoothing or on income diversification. A detailed analysis of these issues is well beyond the scope of this study. In our empirical work, we use both types of insurance measures with qualitatively similar results.

3 Measuring Specialization and Risk Sharing

Measuring risk sharing

We measure how much risk is shared within "risk sharing groups". Each risk sharing group is either a country, consisting of regions, or a group of countries (which are then referred to as "regions"). The representative consumer of each region is a risk averse maximizer of life-time expected utility from consumption. If utility is CRRA and all regions have a common intertemporal discount factor, perfect risk sharing implies $x_{it} = k_i X_t$ for all t and all realizations of uncertainty, where x_{it} and X_t are generic variables representing regional and group-wide income or consumption and k_i is a constant which is independent of time and "states of the world."[14] If perfect risk sharing is achieved via income insurance then x_{it} and

[12]This is documented for U.S. states and OECD countries by Asdrubali, Sørensen, and Yosha (1996) and Sørensen and Yosha (1998), respectively.

[13]In this study, we do not distinguish between insurance obtained via markets and via central fiscal institutions but the inter-regional insurance effect of federal transfers is likely to be dominated by insurance through capital markets; see the findings for the United States in Asdrubali, Sørensen, and Yosha (1996).

[14]k_i reflects the "power" (including initial wealth) of region i in the risk sharing arrangement.

X_t represent both income and consumption (since, in this case, income equals consumption). If perfect risk sharing is achieved only after income insurance *and* consumption smoothing then x_{it} and X_t represent consumption. Notice that $x_{it} = k_i X_t$ implies that, in all regions, x_{it} grows at the same rate as the aggregate X_t.

Earlier empirical work on risk sharing focused on consumption, testing whether the condition $c_{it} = k_i C_t$ holds in the data by asking if consumption of individuals (or countries) responds only to aggregate fluctuations in income (or GDP). Asdrubali, Sørensen, and Yosha (1996) contribute to this literature by measuring the fraction of idiosyncratic GDP shocks (i.e., deviations of a region's GDP from aggregate GDP) absorbed through various channels of inter-regional insurance. Loosely speaking, they measure the amount of inter-regional insurance via capital markets by estimating the sensitivity of regional income to idiosyncratic (region-specific) GDP fluctuations.[15] The International Real Business Cycles literature pioneered by Backus, Kehoe, and Kydland (1992) takes a somewhat different, though closely related, approach: this literature typically proceeds by constructing a full-fledged general equilibrium model and simulating consumption-growth correlations across pairs of countries. These correlations are then compared to corresponding correlations estimated from actual country-level data. When there are no "frictions" (such as adjustment costs of labor and capital), these models imply that the perfect risk sharing relation $c_{it} = k_i C_t$ holds, implying that consumption correlations between countries should be unity—but they are typically found to be much below unity in the data. Recent papers in this tradition (Stockman and Tesar (1995) is a prominent example) explore whether non-traded goods and taste shocks can explain the difference between model implications and empirical data.[16]

We turn to a more detailed description of our measures of risk sharing. Consider the panel regression (across the regions that constitute a risk sharing group), $\Delta \log y_{it} = \nu_t + \beta_1 \; \Delta \log \text{GDP}_{it} + \epsilon_{it}$, where y_{it} and GDP_{it} are region i's year t per capita personal income and GDP, respectively, and ν_t are time fixed effects. The coefficient β_1 measures the co-movement of income with idiosyncratic (region-specific) GDP shocks. The inclusion of time fixed effects is crucial since they control for the growth of group-wide GDP (as well as any

[15] Cochrane (1991) and Mace (1991) test for full consumption risk sharing by examining the sensitivity of (individuals') consumption to idiosyncratic income shocks. Other studies using micro-data include Altug and Miller (1990), Townsend (1994), Attanasio and Davis (1996), and Hayashi, Altonji, and Kotlikoff (1996). Obstfeld (1994b) performs similar tests using country-level data.

[16] See also Canova and Ravn (1996). Sørensen and Yosha (1998), Section 4.2, compare these approaches using OECD National Accounts data. Of related interest is a recent study by Forni and Reichlin (1999).

other aggregate variable)—aggregate output variation cannot be diversified even if there is perfect risk sharing within the group. If income is perfectly insured within the group, each region's personal income grows at the same rate as the risk sharing group's aggregate personal income and is not affected by idiosyncratic fluctuations in GDP, implying $\beta_1 = 0$. If income is not perfectly insured within the group, $\beta_1 > 0$. In fact, β_1 measures the fraction of idiosyncratic GDP shocks that is *not* eliminated through insurance. The coefficient β_K in the regression

$$\Delta \log \text{GDP}_{it} - \Delta \log y_{it} = \nu_t + \beta_K \, \Delta \log \text{GDP}_{it} + \epsilon_{it} \tag{1}$$

measures the fraction of idiosyncratic shocks to GDP that *is* absorbed through inter-regional insurance since $\beta_K = 1 - \beta_1$.[17] In this study, we use β_K as the measure of inter-regional insurance.

Several remarks are in order. First, since β_K is based on personal income, it does not fully separate market-based income insurance from income insurance through social security benefits.[18] Second, β_K incorporates smoothing through patterns of capital stock depreciation and adjustment of corporate saving.[19] Third, we implicitly assume that risk sharing within regions is shared efficiently. Fourth, for groups of countries, we define "personal income" as a country's Net National Income (as in the *OECD National Accounts*) minus corporate saving. This definition gives the closest analogue to personal income that we can construct from the National Accounts data.

In a similar manner we estimate the relation

$$\Delta \log \text{GDP}_{it} - \Delta \log c_{it} = \nu_t + \beta \, \Delta \log \text{GDP}_{it} + \epsilon_{it} \,, \tag{2}$$

[17] If there is no insurance, $\Delta \log \text{GDP}_{it}$ and $\Delta \log y_{it}$ comove perfectly and the left-hand side of (1) does not comove with the regressor, $\Delta \log \text{GDP}_{it}$, and $\beta_K = 0$. If there is perfect insurance, $\Delta \log y_{it}$ is unaffected by region-specific fluctuations in $\log \text{GDP}_{it}$ and (1) boils down to a regression of $\Delta \log \text{GDP}_{it}$ on itself, i.e., $\beta_K = 1$.

[18] Personal income typically includes social security benefits from the federal government. Asdrubali, Sørensen, and Yosha (1996), in their study of risk sharing among U.S. states, construct the variable "state income" that represents the income of a U.S. state prior to *any* federal tax or transfer, but it is not possible to construct a similar variable for all the regions and countries which we study in the present article. The measures of (capital market) risk sharing among communities of Spain, and among regions of Italy and the United Kingdom in Alberola and Asdrubali (1998) and Dedola, Usai, and Vannini (1998), respectively, are also calculated using personal income.

[19] Indeed, firms typically smooth dividend payments. Using country-level National Accounts data, Sørensen and Yosha (1998) show that corporate saving smoothes a significant portion of GDP shocks at the annual frequency but not at the 3-year frequency; see also Mélitz and Zumer (1999).

where β is an estimate of the overall amount of income insurance and consumption smoothing (or, for brevity, a measure of overall consumption insurance).[20] A test for $\beta = 1$ is a test of perfect risk sharing.[21]

Measuring specialization

We calculate a specialization index for manufacturing sectors at the 2-digit International Standard Industrial Classification (ISIC) level. We do not use 1-digit sectors since the level of output in the agriculture and mining sectors is determined mainly by endowments of fertile soil and extractable minerals, and similarly, the size of the government is primarily determined by social and political factors.[22] We were not able to collect consistent data at the 3-digit level.

The specialization index is computed (for each region) for the relevant sample years and averaged over time.[23] It is calculated as follows. Let GDP_i^s denote the GDP of manufacturing subsector s in region i, and GDP_i^M the total manufacturing GDP of this region. We measure the distance between the vector of sector shares in region i, $\text{GDP}_i^s \,/\, \text{GDP}_i^M$, and the vector of average sector shares in the regions other than i in the risk sharing group:

$$\text{SPEC}_i = \sum_{s=1}^{S} \left(\frac{\text{GDP}_i^s}{\text{GDP}_i^M} - \frac{1}{J-1} \sum_{j \neq i} \frac{\text{GDP}_j^s}{\text{GDP}_j^M} \right)^2 , \tag{3}$$

where S is the number of sectors and J is the number of regions in the group. Notice that SPEC_i measures how the composition of manufacturing in region i differs from the composition of manufacturing in the other regions of the risk sharing group. Thus, the different industrial composition of, for instance, Japan relative to other countries in the sample does not affect the specialization indices of Japanese prefectures; but the difference in the industrial composition of Japan and Canada affects the specialization indices of Japan and Canada when they are

[20] If there is no consumption insurance, $\Delta \log \text{GDP}_{it}$ and $\Delta \log c_{it}$ comove perfectly and the left-hand side of (2) does not comove with the regressor, $\Delta \log \text{GDP}_{it}$, so that $\beta = 0$. If there is perfect overall consumption insurance, $\Delta \log c_{it}$ is unaffected by region-specific fluctuations in $\log \text{GDP}_{it}$, and (2) boils down to a regression of $\Delta \log \text{GDP}_{it}$ on itself, implying that $\beta = 1$.

[21] Rearranging, we obtain $\Delta \log c_{it} = \nu_t' + (1-\beta)\, \Delta \log \text{GDP}_{it} + \epsilon_{it}'$, where the hypothesis $1 - \beta = 0$ is a test for perfect risk sharing. Mace (1991) uses this regression without time-fixed effects—controlling for aggregate fluctuations by including aggregate consumption growth as an additional regressor.

[22] We performed exploratory work at the 1-digit level and obtained rather mixed results.

[23] The alternative computation where we first average production over time and then calculate the index yields very similar results.

treated as regions within the OECD.[24]

4 Empirical Analysis

Industrial specialization and insurance by risk sharing group

Table 1 displays the average specialization index of the regions within each risk sharing group. It is clear from the table that regions within countries are much more specialized than countries within groups of countries. The regions of Spain are the most specialized and European Community (EC) countries are the least specialized.

Table 1 also displays the estimated measures, β_K and β, of income insurance and overall consumption insurance by risk sharing group.[25] Italy exhibits the highest amount of insurance according to both measures, while the United States and Canada achieve considerable income insurance relative to the United Kingdom, Japan and Spain. In Japan, there is much overall consumption insurance, as measured by β, in spite of little income insurance. One clear result from this table is that groups of countries, not surprisingly, achieve less income and consumption insurance than groups of regions that constitute countries.

The sample periods were chosen with two considerations in mind. First, we would like the samples used for calculating specialization to overlap with those used for calculating risk sharing. Second, we would like a long sample for calculating risk sharing because we later use the risk sharing measure as a regressor. The longer the sample period, the smaller the standard errors of the risk sharing estimates and the lower the measurement error. For countries with many regions and a reasonably long sample available for calculating both the specialization index and the risk sharing measures, like the United States and the United Kingdom, the longest overlapping sample is used. For the non-EC OECD countries, where there are is a low number of "regions" in the risk sharing group, a longer sample is used for estimating the amount of risk sharing than for calculating the specialization index.[26] Similarly, for Canadian provinces, where specialization can only be calculated for a rather

[24]An alternative to the index in (3) is to use the distance of region i's vector of sector shares to the *weighted* (by manufacturing GDP) average of the sector shares in other regions. We found that such a modification has little effect on the empirical results.

[25]We display the standard errors of the estimated measures of risk sharing (rather than the t-statistics) since it is not evident whether the appropriate null hypothesis is that the coefficient is zero (no risk sharing) or one (perfect risk sharing).

[26]For calculating this index, we used the longest sample of 2-digit manufacturing GDP data available.

short span of years, a longer sample is used for estimating risk sharing than for calculating the specialization index. The results are fortunately not very sensitive to the exact sample periods chosen.

In Figure 1, we display the distribution of the specialization index across regions. It is clearly right-skewed while the log-transformation of the index is almost "bell shaped." To minimize the potential influence of outliers on our results we use the latter index in the regressions.

Determinants of industrial specialization

In our analysis, we regress the specialization index on the measures of risk sharing and other variables that may affect industrial specialization. In this subsection, we describe the variables that are included in our main empirical specification. In the next subsection, we describe additional variables. These additional variables are potentially important for industrial specialization but most of them turned out to be insignificant. Since the degrees of freedom in our regressions are limited, we cannot include all potentially important variables in a single regression.

Wealth, population density, and size

Imbs and Wacziarg (2000) model a trade-off between the (Ricardian) benefits of specialization and (endogenous) trading costs and provide evidence that industrial specialization declines with GDP at earlier stages of development and begins to rise as GDP rises further.[27] In order to allow for such a pattern we include per capita GDP and the square of per capita GDP as regressors. We use the average per capita GDP of the risk sharing group because regional GDP may be endogenous to regional industrial specialization.

Population density is likely to affect industrial specialization, although the predicted sign is not entirely obvious. Krugman (1991) argues that transportation costs determine where manufacturing industries locate. High-transportation-cost firms—which typically are in certain industries—tend to locate in densely populated areas in order to minimize transportation costs. Such entry might drive up congestion costs, making it more attractive for firms in low-transportation-cost industries to settle in less densely populated areas, so it is

[27] The decline in industrial specialization for U.S. states over the past century is documented by Kim (1995). Acemoglu and Zilibotti (1999) provide a model that stresses the decline in specialization in early stages of development.

a priori unclear if specialization increases with population density. Nevertheless, such effects may be important and we include region-by-region population density as a regressor.

The size of regions may also affect their specialization. Larger regions are likely to be less specialized due to greater heterogeneity of the population and of within-region geo-physical characteristics such as climate, landscape, and natural resources. Furthermore, in larger regions, scale economies in production are more likely to be exhausted for some industries. This suggests a negative relation between a region's size and its degree of specialization. In the empirical analysis, we control for size by including region-by-region log-population as a regressor.

Determinants of trade

Regions endowed with natural resources are likely to specialize in the manufacturing of related products. For example, it is reasonable to expect oil-rich regions to specialize in chemical products and agricultural regions to manufacture food products. Harrigan and Zakrajsec (2000) provide evidence for the importance of factor endowments in determining specialization patterns at the country level. We include the region-by-region mining and agricultural production GDP shares as regressors in order to control for such effects.[28]

Trade costs may hamper specialization and are likely to be higher in regions that are far away from their trading partners. This is an old idea that goes back at least to Harris (1954) who argues that the geographic distance to markets is an important determinant of the localization of the manufacturing industry in the United States. This, in turn, may affect specialization patterns: one would expect distant regions to be less specialized since it may be cheaper for them to produce most goods locally.[29]

In order to control for such effects, we construct the variable "distantness" which is closely related to (the inverse of) the indices used by Harris (1954) and, more recently, by Hanson (1998). For each region, we measure the distance from the region's capital city to all other regional capital cities in the risk sharing group.[30] We calculate the weighted average of these

[28]Regional-level physical and human capital intensity are not available. At the regional level, physical and human capital are less likely to be exogenous to specialization patterns, so even if these data were available at the regional level they would not be ideal regressors.

[29]This line of argument has recently been given theoretical and economic underpinnings, and empirical work has followed. Hanson (1998) estimates a reduced form of the Krugman (1991) model of economic geography. He uses an index that closely resembles the index of "market potential" used by Harris (1954). This work has a somewhat different aim than ours. For example, Hanson's work provides estimates of the impact of a shock in one state on wages in neighboring states.

[30]We obtain the latitude and longitude of each capital city and use the Arc View software to calculate the

distances using the GDP shares of the other regions as weights.[31] Weighting the distances to other regions by the GDP share of those regions takes into consideration the larger trade volume with large wealthy regions, other things equal.

Additional determinants of industrial specialization

Access to water transportation

The measure of trade costs described above fails to account for the different cost of shipping goods via land and water. To address this, we construct the dummy variable "coastal" that equals one if a region is located by the sea and, for U.S. states and Canadian provinces, also if it is located by the great lakes or the Mississippi river.[32]

Customs union

Most of the regions in our sample belong to a customs union: regions that constitute countries belong to a customs union since there is free trade within federations and the group of EC countries is a customs union by agreement. The exception is the group of non-EC OECD countries. To control for the possibility that trade among the members of this group is more costly, we include the dummy variable "customs union" that equals one for members of this group and zero otherwise. Notice that it is a very small fraction of our sample that is not in a customs union and the inclusion of this regressor should be seen as an attempt to control for a potential source of bias, rather than an exploration into the importance of customs unions for industrial specialization.

GDP volatility

Ramey and Ramey (1995) and Acemoglu and Zilibotti (1997) stress that in the presence of uninsured risk, countries will be reluctant to take additional risks. Since the volatility of aggregate output cannot be insured, it may affect the degree of regional specialization within the group. It is, therefore, important to control for group-wide risk to ensure that specialization patterns are not driven by differences across risk sharing groups in the amount of uninsurable risk. To this end, we calculate the volatility of group-wide GDP for each risk

great arc distance (in thousands of miles) between each pair of cities.

[31]In symbols: denoting the distance from region i's capital city to region j's capital city by d_{ij}, region i's distantness is defined as $\frac{1}{T}\Sigma_{t=1}^{T}\Sigma_j d_{ij}\text{GDP}_j^t/\text{GDP}^t$ where GDP^t is the year t group-wide GDP, and T is the sample length. (In the calculation of this index, we do *not* use per capita GDP.)

[32]See Harris (1954).

sharing group and include it as an additional regressor.

Human capital

Group-level human capital may be a better indicator of the level of development than per capita GDP—or it may add information beyond that contained in per capita GDP.[33] We, therefore, include a measure of group-level human capital (education) as a further control in the regressions.[34]

The size of the manufacturing sector

If manufacturing is only a tiny fraction of a particular region's GDP, the production risk of the manufacturing sector can easily be diversified within the region. In such a case, the amount of inter-regional risk sharing may be of little importance for specialization in manufacturing. Our main way of addressing this potential effect is to weight the data by real manufacturing GDP by region, but we also perform an estimation where we include the region-by-region manufacturing GDP share as a regressor. Since this variable may be endogenous, we do not include it in our main empirical specifications.

Sample statistics

Table 2 displays descriptive statistics for our sample of regions and risk sharing groups. The number of regions varies considerably across groups. The United States and Japan consist of about 50 regions each while there are as few as 4 or 5 regions in other risk sharing groups. There are substantial differences in many of the variables across risk sharing groups and across regions within groups.

To give an impression of the characteristics of highly specialized regions, we display facts regarding the 15 most specialized regions in Table 3.[35] Not surprisingly, these are all regions within countries. The share of manufacturing in regional GDP varies considerably across the highly specialized regions, from 4 percent in Hawaii and Wyoming to 35 percent in Pais

[33] One reason may be that better education contributes to more effective monitoring of managers as suggested by Acemoglu and Zilibotti (1999).

[34] As mentioned earlier, regional-level data on human capital are not available. Moreover, regional-level human capital is not likely to be exogenous to specialization patterns.

[35] Specialization is not necessarily driven by one sector. The sectors reported in parentheses are mentioned for illustration only and are obtained as follows. Montana, for example, is most specialized in wood relative to other U.S. states in the sense that, in Montana, $\frac{\mathrm{GDP}_i^s}{\mathrm{GDP}_i^M} - \frac{1}{J-1}\sum_{j \neq i} \frac{\mathrm{GDP}_j^s}{\mathrm{GDP}_j^M}$ is largest (over all sectors s) for the wood sector (index i here denotes Montana).

Vasco. There is also considerable variation in the "distantness" of the highly specialized regions. Several highly specialized regions have a small population although some are larger than small OECD countries. We do not show the details, but the least specialized regions tend to be large. The two least specialized regions in our sample are countries—Canada and France—but the following three are regions—the Niigata prefecture in Japan, Quebec in Canada, and Yorkshire and Humberside in the United Kingdom.

Regression analysis

In all our regressions, the dependent variable is the region-by-region specialization index defined in equation (3) and normalized so that the range of values in our sample is from 0 to 1. In Table 4, we display the empirical results from (weighted) OLS estimation. Regressors that vary by risk sharing group, but not by region, are marked with the superscript "*." In order to ascertain that our results are robust to (reasonable) weighting schemes we display results using region-by-region log-manufacturing GDP as weights in the first two columns, results using region-by-region log-population as weights in the middle two columns, and in the last two columns results where the data are weighted by regional log-manufacturing and by the inverse of a group-specific residual standard error.[36]

We see a U-shaped, statistically significant, impact of group-level GDP on the specialization of regions which confirms the results obtained by Imbs and Wacziarg (2000). We also see the expected negative impact on specialization of regional size as measured by log-population. To illustrate how the magnitude of these coefficients should be interpreted, recall that the dependent variable in our sample was normalized to lie between 0 and 1. An increase of 1 in log-population, which corresponds to a near-tripling of the population, will reduce specialization by three to four percent of its range.

Population density has a positive effect on specialization. This suggests that firms in sectors with high transportation costs cluster in densely populated regions while sparsely populated regions do not seem to specialize in sectors with low transportation costs.

The region-by-region GDP share of the mining sector has a positive impact on specialization, suggesting that manufacturers in related industries tend to agglomerate in areas rich in natural resources. Likely, this is due in great part to chemical industry locating in oil-rich

[36]More formally, this assumes that the standard deviation of the error term for region i has the form $\sigma_i = \sigma_{RS(i)} / \log(\text{manufacturing GDP})$, where $RS(i)$ indicates the risk sharing group to which region i belongs. We estimate $\sigma_{RS(i)}$ from the residuals from an initial OLS-estimation.

states. The negative coefficient on the region-by-region GDP share of agriculture suggests that agglomeration of processed food manufacturers does not take place in agricultural states, or that its effect on overall specialization in manufacturing is small (and the negative significant coefficient is due to the share of agriculture proxying for some other determinant of specialization in manufacturing).

We turn to the effect of risk sharing on industrial specialization. We find a significant positive coefficient for both the income insurance measure, β_K, and the overall consumption insurance measure, β, as predicted by the theories that motivate this paper. The magnitude of the coefficient on β_K in the first column of the table is interpreted as follows: moving from no insurance ($\beta_K = 0$) to perfect insurance ($\beta_K = 1$) increases specialization by 19 percent of the range of our sample.[37] The coefficients on income insurance (β_K) and overall consumption insurance (β) in all six columns are very similar.[38]

The coefficient on "distantness" is *positive* and highly significant when the measure of overall consumption insurance is used. Yet, an inspection of the data suggests that "distantness" itself is unlikely to have an impact on specialization—even quite remote regions like Alaska and Montana are highly specialized. Our interpretation builds on the fact that, in our sample, overall consumption insurance, β, is strongly *negatively* correlated with "distantness."[39] This suggests that there is a spatial element in β which renders the estimated coefficient to "distantness" significant. In effect, "distantness" corrects for the spatial patterns in β and, indeed, if "distantness" is omitted from the regressions displayed in Table 4, β is no longer significant. By contrast, the estimated coefficient to income insurance, β_K, is robust to whether "distantness" is included or not, and β_K is not strongly correlated with "distantness" suggesting that there is no strong spatial element in income insurance patterns.[40]

[37]In Table 1, we displayed the risk sharing measures in percent. In the regressions, they take values between 0 and 1.

[38]Since β_K is estimated in preliminary regressions, it is likely to be measured with error. In a univariate regression of specialization on β_K this would bias the estimated coefficient *downward.* It is easily shown that in a multivariate regression, where only β_K is measured with error, the coefficient on β_K is also biased downward. Correcting for such potential bias would, therefore, only strengthen our results. Moreover, it should be noted that instrumental variables estimation is not subject to this downward bias so we do not think that the fact that β_K is a generated variable affects the central message of our empirical results.

[39]We also verified that β shows a strong negative partial correlation with "distantness" controlling for the other regressors.

[40]The spatial patterns in β are not entirely surprising: Sørensen and Yosha (2000) document that consumption smoothing (conditional on income insurance) declines with distance within the United States and

Overall, the regressions in Table 4 provide strong support for a statistically significant relation between risk sharing and industrial specialization when several important determinants of specialization are controlled for. The results are not very sensitive to the weights chosen and we use the log-manufacturing GDP weights in the remaining tables.

Causality: instrumental variables estimation

Exogeneity of inter-regional risk sharing is an issue of importance. In the theoretical models that motivate our study, insurance against regional fluctuations is regarded as exogenous. Causality may run in the opposite direction. One might imagine a federation with geographic or demographic characteristics that render high regional specialization particularly attractive. The amount of risk sharing among regions may then respond to the need for insurance arising from the specialized regional production structure. Fortunately, instruments are available that are less likely to be affected by reverse causality. In particular, we use quantitative indicators of investor protection suggested by La Porta et al. (1997, 1998).[41] They tabulate eight different measures of which we selected the two that provided the best fit to the risk sharing measures in an initial regression.[42] Alternatively, we use the (time-averaged) GDP share of financial services, insurance, and real estate (FIRE). FIRE is a more direct measure of the development of the financial sector and it may be a better determinant of risk sharing. The drawback of using FIRE as an instrument is that it is conceivably endogenous to specialization even if the legal environment indicators are exogenous. The empirical results, displayed in Table 5, show little sensitivity to which instrument we use and the results are very similar to those displayed in Table 4 using OLS. The t-statistics are slightly lower when FIRE is used as an instrument but the coefficients to the risk sharing measures are robustly similar to those obtained using OLS. Overall, the instrumental variables regressions support the conclusions from the OLS regressions and indicate that there is a causal relation running

Rose and Engel (2000) demonstrate that correlations between the consumption growth of pairs of countries decline with the distance between the countries. (A previous version of this article, which did not utilize the "distantness" variable, erroneously concluded that overall consumption insurance is not important for specialization.)

[41]For example, an indicator of investor protection is whether a small fraction of stockholders can call an extraordinary stockholders' meeting.

[42]La Porta et al. (1997) provide evidence that shareholder protection is a determinant of national stock market capitalization (the premier institution for nationwide risk sharing). La Porta et al. (1998) argue that shareholder protection is determined by the "legal environment" which itself is historically determined. See, however, Acemoglu and Zilibotti (1999) and Rajan and Zingales (2000) who argue that institutions that facilitate risk sharing do evolve over time. One may argue, though, that the change is slow so that the institutional structure is taken as given when decisions regarding specializing in production are made.

from insurance to specialization.

Robustness

Are the results driven by the dichotomy "federations versus groups of countries?"

The answer to this question is no. In Table 6, we display OLS and IV regressions for a restricted sample which leaves out groups of countries. The t-statistics are somewhat lower, due to the smaller sample size, and the coefficients are more variable across the columns. Subject to this caveat, the coefficients are remarkably similar to those displayed in the previous tables—the coefficients to the risk sharing measures are actually somewhat larger.

In Figure 2, we display the regression of the region-by-region specialization on the income insurance measure after all the other regressors have been controlled for.[43] The solid regression line is for the entire sample (Table 4) and the dashed line is for the sample that contains no groups of countries (Table 6). Both have a clear positive slope.

These results show that the estimated impact of risk sharing on specialization is not driven by the effect of country-borders—which could proxy for various forms of trading costs.

Controlling for additional variables

Table 7 displays OLS regressions similar to those in Table 4, but with additional control variables. Only one is statistically significant and none affects the estimated coefficients and significance levels of the other regressors.

Group-level GDP volatility (the standard deviation of $\Delta \log \text{GDP}$) affects specialization negatively (with a t-statistic of 1.25) which is consistent with the findings in Ramey and Ramey (1995) and Acemoglu and Zilibotti (1997) who document a negative effect of GDP volatility on GDP growth. An important mechanism behind this result may be that in the presence of *uninsured* risk, countries and regions will be more reluctant to take on additional risks by specializing. This, in turn, can lead to lower growth. (It will take us too far afield to test the latter implication empirically in this article.) In any event, including aggregate volatility does not affect the coefficients of the other variables in the regression.

[43]We regressed the specialization index on the regressors other than β_K and took the residuals which we then regressed on the residuals from a regression of β_K on the other regressors (including a constant). The coefficient on β_K is then exactly the same as the coefficient in the multiple regression. In the graph, we added the mean value of β_K to the observations on the horizontal axis and the mean value of the specialization index to the observations on the vertical axis for easier interpretation.

Higher human capital at the group level (average years of secondary schooling in total population aged over 25) affects specialization positively with a t-statistic of 1.17. While the coefficient is not significant at conventional levels, the result is consistent with the view that human capital provides an indication of economic development beyond that provided by the level of per capita GDP.

Regions with a small manufacturing sector may be able to diversify the risk of having a specialized manufacturing sector *within* the region. When we control for this by including the region-by-region manufacturing GDP share as a regressor, we obtain a positive and statistically significant coefficient. We do not have a convincing interpretation for the sign of this coefficient but, for the present purpose, the important result is that the inclusion of the manufacturing GDP share does not affect the coefficient of the risk sharing measure.

Have risk sharing and specialization changed over time?

A panel regression of the year-by-year specialization indices of each region on a time trend yields a negative coefficient, suggesting that specialization has been slowly decreasing over time (details not shown).[44] It is also true that risk sharing has been increasing over time.[45]

Does this mean that the relation between risk and specialization no longer holds? To address this important question, we split our (relatively short) sample in two. We, indeed, find a slight decline in the average value of the specialization index, from 0.53 to 0.48, and a slight increase in the β_K measure of income insurance, from 35 to 36. We repeated the analysis of Table 4 for each sub-period separately. The results are displayed in Table 8. The coefficients of the various regressors are quite stable across the sub-periods. The coefficient of β_K declines in the late period, but it is positive and statistically significant in both periods. These findings suggest that the relation between risk sharing and specialization remains important despite the slow change in these variables.

An alternative specialization index

[44] This is consistent with Kim (1995) who finds that the specialization of U.S. states has declined markedly since the 1930s.

[45] See Asdrubali, Sørensen, and Yosha (1996) who document an increase in β_K for U.S. states during the period 1963-90.

We replicated the regressions in Table 4 using the index

$$\text{SPEC}'_i = \sum_{s=1}^{S} \left| \frac{\text{GDP}_i^s}{\text{GDP}_i^M} - \frac{1}{J-1} \sum_{j \neq i} \frac{\text{GDP}_j^s}{\text{GDP}_j^M} \right| .^{46}$$

For brevity, we do not tabulate the results, but the main findings were that the coefficient on β_K remains positive. For the full sample it is no longer significant with a t-statistic of 1.02, and for the sample without countries it is positive and border-line significant with a t-statistic of 1.59. The lower t-statistics are not surprising since this index attributes less weight to regions that are very specialized.

5 Summary

We provided evidence that risk sharing and industrial specialization are positively related using a large data set that combines international and intranational (inter-regional) information. We demonstrated that this relation is robust and that our results support a causal relation running from risk sharing to industrial specialization. Further, specialization patterns are not driven by higher barriers to international versus inter-regional trade or factor mobility.

[46] It is a direct generalization of the index suggested by Krugman (1991) for pairs of countries.

Appendix: Data

1. **OECD:** We use data from the **OECD National Accounts Volume 2, Revision 1996**, for population, national Consumer Price Indices (CPI), Gross Domestic Product (GDP), consumption, national income, national disposable income, and corporate saving for the years 1971–93; and for manufacturing GDP by type of activity (at current prices) for the years 1977–93.

   Manufacturing data are available by 2-digit ISIC sectors (see below) for 12 countries (Austria, Belgium, Canada, Denmark, Finland, France, Greece, Netherlands, New Zealand, Norway, United States, West Germany) for the period 1977–93. We use 7 of the 9 ISIC 2-digit manufacturing sectors, leaving out the very heterogeneous sector "Other." No data are available for "wood and wood products."[47] We use Net National Income minus corporate saving as the country level equivalent to personal income. Corporate saving is not available for all countries or years. To avoid using different countries in the calculation of specialization and risk sharing, we used only the countries for which we were able to calculate both indices. This issue is discussed below for the relevant subsets of the OECD sample. Exchange rate data are from the IMF International Financial Statistics database. Land area is from the Statistical Abstract of the United States (1997).

   We form two subsets of OECD data. **EC:** For manufacturing, data are available at the 2-digit level for 6 countries (Belgium, Denmark, France, Greece, Netherlands, West Germany) for the period 1977–93. Greece is omitted since it is an outlier in the group in terms of income per capita. Corporate saving data are not available for Denmark 1971–80, and for the Netherlands 1971–76, making it impossible to construct risk sharing measures that are comparable with the personal income-based measures that we use for regions within countries. Thus, for Denmark and the Netherlands, these years are not used in the measurement of risk sharing, whereas for other countries the entire sample period (1971–93) is used. **non-EC:** We use data for Austria, Canada, Finland,

[47] To get a sense of how serious this omission might be, we exploited the availability of these data for U.S. states, and calculated indices of specialization with and without the wood sector for all U.S. states. The results were not sensitive to the omission of the wood sector so we believe that the non-availability of wood sector data for the OECD countries is a minor issue.

and the United States. We are restricted to this limited sample since corporate saving data are not available for several countries.

2. **United States:** We use state level data from the **Bureau of Economic Analysis (BEA)**. Data for manufacturing Gross State Product (GSP) at current prices at the industry level are available by state for the period 1977–94. (Washington D.C. is very atypical and is omitted.) We utilize BEA data for 21 manufacturing sub-sectors, which we aggregate to 9 ISIC 2-digit levels. Data for total GSP, personal income, personal disposable income, retail sales, and population by state are also from the BEA for the years 1977–94. Data are transformed to fixed prices using the United States national CPI.[48] Land area is from the Statistical Abstract of the United States (1997).

3. **Canada:** Data for Canadian provinces are available from the **CANSIM** database maintained by Statistics Canada. We use manufacturing GDP at factor cost (at current prices) for each industry by province for the period 1987–93. The 3-digit data (21 sectors) are aggregated to the same 2-digit sectors as the United States BEA data. (At the 3-digit level our data sources are not compatible.) The data are available for 5 provinces (Alberta, British Columbia, Manitoba, Ontario, Quebec) for 1987–93. Personal income, consumption, population, and regional CPI are also available from CANSIM. The risk sharing measure is computed for the period 1979–95 for the same 5 provinces. Data are transformed to real terms using each province's own yearly consumer price indices. Exchange rate data are from the IMF International Financial Statistics database. Land area is also from CANSIM.

4. **Japan:** For the manufacturing sub-levels, we use employment data from the **Statistical Yearbook for Japan**, various issues, 1979–93. The data are available at the 3-digit level (21 sectors) and aggregated to 2-digit sectors that are consistent with the data for the United States. Total GDP, personal income, consumption, prefectural CPI and population by prefecture are from the **National Accounts–Japanese Prefectural Data** published by Sinfonica. The risk sharing measure is computed for the period 1975–93. Total manufacturing GDP for Japanese prefectures is from **Annual Report on Prefectural Accounts 1997**, published by the Economic Planning Agency

[48]del Negro (1998) constructs price indices for individual states, but finds that risk sharing regressions are not substantially affected by using state specific price indices rather than the U.S.-wide price index. For other risk sharing groups we found that our results change little if national CPI is used, rather than regional CPIs.

of Japan. It covers all prefectures in various years. We have data for all prefectures for 1975, 80, 85, 90, 91, 92, 93. Current price data are deflated using the prefectural consumer price index. Exchange rate data are from the IMF International Financial Statistics database. Land area is from the Statistical Yearbook.

5. **Italy:** For regional manufacturing 2-digit sectors, we use gross value added at factor cost (at current prices) from Eurostat's regional database **REGIO**. The sample is 1960–95. Unfortunately, there are no data for the wood sector. Total manufacturing GDP, population, and land area are also from this source. The data are available for all Italian regions for the years 1975–94. The risk sharing measure is calculated for the period 1983–92 using all regions. The data are from "Conti economici regionali delle amministrazioni publiche e delle famiglie," Italian National Institute of Statistics—Istituto Nazionale di Statistica (ISTAT).[49] We used total GDP, personal disposable income, consumption, population and total CPI. Personal income is calculated as personal disposable income plus taxes. The indices are also calculated for 1983–92 to be compatible with the risk sharing measure. ECU exchange rate data are from the IMF International Financial Statistics database.

6. **Spain:** For the manufacturing sectors of communities of Spain, we use gross value added at factor cost (at current prices) at the 2-digit level, from Eurostat's regional database **REGIO**. Again, wood sector data are not available. Total manufacturing GDP, population, and land area are also from this source. Data are available for 16 communities of Spain (out of 18) for the period 1980–92. We do not have data for the Baleares and Ceuta y Melilla. The risk sharing measure is calculated for the period 1981–91 using the same 16 communities. Data for regional GDP, personal income, consumption, population, and CPI are available bi-annually from the Spanish National Institute of Statistics— Instituto Nacional de Estadistica (INE)—Regional Accounts of Spain, various issues.

7. **United Kingdom:** For the regional U.K. manufacturing sectors we use gross value added at factor cost (at current prices) from Eurostat's regional database **REGIO**. The data for the wood, non-metallic mineral products, and basic metal industry sectors are

[49] The data were kindly provided by Jacques Mélitz and Frédéric Zumer to whom we are very grateful; see Mélitz and Zumer (1999).

not available. Total manufacturing GDP, population, and land area are also from this source. Data are available for all U.K. regions for the period 1978–93. The risk sharing measure is calculated for the period 1978–93 using data from the Regional Trends 1965–95 CD-ROM from the Office of National Statistics. We further use total GDP, personal income, personal disposable income, consumption, population, and total CPI from the same source.

The 2-digit ISIC manufacturing level codes (Revision 2) are:

ISIC Code	Category
31	Food, beverages and tobacco
32	Textile, wearing apparel and leather industries
33	Wood and wood products, including furniture
34	Paper and paper products, printing and publishing
35	Chemicals and chemical petroleum, coal, rubber and plastic products
36	Non-metallic mineral products, except products of petroleum and coal
37	Basic metal industries
38	Fabricated metal products, machinery and equipment
39	Other manufactured products*

* Not included in our sample

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Table 1: Risk Sharing and Average Specialization: Federations versus Groups of Countries

Risk Sharing Group	Sample for Risk Sharing (Specialization)	$100 \times \beta_K$ Income Insurance within Risk Sharing Group	$100 \times \beta$ Overall Consumption Insurance within Risk Sharing Group	$10 \times$ SPEC Average Specialization for Risk Sharing Group
Italy	1983–92	76.4	98.1	0.46
		(4.4)	(3.0)	
United States	1977–94	63.5	77.6	0.63
		(1.8)	(4.5)	
Canada	1979–95 (87-93)	61.5	73.4	0.43
		(5.3)	(3.3)	
United Kingdom	1978–93	41.6	87.5	0.32
		(5.8)	(8.5)	
Japan	1975–93 (79–93)	21.6	97.3	0.42
		(2.2)	(3.0)	
Spain	1981–91 (80–92)	24.3	70.3	0.73
		(6.0)	(12.4)	
Average for federations		48.2	84.0	0.50
EC countries	1971–93 (77–93)	5.0	21.0	0.13
		(6.5)	(6.5)	
non-EC countries	1971–93 (77-93)	12.7	35.5	0.21
		(6.3)	(3.8)	
Average for groups of countries		8.9	23.8	0.17

Notes: β_K is a measure of income insurance via capital markets and is obtained from the panel regression $\Delta \log \text{GDP}_{it} - \Delta \log y_{it} = \nu_t + \beta_K \, \Delta \log \text{GDP}_{it} + \epsilon_{it}$, where $\Delta \log \text{GDP}$ and $\Delta \log y$ are the growth rates of per capita GDP and personal income. (Since personal income includes social security transfers to individuals, this measure includes some government provided insurance.) β is a measure of overall consumption insurance and is obtained from the panel regression $\Delta \log \text{GDP}_{it} - \Delta \log c_{it} = \nu_t + \beta \, \Delta \log \text{GDP}_{it} + \epsilon_{it}$, where $\Delta \log c$ the growth rate of personal consumption. Standard errors in parentheses.
SPEC is the average across the regions within each risk sharing group of the region-by-region specialization index, $\text{SPEC}_i = \sum_{s=1}^{S} \left(\frac{\text{GDP}_i^s}{\text{GDP}_i^M} - \frac{1}{J-1} \sum_{j \neq i} \frac{\text{GDP}_j^s}{\text{GDP}_j^M} \right)^2$ which is calculated year-by-year and averaged over time.
Risk sharing groups: Italy: all regions. United States: all states excluding DC. Canada: Quebec, Ontario, Manitoba, Alberta, British Columbia. United Kingdom: all regions. Japan: all prefectures. Spain: 16 communities out of 18. EC countries: Belgium, Denmark, France, Germany, Netherlands. Non-EC countries: Austria, Canada, Finland, United States.

Table 2: Descriptive Statistics

	Italy	US	Canada	UK	Japan	Spain	EC	non-EC
No. of Regions	20	50	5	11	47	16	5	4
Data by Risk Sharing Group:								
GDP per capita	18469	21003	21000	16670	22801	11676	18884	20318
Volatility	1.73	2.80	3.46	2.77	2.71	2.50	1.97	2.24
Human Capital	1.66	3.83	3.68	1.81	2.51	1.37	1.55	2.68
Customs Union Dummy	0	0	0	0	0	0	0	1
Data by Region:								
Population								
average	2854	4777	4854	5171	2577	2355	32700	69342
max	8877	26972	10284	17257	11792	6716	78609	238705
min	114	472	1110	1576	613	258	5128	4892
Pop. Density								
average	450	161	13	780	1613	338	623	88
max	1066	1023	29	2240	15143	1544	1199	239
min	89	1	5	170	173	54	262	7
Distantness								
average	0.43	1.87	1.74	0.26	0.56	0.57	0.44	3.69
max	0.68	6.52	2.70	0.43	1.48	1.80	0.79	5.30
min	0.29	1.29	1.00	0.18	0.34	0.38	0.18	2.01
Mining Share								
average	0.03	0.04	0.04	0.05	0.00	0.05	0.02	0.02
max	0.07	0.36	0.14	0.08	0.01	0.16	0.05	0.05
min	0.02	0.00	0.01	0.03	0.00	0.01	0.00	0.00
Agriculture Share								
average	0.06	0.03	0.03	0.03	0.04	0.08	0.03	0.04
max	0.10	0.14	0.04	0.07	0.09	0.15	0.05	0.07
min	0.02	0.01	0.01	0.01	0.00	0.00	0.02	0.02
Manufacturing Share								
average	0.18	0.19	0.13	0.22	0.26	0.22	0.21	0.19
max	0.32	0.32	0.18	0.27	0.46	0.35	0.30	0.21
min	0.07	0.04	0.07	0.16	0.07	0.07	0.15	0.15
Coastal Dummy								
average	0.75	0.56	0.80	0.82	0.85	0.56	1	0.75

Notes: GDP per capita of risk sharing group: 1990 U.S. dollars averaged over the sample period for each risk sharing group. Volatility is the standard deviation of $\Delta \log \text{GDP}$ of the risk sharing group. Human Capital is average years of secondary schooling in total population aged over 25. Customs Union Dummy is 1 if the risk sharing group is not a federation or a customs union.

Population of regions: thousand persons averaged over the sample period for each region. Population density of regions: persons/square miles averaged over the sample period. Distantness of regions: weighted average (by GDP) of the distances in thousands of miles from capital city to capital city. Mining (Agriculture, Manufacturing) GDP Share: average (over the sample) of the share of mining (agriculture, manufacturing) GDP in the GDP of each region. Coastal Dummy is 1 if region has access to the sea or major navigable lakes or rivers. See Table 1 for the relevant sample period.

Table 3: Facts about the 15 Most Specialized Regions

Region	Sector	Region's per Capita GDP	Region's Population	Region's Population Density	Region's Distantness
Montana (US)	33	17322	808	6	2.25
Alaska (US)	31	47572	505	1	3.82
Delaware (US)	35	26355	635	325	1.59
Asturias (SP)	37	10674	113	274	0.57
Hawaii (US)	31	24973	1048	163	6.52
Louisiana (US)	35	22073	4273	98	1.65
Valle D'aosta (IT)	37	21882	114	89	0.57
Wyoming (US)	35	30726	472	5	1.80
Canarias (SP)	31	9994	1440	510	1.80
West Virginia (US)	35	15507	1878	78	1.37
Okinawa (JA)	31	14695	1185	1342	0.87
Kanagawa (JA)	38	22460	7567	8042	0.35
Hokkaido (JA)	31	19068	5647	174	0.87
Extremadura (SP)	31	6912	1098	68	0.51
Pais Vasco (SP)	38	13031	2143	757	0.57

Notes: See notes to Table 2 for variable definitions.
The first column shows the sector in which the region is "most specialized"—see footnote 35 for a precise definition.
31: Food, beverages and tobacco. 33: Wood and wood products including furniture. 35: Chemicals and chemical petroleum, coal, rubber and plastic products. 37: Basic metal industries. 38: Fabricated metal products, machinery and equipment.
IT: Italy, US: United States, SP: Spain, JA: Japan.

Table 4: Regression Results (Weighted OLS)—Full Sample
Dependent variable: Specialization index $\log \text{SPEC}_i$

Weights	A	A	B	B	C	C
GDP*	–1.66	–0.73	–1.80	–0.96	–1.45	–0.48
	(2.70)	(1.46)	(2.97)	(1.93)	(2.16)	(1.20)
(GDP*)^2	0.45	0.16	0.49	0.23	0.38	0.09
	(2.54)	(1.16)	(2.79)	(1.62)	(1.94)	(0.76)
Population Density	0.16	0.16	0.16	0.15	0.17	0.18
	(2.37)	(2.23)	(2.19)	(1.99)	(2.51)	(2.53)
log Population	–0.04	–0.04	–0.04	–0.03	–0.06	–0.06
	(2.56)	(2.38)	(2.38)	(2.06)	(3.97)	(3.82)
Mining GDP Share	0.54	0.50	0.59	0.57	0.64	0.62
	(1.31)	(1.20)	(1.48)	(1.41)	(1.74)	(1.69)
Agriculture GDP Share	–1.49	–1.62	–1.37	–1.47	–1.96	–2.01
	(2.34)	(2.57)	(2.25)	(2.43)	(4.04)	(4.14)
log Distantness	0.03	0.07	0.04	0.07	0.03	0.07
	(1.62)	(3.46)	(1.71)	(3.43)	(1.32)	(3.13)
β^*_K	0.19	–	0.18	–	0.19	–
	(2.41)	–	(2.26)	–	(1.91)	–
β^*	–	0.19	–	0.20	–	0.14
	–	(2.06)	–	(2.24)	–	(1.31)

Notes: "*" indicates a variable which varies by risk sharing group but not by region. GDP* is the per capita GDP of the risk sharing group in 1990 U.S. dollars, averaged over the sample period. For sample periods and the definition of SPEC_i, see Table 1. The dependent variable has been normalized to take values from 0 to 1 in our sample. For the definitions of the other variables see Table 2. 158 observations.
Weights: A: log-manufacturing GDP in 1990 dollars averaged over the sample period; B: log-population averaged over the sample period; C: proportional to log-manufacturing GDP in 1990 dollars averaged over the sample period allowing for a different factor of proportionality for each risk sharing group (estimated by a 2-stage regression). t-statistics in parentheses.

Table 5: Regression Results (Weighted IV)—Full Sample
Dependent variable: Specialization index $\log \text{SPEC}_i$

Instrument	Shareholder Rights	FIRE	Shareholder Rights	FIRE
GDP*	–1.75	–1.69	–0.72	–0.70
	(2.76)	(2.69)	(1.42)	(1.40)
(GDP*)^2	0.47	0.45	0.16	0.15
	(2.60)	(2.52)	(1.10)	(1.06)
Population Density	0.16	0.16	0.15	0.14
	(2.35)	(2.36)	(2.11)	(2.04)
log Population	–0.04	–0.04	–0.03	–0.03
	(2.38)	(2.49)	(1.80)	(1.54)
Mining GDP Share	0.54	0.54	0.49	0.48
	(1.31)	(1.31)	(1.17)	(1.15)
Agriculture GDP Share	–1.46	–1.48	–1.56	–1.53
	(2.28)	(2.32)	(2.46)	(2.39)
log Distantness	0.03	0.03	0.07	0.07
	(1.48)	(1.57)	(3.56)	(3.63)
β_K^*	0.21	0.20	–	–
	(2.44)	(2.34)	–	–
β^*	–	–	0.25	0.28
	–	–	(2.15)	(2.33)

Notes: "*" indicates a variable which varies by risk sharing group but not by region. GDP* is the per capita GDP of the risk sharing group in 1990 U.S. dollars, averaged over the sample period. For sample periods and the definition of SPEC_i, see Table 1. The dependent variable is normalized to take values from 0 to 1 in our sample. For the definitions of the other variables see Table 2. 158 observations.
Weights: log-manufacturing GDP in 1990 dollars averaged over the sample period. t-statistics in parentheses. Instruments: GDP of the FIRE (Finance, Insurance and Real Estate) sector as a fraction of GDP* averaged over time for each risk sharing group; Shareholder Rights (also at the group-level): i) a dummy variable which takes the value 1 if minority shareholders (who own 10 percent of equity or less) can challenge the decisions of management, and ii) the percentage of equity needed to call an extraordinary shareholders' meeting. The first stage regressions on Shareholder Rights yield an R^2 of 0.68 for β_K and 0.55 for β. The first stage regressions on FIRE yield an R^2 of 0.45 for β_K and 0.79 for β.

Table 6: Regression Results—Sample without Groups of Countries
Dependent variable: Specialization index log SPEC_i

Regression	OLS	IV	OLS	IV
GDP^*	–2.72	–3.28	–0.76	–1.08
	(2.16)	(2.23)	(1.21)	(1.61)
$(\text{GDP}^*)^2$	0.74	0.90	0.16	0.21
	(2.05)	(2.13)	(0.92)	(1.21)
Population Density	0.22	0.22	0.23	0.22
	(2.74)	(2.69)	(2.82)	(2.71)
log Population	–0.08	–0.08	–0.07	–0.07
	(3.40)	(3.41)	(3.14)	(2.84)
Mining GDP Share	0.76	0.79	0.67	0.72
	(1.58)	(1.63)	(1.40)	(1.47)
Agriculture GDP Share	–2.06	–2.10	–2.06	–2.34
	(2.76)	(2.81)	(2.65)	(2.90)
log Distantness	0.02	0.01	0.10	0.16
	(0.56)	(0.17)	(2.17)	(2.56)
β^*_K	0.40	0.50	–	–
	(1.91)	(2.00)	–	–
β^*	–	–	0.29	0.80
	–	–	(0.79)	(1.55)

Notes: "*" indicates a variable which varies by risk sharing group but not by region. GDP^* is the per capita GDP of the risk sharing group in 1990 U.S. dollars, averaged over the sample period. For sample periods and the definition of SPEC_i, see Table 1. The dependent variable is normalized to take values from 0 to 1 in our sample. For the definitions of the other variables see Table 2. 149 observations.
Weights: log-manufacturing GDP in 1990 dollars averaged over the sample period. t-statistics in parentheses.
Instruments: GDP of the FIRE (Finance, Insurance and Real Estate) sector as a fraction of GDP^* averaged over time for each risk sharing group; Shareholder Rights (also at the group-level): i) a dummy variable which takes the value 1 if minority shareholders (who own 10 percent of equity or less) can challenge the decisions of management, and ii) the percentage of equity needed to call an extraordinary shareholders' meeting.

Table 7: Robustness (Weighted OLS)—Full Sample
Dependent variable: Specialization index $\log \text{SPEC}_i$

GDP*	–2.00	–1.90	–1.24	–1.75	–1.67
	(2.99)	(2.94)	(1.96)	(2.67)	(2.71)
$(\text{GDP}^*)^2$	0.54	0.53	0.32	0.47	0.45
	(2.84)	(2.80)	(1.78)	(2.51)	(2.55)
Population Density	0.16	0.15	0.20	0.16	0.16
	(2.29)	(2.22)	(2.90)	(2.33)	(2.38)
log Population	–0.00	–0.04	–0.04	–0.04	–0.04
	(2.70)	(2.40)	(2.58)	(2.59)	(2.40)
Mining GDP Share	0.60	0.57	0.83	0.54	0.51
	(1.45)	(1.38)	(1.94)	(1.30)	(1.22)
Agriculture GDP Share	–1.76	–1.74	–0.94	–1.52	–1.52
	(2.63)	(2.60)	(1.41)	(2.37)	(2.40)
log Distantness	0.04	0.06	0.05	0.03	0.03
	(1.90)	(1.96)	(2.46)	(1.10)	(1.58)
Volatility*	–5.64	–	–	–	–
	(1.25)	–	–	–	–
Human Capital*	–	–0.04	–	–	–
	–	(1.17)	–	–	–
Manufacturing GDP Share	–	–	0.51	–	–
	–	–	(2.32)	–	–
Customs Union Dummy*	–	–	–	–0.03	–
	–	–	–	(0.37)	–
Coastal Region Dummy	–	–	–	–	– 0.03
	–	–	–	–	(0.91)
β^*_K	0.20	0.26	0.19	0.21	0.19
	(2.55)	(2.63)	(2.37)	(2.21)	(2.35)

Notes: "*" indicates a variable which varies by risk sharing group but not by region. For sample periods and the definition of SPEC_i, see Table 1. The dependent variable is normalized to take values from 0 to 1 in our sample. For the definitions of the other variables see Table 2. 158 observations.
Weights: log-manufacturing GDP in 1990 dollars averaged over the sample period. t-statistics in parentheses.

Table 8: Sub-Periods (Weighted OLS)—Full Sample

Dependent variable: Specialization index $\log \text{SPEC}_i$

Time Sampling:	Early	Late
GDP^*	–2.41	–1.09
	(3.06)	(2.13)
$(\text{GDP}^*)^2$	0.74	0.26
	(2.90)	(1.98)
Population Density	0.17	0.15
	(2.49)	(2.14)
log Population	–0.04	–0.04
	(3.10)	(2.14)
Mining GDP Share	0.19	0.94
	(0.57)	(1.72)
Agriculture GDP Share	–1.25	–1.71
	(2.32)	(2.26)
log Distantness	0.01	0.04
	(0.56)	(2.06)
β_K^*	0.23	0.15
	(2.71)	(1.93)

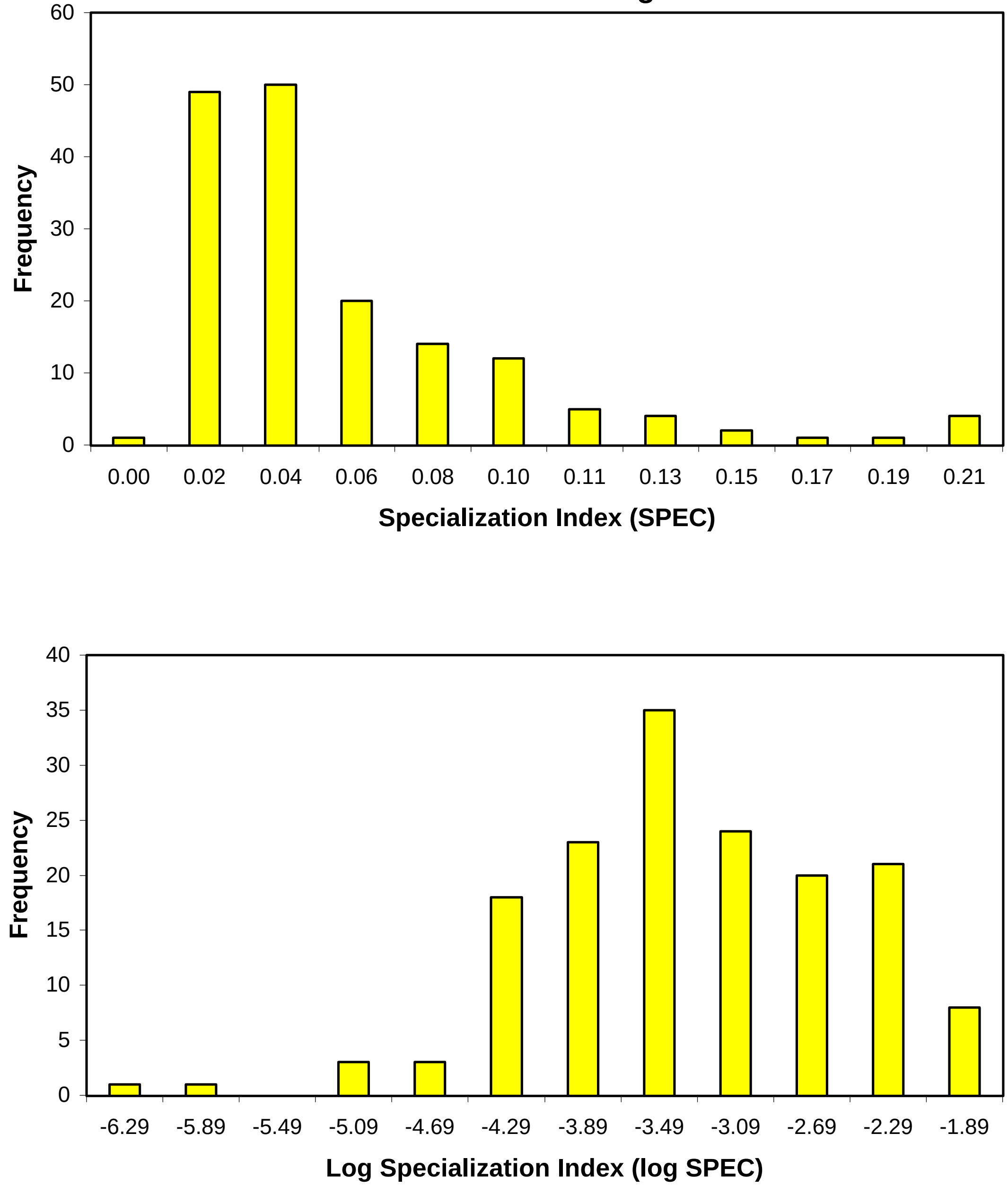
Notes: "*" indicates a variable which varies by risk sharing group but not by region. For sample periods and the definition of SPEC_i, see Table 1. The dependent variable is normalized to take values from 0 to 1 in each sub-sample. For the definitions of the other variables see Table 2. 158 observations.

Weights: log-manufacturing GDP in 1990 dollars averaged over the sample period. t-statistics in parentheses.

Time sampling: β_K measures ($\log \text{SPEC}_i$ measures and other variables) are calculated for the following time periods: "Early:" Italy: 1983-87, US: 1977-85, UK: 1978-85, Japan 1975-85 (1979-85), Spain 1981-85 (1980-85), EC 1971-85 (1977-85), non-EC 1971-85 (1977-85). "Late:" Italy: 1988-92, US: 1986-94, Canada: 1986-95 (1987-93), UK: 1986-93, Japan: 1986-93, Spain: 1986-91 (1986-92), EC: 1986-93, non-EC: 1986-93.

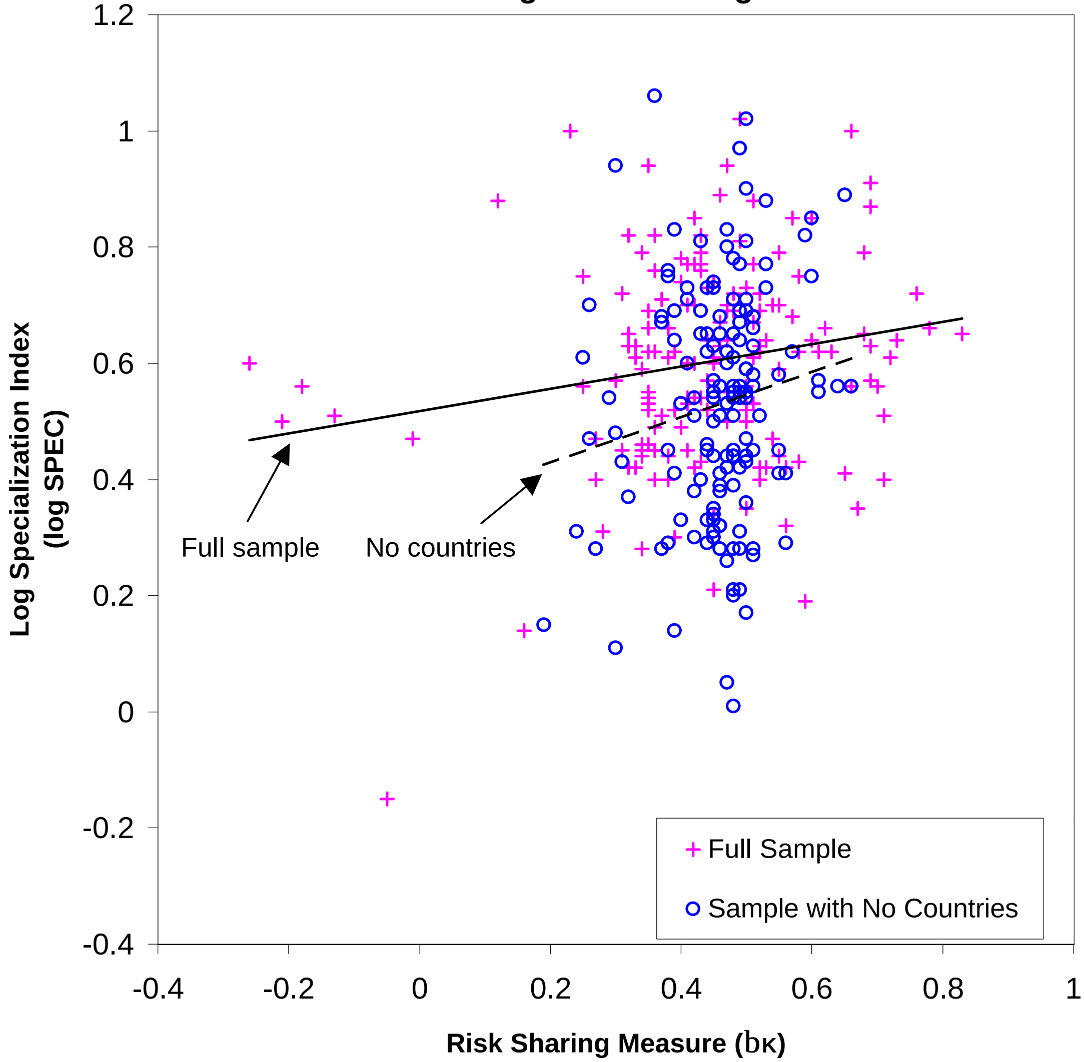
The early sample does not include Canada due to data availability.

Figure 1: Frequency Distribution of Specialization in Manufacturing



Note: The figure displays the frequency distribution of regional-level specialization in manufacturing for the 158 observations in our sample. See equation (3) for the exact formula. We use manufacturing sectors at the 2-digit International Standard Industrial Classification (ISIC) level. The specialization index is computed, for each region, for the relevant sample years and averaged over time. The index measures the extent to which a region differs, in terms of the composition of manufacturing, from the other regions in the risk sharing group to which it belongs, not from all the regions in the sample.

Figure 2: Regression of Region-by-Region Specialization on Group-Level Risk Sharing After Controlling for Other Regressors



Note: We first regressed the specialization index on the regressors other than β_K, and took the residuals which we then regressed on the residuals from a regression of β_K on the other regressors (including a constant in both regressions). The coefficient on β_K is then exactly the same as the coefficient in the multiple regression. In the graph, we added the mean value of β_K to the observations on the horizontal axis and the mean value of the specialization index to the observations on the vertical axis for easier interpretation. The solid regression line is for the entire sample (Table 4) and the dashed line is for the sample that contains no groups of countries (Table 6).