Neighborhood Bias, Commuter Flows, and Incomplete Capital Market Risk Sharing among US Federal States

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Abstract

This paper examines risk sharing among US federal states. We find that insurance against own idiosyncratic shocks has increased substantially over time. At the same time, however, factor income flows have become substantially biased towards neighboring states in recent years. Therefore, our study suggests that the overall amount of income insurance that is achieved in recent years is more limited than reported in previous studies, which did not take the neighborhood bias into account. Candidate explanations for the neighborhood bias are local biases in capital income flows and commuter flows across state borders. We show that the increasing dependence on neighbor's output fluctuation can be explained by better commuting possibilities across state borders. This finding implies that risk sharing is a complex phenomenon which should not be attributed to capital markets solely.

JEL-classification: E22, G10, R11, C21
Keywords: risk sharing, capital markets, home bias, commuter flows, spatial error model

1 Introduction

At the heart of interregional risk sharing stand the fundamental differences between state-level Gross Domestic Product (GSP) and state-level income. While GSP corresponds to a state's production and hence attributes to a state the amount of economic production generated within it, income explicitly includes net factor payments from other states. Thus, income equals output plus net factor income flows, whereas factor income flows comprise claims to output produced in other states.

The general idea of capital market (or income) risk sharing is that, by holding claims to output produced in other regions, individuals can smooth away shocks to their own

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income caused by variations in their home region's production. This means that individuals can share their own idiosyncratic output risk by diversifying their asset portfolios. Aggregate output risk, by contrast, cannot be insured at the capital market. In the extreme case of full insurance against idiosyncratic output risk, the value of output is fully pooled through cross-ownership of productive assets and all agents hold an identical 'world' mutual fund of securities.[1]

At the macroeconomic level, we may think of the 'world' mutual fund of assets as a perfectly diversified portfolio of so-called Shiller-securities, following the ideas brought forward by Shiller (1993). Shiller-securities have returns that are directly linked to the growth of output, which means that these assets comprise perpetual claims to the entire output stream of a country or region. Countries or regions can then sell the right to their own output and invest the proceed in claims to output of other countries (Sørensen, Wu, Yosha, and Zu, 2005). If each country is going short in the claims to its own output, output risk is shared via the identical 'world' mutual fund of Shiller-securities (Kalemli-Ozcan, Sørensen, and Yosha, 2004). A state's income is then just the weighted average of all per capita output, independent of uncertainty.[2]

For the international economy, however, it is observed that investors tend to ignore foreign investment opportunities. This means that actual portfolios deviate substantially from the benchmark of the perfectly diversified fund of Shiller-securities. There is a strong preference for domestic equities, which is at odds with the diversification of risk. This observation is referred to as the 'home bias' puzzle in equity holdings, see for example French and Poterba (1991), Tesar and Werner (1995), and Lewis (1999). At the same time, it is well-documented that international risk sharing among OECD countries is rather scarce, see for example Sørensen and Yosha (1998), Asdrubali and Kim (2004), or Becker and Hoffmann (2006). Recent research by Sørensen, Wu, Yosha, and Zu (2005) and Artis and Hoffmann (2005) has shown that risk sharing from international cross-ownership of assets is higher in countries that hold a higher amount of foreign equity, i.e., countries that are subject to less home bias enjoy more risk sharing.

From micro-based studies there is considerable evidence that some form of home bias is present even *within* countries (see Coval and Moskowitz, 1999 and Huberman, 2000, 2001). In particular, regional asset portfolios in the US have been shown to be characterized by a disproportionate high fraction of assets issued in geographically close areas, but not necessarily the 'home' region. This local bias is related to economic distance and

[1] The financial literature typically motivates this 'world' market portfolio from the benchmark of the international Capital Asset Pricing Model (CAPM). In terms of the CAPM, the identical market portfolio implies that all agents have similar mean-variance utility trade-offs (see Sørensen, Wu, Yosha, and Zu (2005) and Huberman (2000) for a brief survey of the literature on CAPMs).

[2] Although Shiller-securities are not actually traded in reality, many assets in real-life can be thought of having very similar properties, see Artis and Hoffmann (2005) and Sørensen, Wu, Yosha, and Zu (2005) for brief discussions. A non-exclusive list of financial instruments through which diversification can occur in reality includes corporate equity, direct investment, real estate, bank deposits, trade on forward markets, and investment in bonds and shares. For instance, if mutual funds or pension funds in one region invest in other regions, the income of the citizens in that state includes factor income from other regions and will partly co-move with the output in other regions. Another example is that if financial intermediaries in one state lend to firms in other states, the flow of interest payments smooths the income of citizens in the lending state (these examples have been taken from Kalemli-Ozcan, Sørensen, and Yosha, 2004, p. 5).

geographical proximity. Therefore, we dub this kind of bias as a 'neighborhood bias'. Using the terminology of the concept of Shiller-portfolios, a neighborhood bias in capital income flows means that agents hold a disproportionate high fraction of claims to output produced in neighboring regions.

There are several theoretical explanations for a neighborhood bias in capital income flows. In particular, one would expect that many explanations which have been put forth to explain the home bias phenomenon should similarly apply for a local bias which is related to economic distance.[3] Most prominent frictions which also arise even in the absence of country borders are information asymmetries and familiarity biases which are related to behavioral explanations.

The core of information-based explanations is the argument that investors may have superior access to information about firms located near to them or about local economic conditions.[4] Indeed, the seminal paper of Coval and Moskowitz (1999) finds that US investment managers exhibit a strong preference for locally headquartered firms and that US investors hold more than a proportional amount of assets issued in the geographical region close to them. Specifically, distance is found to play an important role in determining the composition of asset portfolios. Therefore, Coval and Moskowitz (1999) suggest that an information advantage in local stocks is an explanation for the preference for geographically proximate investments within the US.[5]

Huberman (2000, 2001) argues that a cognitive bias for the familiar may play an important role in explaining local biases in the US. The preference for investing close to one's home may be driven by a psychological desire to invest in local companies. Possibly, agents simply feel comfortable investing in a business that is visible to them and therefore overweigh investments close to their place of living. Moreover, investors may have to learn about risk sharing and therefore try to gain experience by buying assets which are closely related to their home region.

Irrespective of the precise theoretical explanation, a neighborhood bias in capital income flows has consequences for the effectiveness of regional income insurance. If there is a neighborhood bias, a state's income will (partly) co-move with idiosyncratic output shocks that hit neighboring states. Taking into account a potential neighborhood bias in capital income flows may therefore lead to a more qualified picture of capital market risk sharing within the US. Even if own idiosyncratic output shocks are comparatively well insured—as it has been suggested by previous studies—the welfare effects of income

[3]However, some home bias explanations are indeed unique to the international economy, such as exchange rate fluctuations, variation in regulation, culture, taxation, and sovereign risk.

[4]For the home bias in international capital markets, such asymmetric information-based explanations have been offered, among others, by Coval (1996), Brennan and Cao (1997), Zhou (1998), Hatchondo (2004), and Ahearne, Griever, and Wanrock (2004). The empirical studies of Portes and Rey (2000, 2005) also suggest that information asymmetries across countries are a major source of home bias effects, and that capital flows are affected by both, geographic distance and informational proximity. Similarly, Tesar and Werner (1995, p. 485) summarize that 'geographic proximity seems to be an important ingredient in the international portfolio allocation decision'. In line with this, Kilka and Weber (2001) show that investors tend to perceive the domestic market as less volatile than foreign markets.

[5]However, Huberman (2000) criticizes arguments based on asymmetric information. Specifically, Huberman points out that uninformed investors can still buy an *index* of the equities about which they know very little. Moreover, superior information is usually short-lived. Lastly, being better informed will induce many 'buy' opportunities, but also many 'sell' opportunities.

fluctuations caused by output shocks in geographically close states may be non-negligible if there is a pronounced neighborhood bias. The aim of this paper is to examine the neighborhood bias within the US from a macroeconomic perspective and its consequence for the overall amount of income risk sharing that is achieved among US federal states.

Unfortunately, a direct-attack approach to estimating the neighborhood bias is not possible. Data on the composition of regional asset holdings across US federal states is simply not available—as it is not for many other countries. Going back to the micro-level and analyzing individual asset holdings directly seems not a proper solution since our interest is not only in regional portfolio diversification, but also in its consequences for aggregate (regional) risk sharing.

Instead, we propose an alternative solution which allows us to address the neighborhood bias and risk sharing at the regional level: we extend the standard risk sharing model to a spatial model. One particular advantage of the spatial modelling strategy is that we can estimate our model using the same macroeconomic data that is usually used to study risk sharing among US federal states.[6]

This spatial model allows us to examine whether the fluctuation of factor income flows between states and their neighbors is disproportionately high—in comparison to a balanced portfolio which assigns fair weights to each others output. Or to put it differently, we take the perspective of an average federal state and provide evidence whether its neighbor's output fluctuation also constitutes a risk factor which is transmitted to the home state's idiosyncratic income via factor income flows.[7]

As mentioned earlier, factor income income flows are reflected in the National Accounts data as the difference between GSP and income. More precisely, the difference between GSP and income not only reflects capital income flows (such as dividends from cross-holdings of productive assets) but also retained earnings in the form of capital depreciation and corporate saving, and commuters income. This means that the wedge between output and income is not driven by capital markets solely.[8]

Athanasoulis and van Wincoop (2001) argue that retained earnings do not alter the economic interpretation of capital market risk sharing substantially because retained earnings reflect an investment that contributes to dividends in the future.

However, claims to labor income in the form of commuters income may alter the

[6]See for example Asdrubali, Sørensen, and Yosha (1996), Sørensen and Yosha (1998), Mélitz and Zumer (1999), Athanasoulis and van Wincoop (2001), Asdrubali and Kim (2004), Asdrubali and Kim (2005), Kalemli-Ozcan, Sørensen, and Yosha (2004), Becker and Hoffmann (2006). The overall pattern of risk sharing among US federal states documented by these studies is generally found to be much richer than that for international risk sharing. Most studies agree that in the US, a considerable amount of income smoothing takes place via capital markets, indicating that much of a state's product is owned by residents of other states. This cross-ownership of productive assets provides important hedging against idiosyncratic output shocks. On average, almost 40%-50% of an idiosyncratic shock to output is smoothed via cross-state capital income flows.

[7]On the one hand, a neighborhood bias may constitute additional risk but at the same time it may also induce additional insurance, because a limited amount of diversification takes places. We will take this ambiguous role of the neighborhood bias into account.

[8]According to the author's view, this aspect has been largely ignored in the literature. While commuter flows may be of minor importance for the international economy, they should not be ignored in the context of an interregional study. As it will turn out, risk sharing among US federal states is indeed driven substantially by commuter flows.

economic interpretation of a potential neighborhood bias substantially. Especially at the regional level, commuting across state borders is a way of hedging idiosyncratic output risk because it allows individuals to insure their human capital risk. For instance, if workers commute from their place of living to their place of work in a neighboring federal state, they contribute to the output of the neighboring state while their income crosses state borders. This means that a potential neighborhood bias in factor income flows does not necessarily reflect a neighborhood bias in portfolio holdings. Our analysis will take this aspect into account.

The aims of this paper are therefore twofold. Firstly, we want to quantify how strongly a potential neighborhood bias in factor income flows influences the overall amount of income insurance that is achieved among US federal states. Secondly, we want to examine which economic factors drive the neighborhood bias in factor income flows.

The paper is structured as follows. Our spatial model of capital market risk sharing is presented in the second section. In the third section, we estimate the neighborhood bias in factor income flows among US federal states and its consequences for the overall degree of income risk sharing. Thereafter, we extend the analysis to include commuter flows in order to test whether the neighborhood bias can be explained by commuting across state-borders. In Section 5, we discuss some extensions for future work. The last section summarizes our main findings.

2 A spatial model of capital market risk sharing

2.1 Summary of the empirical strategy

Before we formalize our empirical model to measure risk sharing and a potential neighborhood bias in factor income flows, we summarize the general idea of our approach.

If idiosyncratic output risk is fully shared among a group of regions, then a region's idiosyncratic income should only be affected by aggregate fluctuations in output. Other things such as an idiosyncratic shock that hits the region's output or idiosyncratic shocks to other regions should not be transmitted to income. To test for these hypotheses, our empirical model allows for both, output shocks that hit the home state and output shocks to neighboring states. The latter shocks are measured by the weighted average output fluctuation in neighboring states—in idiosyncratic and per capita terms.

The test for no bias in factor income flows towards these neighboring states is then straightforward. If factor income flows are not subject to a neighborhood bias, i.e., if agents prefer a balanced and diversified portfolio, then any change in idiosyncratic output of neighboring states should have no influence on idiosyncratic income of the home state.

For instance, if idiosyncratic output growth of neighboring states is positive, factor income flows to the home state and hence the home state's income increase due to increased returns of Shiller-securities issued in those neighboring states—but this effect shows only part of the picture. The positive idiosyncratic output growth of neighbors must by construction be offset by a negative idiosyncratic output growth of other, non-neighboring states.[9]

[9] Holding constant aggregate risk, the sum of idiosyncratic ouput risk equals zero by construction (accounting for population weights).

Under the assumption that the cross-ownership of productive assets (i.e., factor income flows) is balanced, both effects cancel out and the idiosyncratic income of the home state remains unchanged. If, by contrast, we find a positive effect of the increase in neighbor's idiosyncratic output on the home states' idiosyncratic income, this implies that the citizens of the home state own a disproportionate large fraction of claims to output produced in neighboring states.[10]

2.2 Model specification

Let inc_{it} and gsp_{it} denote state i's year t real per capita income and output, respectively. The real and population-weighted average per capita income and output for the US as a whole are denoted as inc_t^* and gsp_t^*. All data has been transformed to real figures by dividing by the US-wide Consumer Price Index (CPI).

The key variables in our study are the state's logarithmic or percentage deviations from the US-wide average per capita values of production and income:

$$\begin{aligned} y_t &= \log inc_{it} - \log inc_t^* \\ x_t &= \log gsp_{it} - \log gsp_t^*. \end{aligned} \tag{1}$$

To keep the notation as simple as possible we omit the index i for the states and denote stacked vectors as y_t and x_t (instead of y_{it} and x_{it}). Throughout the paper, we refer to the variables y_t and x_t as 'relative' or 'idiosyncratic' variables.

A direct approach to measuring risk sharing at the regional level is to consider the following set of cross-sectional regressions (one regression for each year t):

$$\Delta y_t = \alpha_t + \beta_{K,t} \Delta x_t + \varepsilon_t, \tag{2}$$

where α_t denotes a constant term and ε_t a white-noise error term (also in stacked form).[11] The risk sharing coefficient $\beta_{K,t}$ measures the average co-movement of the regions' idiosyncratic income growth with their idiosyncratic output growth in year t. The smaller the co-movement, the more income is buffered against own output fluctuations. If income smoothing is perfect then idiosyncratic income y_t does not co-move with idiosyncratic output x_t at all and the coefficient $\beta_{K,t}$ takes the value 0. In the situation with no risk sharing, income moves one-to-one with output and $\beta_{K,t} = 1$. We follow the literature in defining $(1 - \beta_{K,t})$ as our measure of risk sharing through interregional factor income flows. Thus, if no state-specific risk is hedged we find $\left(1 - \beta_{K,t}\right) = 0$.

It is also possible to pool the data and to estimate equation (2) as a panel data model:

$$\Delta y_t = \pi_i + \beta_K \Delta x_t + \varepsilon_t. \tag{3}$$

In equation (3), π_i denotes fixed effects which capture unobserved heterogeneity among

[10] The effect of commuter flows will be taken into account in the next section.

[11] This risk sharing regression or similar variants have been conducted, among others, by Asdrubali, Sørensen, and Yosha (1996), Sørensen and Yosha (1998), Mélitz and Zumer (1999), Becker and Hoffmann (2006), and Sørensen, Wu, Yosha, and Zu (2005).

states, e.g. non time-varying differences in growth performances.[12] The common slope parameter β_K—more precisely $(1-\beta_K)$— can be interpreted as the average amount of capital market risk sharing during the sample period, see the paper of Asdrubali, Sørensen, and Yosha (1996) for a discussion.

The novelty of this paper is to consider an extended risk sharing regression which also takes into account the effect of the idiosyncratic output growth of neighboring states. This spatial extension of the risk sharing regressions (2) and (3) allows us to shed light on a potential neighborhood bias in factor income flows.

The cross-sectional variant of our spatial risk sharing model reads as:

$$\begin{aligned} \Delta y_t &= \beta_{K,t}\Delta x_t + \beta_{N,t}\Delta \tilde{x}_t + u_t, \\ u_t &= \rho_t W u_t + \varepsilon_t. \end{aligned} \tag{4}$$

The additional regressor $\Delta\tilde{x}_t$ is designed to measure the weighted average idiosyncratic output shock (in per capita terms) in neighboring states. To illustrate how this variable is constructed, we can consider as an example one element k of the vector $\tilde{x}_t$.

Dropping the time index t for simplicity, this element $\tilde{x}_k$ can be written as

$$\tilde{x}_k = \frac{\sum\limits_{i \epsilon N_k} b_i \cdot x_i}{\sum\limits_{j \epsilon N_k} b_j}. \tag{5}$$

In this expression, N_k comprises all states which are neighbors to state k. The term b_i denotes the population size of state i. Hence, the numerator $\sum\limits_{i \epsilon N_k} b_i \cdot x_i$ is the sum of (idiosyncratic) output produced in neighboring states—in absolute, not in per capita terms. The total idiosyncratic output of neighboring states is divided by the total population in those states. Thus, the variable $\Delta\tilde{x}_k$ measures the average idiosyncratic output change in neighboring states, expressed in per capita terms. As we will explain in more detail below, we will test the hypothesis that $\beta_{N,t} = 0$. If $\beta_{N,t} > 0$, this means that income does co-move with neighbor's output shocks and consequently that factor income flows are subject to a neighborhood bias.

The regressor $\Delta\tilde{x}_t$ is a so-called 'spatial lag' of Δx_t and we can use this concept known from spatial econometric techniques in order to compute (5). Usually, a spatial lag of some variable is computed by pre-multiplying this variable by a matrix W. The matrix W is a known $i \times i$ spatial weighting matrix which contains the neighboring relationships among the i regions. In the simplest case, the matrix W defines the binary contiguity relationships of neighbors. This means that in the matrix W values of unity are placed in positions i, j, where j indicates regions that have borders touching region i.[13]

[12] There is no need to include time fixed-effects because our variables are already formulated relative to the national average.

[13] We experiment with several possibilities to construct the contiguity matrix W. A common method is based on polygon centroid coordinates. These coordinates can be used to produce an adjacency matrix from so called 'Delaunay triangles'. Another possibility to construct W is to find a certain number of nearest neighbors to each region. In any case, the matrix W has entries of zeros for non-neighbors and

In order to match the definition (5) of $\tilde{x}_k$ we additionally have to assign *population-based* geographic weights to each neighbor. This means that larger neighboring states must be given more weight than smaller ones. To illustrate the need for a proper weighting we can consider the neighboring relationships for a specific state, say Nevada, as an example. Assume that the neighborhood criterion has assigned five neighbors to Nevada. If we were not to assign population weights to each neighbor, we would assume that it is optimal to hold the same amount of claims to output in each neighboring state, irrespective of the size of the states. Such investment, however, is not optimal. The neighboring states with a large population, such as California, should get a large portfolio weight. Thus, our population-based geographic weights capture the optimal portfolio weights of Shiller-securities.

We therefore construct a $i \times i$ matrix of the state's population size which is denoted as B_t. The columns of B_t contain the population size of the states. All rows of B_t are the same, which means that the row containing the different population values is stacked one below the other.[14] Since the population of each state changes over time, also the matrix of the state's population (weights) B_t is not constant. Therefore, we compute a matrix B_t for each year in the sample.

An element-wise multiplication of the matrices W and B_t yields a weighting matrix that takes into account the population-weights. By construction, the sum of all population weights is one, but the sum of all population weights for neighbors is smaller than one, since neighboring states are only a subset of all US states. Therefore, the last step in constructing the final weighting matrix is to standardize the element-wise matrix product $[WB_t]$ so that the row sums equal unity.

The matrix product of the standardized matrix $[WB]$ and the regressor x_t then produces an average of the idiosyncratic output shocks of states meeting the definition of neighbors. This allows us to rewrite our spatial risk sharing model in terms of the idiosyncratic output shock x_t by replacing the spatial lag $\Delta\tilde{x}_t$ with the matrix product $[WB_t]\Delta x_t$:

$$\begin{aligned} \Delta y_t &= \beta_{K,t}\Delta x_t + \beta_{N,t}[WB_t]\Delta x_t + u_t, \\ u_t &= \rho_t W u_t + \varepsilon_t. \end{aligned} \tag{6}$$

The error term u_t in model (2) is assumed to follow a spatial moving average process. This error process may capture further spatial autocorrelation which is not eliminated

ones for neighbors, with zeros on the main diagonal.

[14] It does not matter whether the matrix B_t contains the absolute population size of the states or their population weight, i.e. their relative population size. If one uses population weights instead of the absolute population size, equation (5) reads as

$$\tilde{x}_k = \frac{\sum\limits_{i \epsilon N_k} \frac{b_i}{\sum\limits_s b_s} \cdot x_i}{\sum\limits_{l \epsilon N_k} \frac{b_l}{\sum\limits_s b_s}},$$

whereas the sum running over the index s contains all states in the sample, not only neighbors to state k. This definition of $\tilde{x}_k$ is equivalent to (5).

through the inclusion of our spatial regressor $[WB_t]\Delta x_t$. In the next section we will provide empirical evidence that the spatial error specification is indeed more appropriate (i.e., more efficient) than the assumption of a white-noise error process. In equation (6), the parameters to be estimated are $\beta_{K,t}$, $\beta_{N,t}$ and ρ_t.

If we are not interested in the variation of the point estimates over time but in quantifying the average amount of risk sharing during a specific sample period, we can pool the data and estimate the β coefficients and ρ from a panel data model:

$$\begin{aligned} \Delta y_t &= \pi_i + \beta_K \Delta x_t + \beta_N [WB_t]\Delta x_t + u_t, \\ u_t &= \rho W u_t + \varepsilon_t. \end{aligned} \tag{7}$$

Elhorst (2003) has developed a Maximum-Likelihood estimator for static panel data models with fixed effects π_i and a spatial error process u. We will use this estimator to estimate (7).

3 Estimating risk sharing and the neighborhood bias

3.1 Data

The state-level data used in this study is the same as the data constructed by Asdrubali, Sørensen, and Yosha (1996) and we refer to their data appendix for an extensive description on how the data is constructed. This data has also been used, among others, by Mélitz and Zumer (1999), Crucini and Hess (2000), Athanasoulis and Wincoop (2001), Asdrubali and Kim (2004a), Asdrubali and Kim (2004b), Sørensen, Wu, Yosha, and Zu (2005), and most recently by Artis and Hoffmann (2005) and Becker and Hoffmann (2006). In the meantime, the database constructed by Asdrubali, Sørensen, and Yosha has been updated. While the aforementioned papers (those which are already published) use data for 1963-1990, our estimations refer to the extended sample period 1963-1998.[15]

One major advantage of this extended data is that it covers the period which is usually referred to as the 'globalization period'. After the 1980s, but especially after the 1990s, international financial markets have become increasingly integrated, see the discussion in Artis and Hoffmann (2005). Hence, we would also expect a change—in particular, an increase—in risk sharing among countries, but also among regions. For countries, this relationship has been corroborated by Artis and Hoffmann (2005). For US states, the paper by Kalemli-Ozcan, Sørensen, and Yosha (2004) provides updated evidence for the extended sample period 1963-1998. This is also the period of time examined in our paper.

Our empirical analysis takes data on Gross State Product and state income into account. State income as constructed by Asdrubali, Sørensen, and Yosha consists of personal income after substracting out all federal transfers and allocating all non-personal taxes to income. Further, income of state governments that is not derived from personal taxes is also included in state income (see Kalemli-Ozcan, Sørensen, and Yosha, 2002, footnote 27). Hence, one important feature of the income data constructed by Asdrubali, Sørensen, and Yosha (1996) is that it is adjusted for federal transfers and

[15] I thank Mathias Hoffman for providing the data to me.

contributions. For the exact definition of the variables we refer to the original paper by Asdrubali, Sørensen, and Yosha (1996). Population data stems from the Bureau of Economic Analysis (BEA).

One difference to related studies is that we restrict the analysis to the 48 continental US states because we want to use a consistent concept of neighbors. Previous studies included the full set of states in the analysis (including Hawai, Alaska, and sometimes Washington D.C.).

For the spatial contiguity matrix W we tried several alternatives which we have discussed above, i.e. based on physical contiguity, Delaunay triangulization, and nearest neighbors. According to some pre-testing, our results are not exceedingly sensitive to the particular choice for W. For brevity, we will only present the results obtained with the contiguity matrix based on Delaunay triangles.

3.2 Cross-sectional analysis

To set the scene, we estimate the risk sharing models (2) and (6) year-by-year from the cross-sections of states. The aim of this exercise is to get a sense of the variation in the point estimates over time. The non-spatial model (2) is estimated with simple OLS while the spatial model (6) is estimated using the Maximum Likelihood estimator for spatial error models described in Anselin (1988).[16] Thereafter, we pool the data and turn to a panel estimation of models (3) and (7).

Figure 1 provides an overview about the estimation results of the risk sharing parameter $\beta_{K,t}$, which measures the co-movement of income with own output shocks. Each sub-plot contains two graphs. The thin line displays the sequence of $\beta_{K,t}$ obtained with the non-spatial model (2) while the thick line shows the estimates of $\beta_{K,t}$ from the spatial model (6).

The top panel in Figure 1 displays the raw point estimates of $\beta_{K,t}$. Since we are interested in the trend-movements in the series, we smooth the sequence of point estimates at neighboring time-periods (see the bottom panel in Figure 1).

The bottom-left panel displays the smoothed series of $\beta_{K,t}$ using a Normal kernel smoother. The bandwidth in the local linear regression has been selected by using the Ruppert, Sheather, and Wand (1995) Plug-In method.

As an alternative smoothing procedure we use the Hodrick-Prescott (1997) (HP) filter. Since our data are observed at annual frequencies we use a smoothing parameter of $\mu = 100$ for the HP-filter. This choice for μ is widely accepted in the business cycle literature. However, Ravn and Uhlig (2002) proposed a different smoothing parameter of $\mu = 6.25$ for yearly data. For the sake of completeness we tried both values for μ. The remaining two subplots in the lower panel of Figure 1 present the results for the HP-filtered estimates.

[16] As a robustness test, we also left out the spatial moving average process in the error term and estimated the spatial model (6) with simple OLS (the spatial regressor $[WB_t]\Delta x_t$ does not cause any problems for OLS since it is assumed to be exogenous). The point estimates of the β coefficients turned out to be very similar across both estimations. This similarity reflects that OLS remains an unbiased estimator if the spatial dependence only affects the error term. The Maximum-Likelihood estimator, however, is more efficient than OLS in the presence of significant spatial autocorrelation.

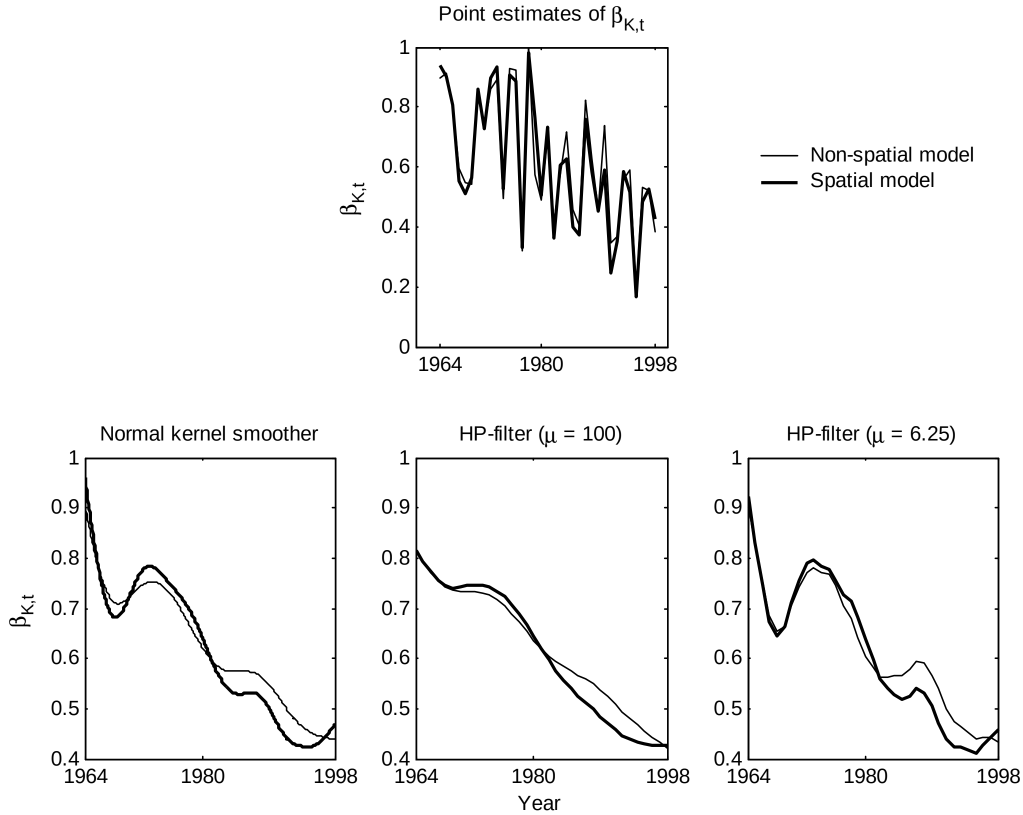

Figure 1: Capital market risk sharing of own idiosyncratic output shocks among US federal states, 1963-1998. Top: raw point estimates of $\beta_{K,t}$ against time. Bottom: smoothed sequences of $\beta_{K,t}$ against time.

Consider first the series of raw point estimates for $\beta_{K,t}$ (top). It can be seen that the degree of capital market risk sharing varies considerably over time. This variation seems to be driven by business cycle fluctuations but a deeper analysis of this issue is beyond the scope of this paper. Our primary focus will be on the smoothed series of $\beta_{K,t}$ (bottom).

The graph obtained with the HP-filter and a smoothing parameter of $\mu = 100$ is the smoothest one (middle). The other graphs appear to be somewhat undersmoothed. Therefore, we regard the results obtained with the HP-filter and a smoothing parameter of $\mu = 100$ as our preferred ones. It should be noted that the general pattern of the variation of the point estimates over time is quite similar across the different procedures to smooth the point estimates.

In particular, there are two main facts which emerge from Figure 1. First, insurance against own idiosyncratic output fluctuations increases substantially over time, as reflected by the decline in $\beta_{K,t}$. Second, the estimated amount of risk sharing is very similar across the non-spatial and spatial specifications.[17]

In both models, the $(1 - \beta_{K,t})$'s measure the percentage of smoothing of a state's

[17] With spatial model specification, we mean the model which includes neighbor's output shocks and the spatial error term (see equation 6).

GSP shock carried out by capital markets and we expect $\beta_{K,t} = 0$ if there is full risk sharing through capital income flows. If $\beta_{K,t}$ is taken from the spatial model (6) the parameter has to be interpreted conditional on the assumption that the idiosyncratic output of neighbors remains unchanged.

In the early 1960s only about 20 percent of an idiosyncratic output shock is smoothed by capital income flows. Starting off from this low level, interstate risk sharing has increased substantially over time. Until the 1990s, there has been a steady positive trend in the risk sharing parameter $(1 - \beta_{K,t})$ up to a level of about 50-60 percent. This means that today only 40 percent of an idiosyncratic shock to the GSP of individual states are not insured through the capital market channel.

These estimates are well in line with those numbers which have been reported in previous studies. We can compare our cross-sectional results in particular to the ones documented in Kalemli-Ozcan, Sørensen, and Yosha (2004). This paper discusses that the apparent increase in insurance through inter-state capital income flows is indeed statistically significant and not due to pure sampling variation.

Concerning our two different models to estimate the sequence of $\beta_{K,t}$, we find that the estimates are quite similar across the non-spatial and spatial specifications. After the 1980s, the spatial model yields a higher degree of risk sharing than the non-spatial one, i.e., the $\beta_{K,t}$'s for the spatial model are closer to zero than the ones for the non-spatial model. The overall pattern of smoothing of own output risk, however, is found to be the same across both models.

In order to motivate the spatial moving average specification in the error term of our extended risk sharing model (see equation (6)), we estimate this model without the spatial error process by simple OLS and analyze the residuals. We test for spatial autocorrelation in the residuals ε_t of each cross-sectional regression by performing a Moran's I test on the residuals. To save on space, we only discuss the overall result of this exercise. In about half of all years (51 percent) the Moran's I test statistic is significant at least at the 10 percent level. This means that the null hypothesis of no spatial autocorrelation is rejected for half of the cross-sectional regressions.

The spatial moving average process in the error term (see equation (6)) captures any remaining spatial autocorrelation which is not eliminated by including the spatial regressor $[WB_t]\Delta x_t$. In most time periods, the estimate for the spatial autocorrelation coefficient ρ is significantly different from zero, as we would expect from the test results obtained with Moran's I test. We do not report the point estimates for ρ since this nuisance parameter is not in the focus of our paper. More details concerning the magnitude of ρ will become apparent from the panel-based estimations in the next sub-section.[18]

The overall picture suggested by the cross-sectional regressions is that, although insurance among US states is considerable, the hypothesis of *full* risk sharing ($\beta_{K,t} = 0$) is clearly rejected. The still large amount of idiosyncratic risk which is not diversified

[18] The finding of spatial dependence in US state-level data is well in line with studies which focus on the consequences of spatial interaction effects on convergence analyses. For instance, the study of Rey and Montouri (1999) provides strong evidence of positive spatial dependence in both, levels and growth rates of income per capita in the US.

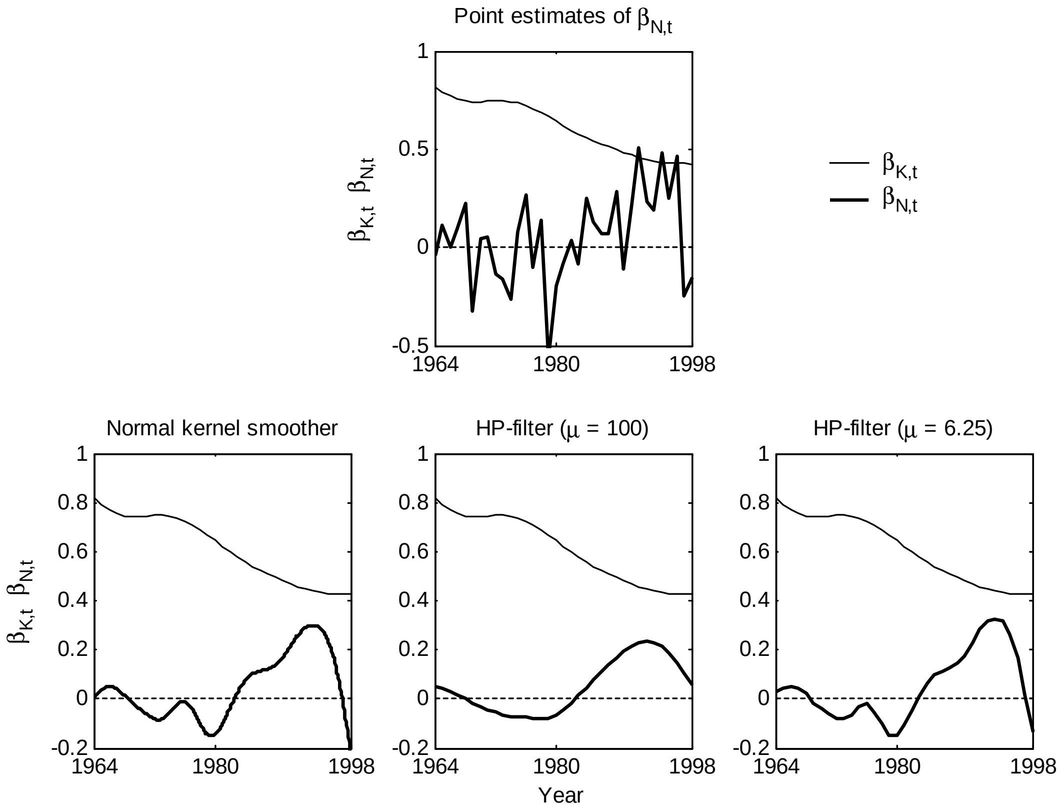

Figure 2: Bold line: neighborhood bias in factor income flows among US federal states, 1963-1998. Thin line: smoothed sequence of $\beta_{K,t}$ against time, see Figure 1. Top: raw point estimates of $\beta_{N,t}$ against time. Bottom: smoothed sequence of $\beta_{N,t}$ against time.

indicates that US states are subject to some form of home bias, in a sense that regional portfolios seem to deviate substantially from the perfectly diversified portfolio which would lead to perfect risk sharing and $\beta_{K,t} = 0$. An inspection of the parameters $\beta_{N,t}$ sheds light on the question whether a neighborhood bias in factor income flows constitutes an additional risk factor which influences the overall degree of income insurance.

Similar to the risk sharing coefficient $\beta_{K,t}$, this parameter should be zero if no neighborhood bias is driving interstate factor income flows. An extreme case might be helpful to illustrate this. If risk sharing is complete and agents hold perfectly diversified portfolios of Shiller-securities, for each state income growth equals the US-wide income growth. Then, *both* coefficients $\beta_{K,t}$ and $\beta_{N,t}$ take the value 0 simply because the left-hand side of equation (6) is always 0.

Figure 2 summarizes the estimation results for $\beta_{N,t}$, obtained with the spatial risk sharing model (6). In order to illustrate the joint development of $\beta_{N,t}$ and $\beta_{K,t}$ over time, we also include the HP-filtered series of $\beta_{K,t}$ as a thin line in the graphs.

While the raw point estimates of $\beta_{N,t}$ fluctuate considerably (top), the smoothed series (bottom) suggest more clearly that the overall development of $\beta_{N,t}$ may be divided into two (or three) sub-periods. During 1963-1980, the point estimates for $\beta_{N,t}$ fluctuate around zero and are small in absolute terms. In fact, for most of these estimates we cannot reject the hypothesis that they are zero. Thus, during the first sub-period interstate factor income flows are not subject to a substantial neighborhood bias. By contrast, the point estimates for $\beta_{N,t}$ are larger during the second sub-period 1980-1998. What can also be seen from Figure 2 is an increase followed by a decline in β_N during this second sub-period.

3.3 Panel-data estimation

We corroborate the preliminary impressions from the cross-sectional analysis by estimating the panel model (7), both for the periods 1963-1980 and 1980-1998, as well as for the most recent sub-period 1990-1998. This exercise allows us to boil down the sequence of point estimates into overall averages during the respective sub-periods. Moreover, the pooled estimation has higher power than the cross-sectional regressions which makes the test of no neighborhood bias ($\beta_N = 0$) more reliable.

The regression results of the pooled model (7) are displayed in Table 1. We estimated the model with the estimator for spatial panels with fixed effects and spatial error autocorrelation developed by Elhorst (2003).[19]

The first thing to note is that the spatial autocorrelation coefficient ρ is statistically different from zero in all estimations. Therefore, the spatial panel estimator employed is indeed a more efficient estimator than simple OLS. Though, the point estimates of β_K and β_N reported in Table 1 are very similar to an OLS regression with fixed effects. A candidate interpretation of the nuisance spatial dependence in the error term is that it results from measurement problems such as the mismatch between the pattern of regional risk sharing and the boundaries of US federal states (see Magrini (2004) for a similar argument).

More important is that the results of the panel-data estimations confirm our previous examinations of Figures 1 and 2. During the first sub-period, capital market risk sharing was rather scarce. The estimate of $\beta_K = 0.71$ implies that only about 30% of an own idiosyncratic output shock is smoothed via this channel. At the same time, the point estimate for $\beta_N = -0.02$ is not significantly different from zero, as we would expect from Figure 2.

Since we find the parameter β_N to be insignificant, there is evidence that capital market linkages with neighboring states have not been more pronounced than linkages with other states during the first sub-period. Taken together, the coefficients β_K and β_N imply that an idiosyncratic output shock which hits the representative state is transmitted substantially to a change in the state's own income but output shocks to neighboring states do not affect the income of the home state significantly.

In order to quantify the overall amount of income insurance that is achieved we can add the coefficients β_K and β_N (see Table 1). This sum measures how strongly a state's idiosyncratic income changes if both, the home state and the neighbors are hit by idiosyncratic shocks. Or to put it differently, we can interpret the sum of β_K and β_N as the co-movement of state-level income with shocks that hit larger geographical

[19] A MATLAB procedure for this estimator is freely downloadable from the website `www.spatialeconometrics.com`.

Table 1: Spatial risk sharing model with spatial error autocorrelation and fixed effects, estimated using the estimator developed by Elhorst (2003)

	1963-1980			**1980-1998**		
	Coeff.	*t-stat*	*z-Prob.*	*Coeff.*	*t-stat*	*z-Prob.*
Own idiosyncratic output shock: Δx (β_K)	0.71	(39.76)	(0.00)	0.48	(27.87)	(0.00)
Neighbor's idiosyncratic output shock: $[WB_t]\Delta x_t$ (β_N)	-0.02	(-0.63)	(0.53)	0.08	(2.22)	(0.03)
Overall insurance: $\beta_K + \beta_N$	0.69			0.56		
Spatial autocorrelation coefficient (ρ)	0.44	(10.21)	(0.00)	0.35	(7.90)	(0.00)
log-likelihood	2429.502			2706.78		
Number of observations	816			912		

	1990-1998		
	Coeff.	*t-stat*	*z-Prob.*
Own idiosyncratic output shock: Δx (β_K)	0.45	(14.52)	(0.00)
Neighbor's idiosyncratic output shock: $[WB_t]\Delta x_t$ (β_N)	0.23	(3.53)	(0.00)
Overall insurance: $\beta_K + \beta_N$	0.68		
Spatial autocorrelation coefficient (ρ)	0.19	(2.68)	(0.00)
log-likelihood	1314.75		
Number of observations	432		

areas. During 1963-1980 the influence of β_N is negligible since the parameter is small and insignificant and one arrives at an overall amount of unsmoothed shocks of 0.69.

During the second sub-period 1980-1998 we find a different picture. As can be seen from the right-most columns in Table 1, the average amount of risk sharing of an own idiosyncratic output shock is substantially higher and corresponds to roughly 50 percent. As we could already infer from the graphical analysis before, also the neighborhood bias has increased during this period. The point estimate for β_N is 0.08 and we can reject the hypothesis that the coefficient is 0.

In order to corroborate that the neighborhood bias has increased substantially over time we also estimate our panel model for the most recent period 1990-1998 only. This period may best reflect the influence of globalization on risk sharing and neighborhood bias.

From Table 1 (bottom) it can be seen that insurance against own idiosyncratic risk is highest during this recent period ($\beta_K = 0.45$). By sharp contrast, the co-movement of state-level income with neighbor's output has increased substantially. While the coefficient of the spatial lag of the idiosyncratic output shock was insignificant during the first period 1963-1980, it takes a value of $\beta_N = 0.23$ in recent years.

These findings indicate that we may have to qualify the overall increase in income insurance that is achieved during the second sub-period, and especially during more recent years. If we were to rely solely on a comparison of the β_K's over time we would arrive at an impressing increase in capital market risk sharing from the first (1963-1980: $\beta_K = 0.71$) to the second sub-period (1980-1998: $\beta_K = 0.48$). If we account for spatial linkages among states, however, we find that the overall amount of income insurance measured by $48\% + 8\% = 56\%$ is still larger than the insurance achieved during the first period, but the increase is less pronounced than suggested by the β_K's alone. This picture becomes even more pronounced during the period 1990-1998. Since the neighborhood bias has gained substantially in importance, the average federal state is insured only moderately against shocks that hit a larger geographical area. In fact, the sum of the βs during the most recent period (1990-1998: $\beta_K + \beta_N = 0.68$ (!)) is found to be the same as during 1963-1980.

However, this preliminary conclusion neglects one important aspect, namely to account for the variance of neighbor's idiosyncratic output risk relative to one's own output risk. To illustrate this point we may consider two extreme cases. If there is no diversification at all, agents hold claims to the output produced in their own state only and consequently we would find $\beta_K = 1$ and $\beta_N = 0$. The other extreme case is that agents hold claims to output in neighboring states solely. In this scenario it holds that $\beta_K = 0$ and $\beta_N = 1$.

Both extreme scenarios have different consequences for the overall effectiveness of income insurance. In the second scenario of a complete neighborhood bias one's income will fluctuate *less* than in the first scenario of a complete home bias 'at home'. The reason is that the output fluctuation of neighbors is smaller than the output variability at home. In other words, a disproportionate high engagement in neighbor's output stream reduces the variability of income at home because a limited amount of diversification takes place.

Table 2: Standardized estimates of the neighborhood bias

	1963-1980	**1980-1998**	**1990-1998**
$\tilde{\beta}_N = \frac{\beta_N}{std(\Delta x_t)} \cdot std\left([WB_t]\Delta x_t\right)$	-0.01	0.04	0.12
Overall insurance: $\beta_K + \tilde{\beta}_N$	0.70	0.52	0.57
Own idiosyncratic output shock: β_K [taken from Table 1]	0.71	0.48	0.45

In fact, if all states had independent idiosyncratic risk, investing one more dollar in the output stream of neighboring states (equally split) would reduce the fluctuation of income at home by a factor $1/N_k$, where N_k is the number of neighbors.

In order to account for this effect we scale the coefficient associated with the neighborhood bias, β_N, by the ratio of the standard deviations of neighbor's and one's own output risk. Specifically, we transform the point estimate of β_N as

$$\tilde{\beta}_N = \frac{\beta_N}{std\left(\Delta x_t\right)} \cdot std\left([WB_t]\Delta x_t\right).$$

We report the standardized estimates of $\tilde{\beta}_N$ for the three sub-periods in the first row of Table 2. As expected, our previous conclusion concerning the destabilizing effect of the neighborhood bias has to be qualified. Once we account for the smaller variance of neighbor's output relative to one's own output we arrive at smaller estimates for $\tilde{\beta}_N$. Quite symmetrically, the estimates decline by roughly one half. Therefore, we note that our estimates reported in Table 1 cast a too damning light on the neighborhood bias.

More important is, however, that we find a similar development of the neighborhood bias over time even if we account for the potential gain in variance reduction in one's own income. Specifically, the standardized neighborhood bias is found to be unimportant during 1963-1980 but it is becoming more pronounced during 1980-1998. Especially during the most recent period 1990-1998, the magnitude of the (standardized) $\tilde{\beta}_N$ coefficient is clearly significant also in economic terms.

The second row of Table 2 displays the overall degree of income insurance which is achieved once we account for the smaller variance in neighbor's output fluctuation, calculated as $\beta_K + \tilde{\beta}_N$. The numbers provide evidence that the amount of risk sharing is indeed larger during the second sub-period than during the first one. However, the increase is still less pronounced than suggested by a comparison of the β_K's alone. These estimates are replicated in the last row of Table 2 for ease of comparison.

The overall conclusion suggested by our spatial risk sharing model can be summarized as follows. As also documented by Kalemli-Ozcan, Sørensen, and Yosha (2004), income fluctuations have indeed become substantially decoupled from fluctuations in one's own output. At the same time, state-level income has become more dependent on neighbor's output fluctuation than in the past. The net effect of both developments is a more moderate increase in income insurance provided by capital markets than documented in previous studies which did not take the neighborhood bias into account.

4 Accounting for commuter flows

Having shown that the neighborhood bias in factor income flows has become more pronounced over time, a next step in the analysis is to examine which economic factors drive the development of the neighborhood bias. As we have discussed in the Introduction, the neighborhood bias in factor income flows may be driven by capital income flows, but also by labor income flows. Both income components are reflected in the wedge between GSP and income.

In order to assess the relative importance of both factors we extend the analysis to include commuter flows across state borders. The role of commuter flows has been emphasized in a different area of economic research, namely that of growth and convergence. A prevalent finding in this literature is that changes in commuter patterns represents an important source of spatial adjustment (see Magrini, 2004). Therefore, it is important to examine how much of the neighborhood bias may be explained by commuter flows.

If workers commute from their place of residence to their place of work in another federal state, their output is attributed to the GSP of the neighboring state, while their income is measured at their state of residence. Idiosyncratic output shocks that hit neighboring states may then be transmitted to the home state's income because workers, who commute to their place of work, take their output produced in other states with them (in the form of income).

To the best of our knowledge, consecutive time-series data on commuter flows across US federal states is not available. The only data which is available are special tabulations from the decennial Censuses of 1960, 1970, 1980, 1990, and 2000 which show the commuting flows between counties.[20]

We aggregate the county data for 1990 and 2000 to the federal state level and compute the flow of commuters into and out of each federal state at both points in time. Moreover, we compute the net inflow of commuters into each state. All numbers are normalized by the state's employment in order to obtain commuter rates.

For instance, a positive value of the net commuter rate indicates that more workers commute from neighboring states into that state than in the opposite direction. In other words, a positive net commuter rate indicates that employment measured at the workplace is larger than employment measured at the place of residence. To illustrate the overall commuting patterns among US federal states Figure 3 presents a map of net commuter rates for 1990 and 2000.

In what follows, we analyze whether states that have high commuter flows are more or less successful in decoupling their incomes from the output fluctuation in neighboring states. This means that we relax the assumption that β_N is the same for all federal states. To capture the impact of commuter flows on our measure of neighborhood bias,

[20] The data for 1990 and 2000 can be downloaded from `http://www.census.gov/population/www/cen2000/commuting.html`. We do not have access to data from earlier years. Data for 1960-1980 will be considered in a later version of this paper.

Figure 3: Net commuter rates across US federal states, 1990 (top) and 2000 (bottom)

we postulate that β_N may vary across states and is given by

$$\beta_{N,k} = \kappa' \left(c_{k,t} - \bar{c}_t\right) \tag{8}$$

where $c_{k,t}$ is a vector of data on commuter flows and $\bar{c}_t$ is the vector of cross-sectional means of $c_{k,t}$. The associated parameter vector is denoted as κ. Before we discuss how to interpret (8) we note that the vector $c_{k,t}$ could contain different measures of commuter flows. For instance, $c_{k,t}$ may include commuter flows (rates) into and out of each federal state. Alternatively, we could focus on the net rate of commuter flows. Lastly, we could emphasize the role of gross commuter flows rather than net flows by adding commuter flows in both directions (see below).

Each of these possibilities to parametrize $\beta_{N,k}$ has pros and cons and we have no strong prior which specification is preferable. To set the scene, we start with a general specification and include both, commuting into and commuting out of a federal state into the vector $c_{k,t}$. Thereafter, we turn to an alternative specification which emphasizes the effect of gross flows.

For our first parametrization we define commuter rates as

$$z_{k,t}^{in} = \frac{Z_{k,t}^{in}}{E_{k,t}} \quad \text{and} \quad z_{k,t}^{out} = \frac{Z_{k,t}^{out}}{E_{k,t}},$$

where $Z_{k,t}^{in}$ measures commuter flows into a state and $Z_{k,t}^{out}$ measures commuting out of a state. Both numbers are normalized by total employment $E_{k,t}$, so that the lower-case variables z measure commuter rates.

Then, we define the parametrization of $\beta_{N,k}$ as

$$\beta_{N,k} = \bar{\beta}_N + \kappa_1(z_{k,t}^{in} - \bar{z}_t^{in}) + \kappa_2(z_{k,t}^{out} - \bar{z}_t^{out}). \tag{9}$$

We note that we do not have a consecutive time-series on commuter flows. Therefore, we stacked commuter flows in 1990 and 2000 so that the period 1980-1990 is matched with commuter flows in 1990 and the remaining years between 1990-1998 are matched with commuting data in 2000. Although this crude procedure is far from being satisfactory, it seems the best we can do at the moment due to the aforementioned data limitations. We hope that this exercise provides us at least with an idea of how strongly differences in commuter flows affect the estimate for β_N.

We substract the vectors of cross-sectional means (indicated with an upper-bar, see equation (9)) from each commuter rate. This allows us to interpret the coefficient $\bar{\beta}_N$ as the cross-sectional average of $\beta_{N,k}$. Plugging the relation (9) into (7) then yields a panel regression from which the coefficients κ_1 and κ_2 can be estimated.

The estimation results are reported in Table 3 (top). The most important finding is that the commuter variables are not statistically significant during both sub-periods. This finding implies that a federal state which is characterized by above-average commuter flows has a similar degree of neighborhood bias than a state which is characterized by an

Table 3: Impact of commuter flows on the neighborhood bias, Part I

Parametrization I: $\beta_{N,k} = \bar{\beta}_N + \kappa_1(z^{in}_{k,t} - \bar{z}^{in}_t) + \kappa_2(z^{out}_{k,t} - \bar{z}^{out}_t)$

	1980-1998			**1990-1998**		
	Coeff.	*t-stat*	*z-Prob.*	*Coeff.*	*t-stat*	*z-Prob.*
Own idiosyncratic output shock: β_K	0.49	(27.94)	0.00	0.44	(14.13)	0.00
Neighbor's idiosyncratic output shock: $\bar{\beta}_N$	0.09	(2.56)	0.01	0.26	(3.89)	0.00
Commuter rate (in): κ_1	0.49	(0.27)	0.78	2.46	(0.67)	0.50
Commuter rate (out): κ_2	1.63	(1.48)	0.14	1.77	(0.75)	0.45
Spatial autocorrelation coefficient ρ	0.35	7.99	0.00	0.19	(2.65)	0.01

Parametrization II: $\beta_{N,k} = \beta_N + \kappa_3 z^{gross}_{k,t}, \qquad z^{gross}_{k,t} = \left(Z^{in}_{k,t} + Z^{out}_{k,t}\right)/E_{k,t}$

	1980-1998			**1990-1998**		
	Coeff.	*t-stat*	*z-Prob.*	*Coeff.*	*t-stat*	*z-Prob.*
Own idiosyncratic output shock: β_K	0.49	(27.98)	0.00	0.44	(14.19)	0.00
Neighbor's idiosyncratic output shock: β_N	-0.01	(-0.13)	0.90	0.08	(0.78)	0.44
Gross commuter rate: κ_3	1.25	(2.47)	0.01	2.03	(1.99)	0.05
Spatial autocorrelation coefficient: ρ	0.35	(7.92)	0.00	0.19	(2.65)	0.01

average amount of commuter flows.[21]

The parametrization according to (9) illustrates whether *deviations* from *average* levels of commuter flows have an influence on the neighborhood parameter β_N and we found that this is not the case. It is also of importance, however, to examine whether the magnitude of β_N changes substantially once a (fictitious) federal state is *completely* isolated from other states in terms of commuting. In order to test whether the neighborhood bias in factor income flows vanishes once commuter flows are (artificially) set to zero, we consider the following parametrization of $\beta_{N,k}$:

$$\beta_{N,k} = \beta_N + \kappa_3 z_{k,t}^{gross}, \tag{10}$$

where the regressor $z_{k,t}^{gross}$ measures the sum of gross commuter flows (rather than the net flow). We calculate $z_{k,t}^{gross}$ as

$$z_{k,t}^{gross} = \frac{Z_{k,t}^{in} + Z_{k,t}^{out}}{E_{k,t}}.$$

In this formula, $Z_{k,t}^{in}$ measures commuter flows into a state, $Z_{k,t}^{out}$ measures commuter flows out of a state, and $E_{k,t}$ is total employment of state k at time t. Different from the previous parametrization we do not subtract the cross-sectional averages of $z_{k,t}^{gross}$. This allows us to interpret the coefficient β_N in equation (10) as the amount of neighborhood bias if there were no commuter flows (at all).

Table 3 (bottom) reports the results obtained with this specification. It can be seen that the results change substantially. The point estimates for β_N become insignificant while the interaction term with the commuter variable becomes significant in both periods. These estimates suggest that if there were no commuter flows, there would also be no neighborhood bias in factor income flows.

However, it might be that the β_N coefficient is imprecisely estimated due to problems of multi-collinearity.[22] In any case, it is important to note that the point estimate of β_N during the period 1990-1998 declines substantially from 0.23 (see Table 1) to 0.08 (see Table 3). Hence, if there were no commuter flows, the neighborhood bias would decline to a magnitude of 0.08 (whilst being insignificant).

In order to illustrate the quantitative effects associated with the parameter of the interaction term, κ_3, we consider a one standard-deviation increase in gross commuter flows as an example. If the gross commuter rate increases by one standard deviation this induces an increase in β_N of 0.14.

[21] As a robustness test we also estimated the panel model without fixed-effects. This exercise illustrates if potential cross-sectional variation in $\beta_{N,k}$ through differences in commuter flows becomes significant once we omit the fixed-effects which also pick up heterogeneity across states. We do not report detailed results of this exercise because none of the κ coefficients becomes significant even if fixed-effects are omitted.

[22] The correlation between neighbor's idiosyncratic output shock $[WB_t]\Delta x_t$ and the interaction term is of magnitude 0.8.

5 Extensions for future research

In this paper, we have established a first link between the literatures on spatial econometrics and risk sharing. We are convinced that our study suggests a number of promising directions for further inquiry.

One extension is to measure risk sharing among larger geographical areas than at the state level. Such experiment can illustrate whether the apparent neighborhood bias in factor income flows vanishes once state-level data are aggregated. We would expect that the amount of risk sharing among larger geographical areas is smaller than suggested by previous studies which used state-level data and did not account for the neighborhood bias in factor income flows.

Secondly, it appears promising to take our spatial approach to the international economy. We suppose that the neighborhood bias may turn out to be important, given the vast distances separating investors from potential investments in the global setting. At the same time, commuter flows between states are expected to play a minor role for the international economy.

For the international economy, several studies have documented a gradual removal of country portfolio home bias in recent years. For instance, Lane and Milesi-Ferretti (2001, 2003) document a dramatic increase in international cross-holdings of financial assets. Since data on international asset holdings is available we could use this data to test how well our spatial model picks up the development of local biases in investment portfolios over time.

If idiosyncratic output risk is not fully shared through capital market linkages, there is scope for further consumption smoothing through savings behavior. This intertemporal consumption smoothing may further buffer *consumption* from income fluctuations (see for example Becker and Hoffmann, 2006, and Artis and Hoffmann, 2005). Another step in the analysis might therefore be to re-consider the approach taken by Artis and Hoffmann (2005). While our model relied solely on output and income data which have been rendered stationary through first-differencing, this study demonstrates how to use the information implicit in the levels of relative *consumption* and output. The advantage of the level specification is that it allows one to pick up longer-term trends in the extent of consumption risk sharing that remain blurred in the first-differenced specification for capital market risk sharing. Some pre-testing makes us confident that spatial effects are highly relevant in the levels model. On the side of the econometric analysis, a spatial risk sharing analysis in levels needs to combine cointegration and spatial econometric techniques.

6 Conclusion

Previous risk sharing studies have analyzed how well income is insured against idiosyncratic fluctuations in one's own output. From micro-based studies we know, however, that regional asset portfolios are characterized by a preference for geographically proximate investments which is related to distance and information asymmetries among regions. This implies that output fluctuations in neighboring states may also exert a destabilizing effect on state-level incomes. We have referred to this phenomenon as a 'neighborhood bias'.

The question of this paper has been how strongly a potential neighborhood bias influences the overall amount of income insurance that is achieved among US federal states. Or to put it differently, we have examined whether output fluctuations in neighboring states also constitute risk factors which are transmitted to the home state's idiosyncratic income via factor income flows. This paper is the first one that puts local biases in factor income flows into a regional perspective.

Similar to previous studies, we found that insurance against own idiosyncratic shocks has increased substantially over time. This means that state-level income has become more and more buffered against region-specific shocks to GSP.[23] At the same time, however, factor income flows have become substantially biased towards neighboring states in recent years. This means that factor income flows between states and their neighbors are disproportionately high in comparison to a portfolio which only takes into account the fraction of a state's output. As a consequence, state-level income co-moves not only with own idiosyncratic output fluctuations, but also with output growth of neighboring states. Therefore, our study suggests that the overall amount of income insurance is more limited than reported in previous studies which did not take the neighborhood bias into account.

In a second step, we have examined which economic factors drive the neighborhood bias in factor income flows. There are two candidate explanations for the neighborhood bias. Firstly, local biases in capital income flows caused by local biases in portfolio holdings and secondly, commuter flows across state-borders.

We incorporated commuter flows into the analysis in order to shed light on the relative importance of both factors. We found that a fictitious federal state which is completely isolated from other states in terms of commuting is not subject to a neighborhood bias in factor income flows—at least the statistical significance of the neighborhood bias vanishes for this state. Thus, the apparent neighborhood bias in factor income flows does not primarily reflect a preference for geographically proximate investments, but rather the effect of commuting linkages among states. We believe that this result is of utmost importance since it also suggests that risk sharing itself is not an issue of capital markets solely.

These results were derived by extending the standard risk sharing model to a spatial model. Besides the empirical results of our estimations, a further contribution of our paper is to have established a first link between the risk sharing and the spatial econometrics literature. These fields have been unrelated so far.

[23] Further smoothing of income can be achieved through federal taxes and transfers and by borrowing and lending at the credit market. These channels were not in the focus of this paper.

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