Does Foreign Direct Investment Promote Regional Development in Developed Countries? A Markov Chain Approach for US States

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Abstract:

This paper investigates the effects of inward FDI on per-capita income and growth of the US states since the mid-1970s. Using a Markov chain approach, it shows that both quantitative and qualitative characteristics of FDI affect per-capita income and growth. The empirical findings suggest that employment-intensive FDI, concentrated in richer states, has been conducive to income growth, while capital-intensive FDI, concentrated in poorer states, has not. Consequently, FDI has tended to be associated with weaker rather than stronger income convergence among US states. It appears to be less important whether FDI has been undertaken in the manufacturing sector of US states or in other sectors.

JEL: F23; O18; O51

Keywords: Markov transition probability; likelihood ratio test; FDI; per-capita income; regional development; United States of America

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1 INTRODUCTION

The United States (US) hosted about 1.6 trillion US$ of inward foreign direct investment (FDI) stocks in 2005, which is only 20 percent less than the FDI stocks the US held abroad (UNCTAD 2006, p. 303). In terms of FDI inflows in 2003-2005, the US ranked at the top of all recipient countries (275 billion US$), followed by the United Kingdom and China. The US is also the most favored location for affiliates of the top 100 multinational companies (UNCTAD 2006, p. 34–35). Hence, it is fairly surprising that the economic impact of inward FDI in the US has received only scant attention in the literature, whereas the economic impact of inward FDI in less advanced economies such as China or India as well as its possible repercussions on advanced home countries has been investigated in a large number of studies.

Empirical evidence is particularly scarce when it comes to the question whether inward FDI helps less advanced US regions to narrow the income gap to more advanced US regions (Torau and Goss 2004). This is again in striking contrast to less developed host countries such as China, where it has been shown that FDI inflows contributed to widening regional income disparities, rather than narrowing them (Mody and Wang 1997; Zhang and Zhang 2003; Xing and Zhang 2004). This neglect is rather surprising considering that, even if Washington, DC, is excluded, per-capita income differed by a factor of almost two in 2005 between the most and least advanced US states (Connecticut and Louisiana, respectively).

US states compete aggressively for FDI, especially for new manufacturing plants (Head et al. 1999; Torau and Goss 2004). Graham and Krugman (1995) observe that bidding between US states was fierce even at times when a flood of popular articles and books expressed concern that FDI would reduce employment, worsen the trade deficit and inhibit technological progress in the US.[1] Obviously, regional policymakers offering all sorts of incentives and outright subsidies to foreign investors work on a different assumption, namely that FDI inflows help improve income and employment prospects.[2]

The impact of FDI on regional growth in the US is theoretically ambiguous. Moreover, previous empirical studies on FDI-induced convergence (or divergence) across various host countries or within less advanced host countries offer only limited insights for the US. And the

[1] Casey (1998) lists various state measures through which regional policymakers lured foreign investors. For instance, the state of Alabama is reported to have spent US$ 150,000 per job created to attract a new Mercedes plant in 1994 (Keller and Yeaple 2009).

[2] The Organization for International Investment, the business association representing the US subsidiaries of international companies, reckons that policymakers are right in promoting FDI and stresses FDI-induced employment generation at the state level; for details, see: http://www.ofii.org/insourcing/map/. By contrast, Leichenko and Erickson (1997) note that its minimal impact on regional employment has been one of the key criticisms of FDI in the US.

literature on location choice by foreign investors in the US provides at best indirect evidence on the growth effects of FDI at the state level.

Hence, it is still open to debate whether competition for FDI among US states is just a "mad scramble for the crumbs" (Glickman and Woodward 1989). This paper contributes to this debate by assessing empirically the effects of inward FDI on per-capita income growth of US states since the mid-1970s. Using a Markov chain approach, the paper focuses on whether inward FDI helps poorer states catch up with richer states.

It turns out that the effects of FDI on income growth depend not only on quantitative measures of the density of FDI, but also on qualitative characteristics of FDI. In particular, *employment-intensive* FDI is conducive to long-run income growth, while *capital-intensive* FDI is not. The probability of staying or becoming rich in the long run is significantly higher for US states that have received larger amounts of employment-intensive FDI. Since growth enhancing employment-intensive FDI is concentrated in richer states, FDI has tended to be associated with weaker rather than stonger income convergence among US states since the mid-1970s. These major findings are robust against variations of the empirical setup, and there is little evidence for reverse causality.

The next section discusses the analytical background and the previous literature. Section 3 describes the methodology and the data, Section 4 presents the results, and Section 5 summarizes and offers policy conclusions. The data and SAS code used for this paper are available at http://hdl.handle.net/1902.1/15083.

2 ANALYTICAL BACKGROUND AND PREVIOUS FINDINGS

FDI is widely regarded as a composite bundle of capital inflows, knowledge, and technology transfers (Balasubramanyam et al. 1996). Hence, the impact of FDI on growth is expected to be manifold (Romer 1993; De Mello 1997). FDI may complement local investment and can thus add to production capacity. In addition, FDI can promote growth through productivity gains resulting from spillovers to local firms. As noted by Borensztein et al. (1998), the rate of growth of host economies depends on the extent to which they adopt superior technologies over which multinational companies command. While technology can be diffused through various channels, FDI is considered a major mechanism through which host economies may access advanced technologies (see also Findlay 1978). Likewise, the managerial expertise and knowledge of multinational companies may spill over to local companies. This may promote growth by relaxing human capital constraints in the host economy. Taken together, FDI is supposed to help overcome various bottlenecks which the new growth theory considers essential to prevent returns to capital from decreasing.

This reasoning is fairly common in the literature on the FDI-growth link across countries. Mullen and Williams (2005) argue that the role of FDI in stimulating *regional* growth is similar to that in the national context. Girma and Wakelin (2001) offer several arguments why FDI should have a regional dimension. FDI-related spillovers, including demonstration effects, the acquisition of skills as well as technology transfers, are expected to benefit primarily the region where FDI is located. Accordingly, less advanced regions should have better chances to catch up economically to more advanced regions if they succeed to attract FDI. Alternatively, it may be suspected, however, that FDI-related spillovers are weaker in less advanced regions than in more advanced regions. FDI could rather widen regional disparities if less advanced regions lacked the absorptive capacity to benefit from spillovers. This argument resembles the development economics literature where it has been shown that too large a technological gap between the home and host country tends to compromise the growth effects of FDI in the host country.[3]

The theoretical predictions become still more ambiguous when assessing the role of FDI at the regional level of highly developed countries such as the US. For a start, the capital-augmenting effect of FDI may be less relevant than in a developing country context.[4] Capital mobility within the US is considerably higher than that across countries, as US financial markets are well developed and the home bias of investors affects capital flows within the US to a lesser degree than capital flows in less developed countries.[5]

Additional ambiguity arises once it is taken into account that most theoretical discussions on the positive role of FDI in the host countries refer to the transmission of superior technology, taking it for granted that foreign-owned firms possess superior technology.[6] However, this assumption may not hold if foreign companies undertake FDI in a technologically most

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3 See Mayer-Foulkes and Nunnenkamp (2009) and the references given there. Findlay (1978: 2) argues that the larger the gap in technology, the faster the transmission, provided that “the disparity must not be too wide for the thesis to hold”. Blomström and Kokko (1998) as well as Blomström et al. (2001) conclude from reviews of the literature that spillovers depend on the absorptive capacity of local firms, with small gaps encouraging spillovers and large gaps inhibiting them.

4 The capital-augmenting effect of FDI in the US may also be constrained by the prominent role of mergers and acquisitions (M&As) (Bobonis and Shatz 2007). Unlike greenfield FDI, M&As amount to a change in ownership of existing production capacity. Nevertheless, M&As are not necessarily inferior to greenfield FDI. Both types of FDI may involve transfers of technology and managerial skills, and they may offer access to new foreign markets and sources of intermediate inputs. While the empirical evidence on the growth effects of different types of FDI is ambiguous, the findings of several studies suggest that advanced host countries such as the US tend to benefit from M&As (e.g., Conyon et al. 2002; Wang and Wong 2009).

5 Barro et al. (1995) note that substantial borrowing and lending flows across US state borders. The assumption of a closed economy would thus be difficult to justify for US states (see also Mullen and Williams 2005). This is in contrast to Chinese provinces where factor market segmentation prevented the equalization of returns to capital and labor (Zhang and Zhang 2003). Yet, the model of Barro et al. (1995) implies that physical capital mobility tends to raise the rate of convergence only modestly unless human capital, too, is mobile. Francis et al. (2007) report evidence of a home bias of investments in the US which is primarily due to a lower effectiveness of external monitoring across larger geographical distances.

6 According to Lipsey (2002, p. 34), “the benefits to the host country, if they exist, stem mainly from the superior efficiency of the foreign-owned operations.” Likewise, Girma and Wakelin (2001, p. 2) stress that the firm-specific assets that multinational companies are supposed to have provide the theoretical basis for the expectation of spillovers from foreign affiliates.

advanced country. Keller and Yeaple (2009) argue that the productivity of US firms is perhaps higher than in any other country of the world.[7] Hence, the US should attract a different type of FDI than less developed host countries, namely an asset seeking rather than an asset exploiting type (Dunning 1999). Asset seeking FDI, which has also been termed technology or knowledge seeking FDI (Cantwell 1989), is motivated by the investing company's search of knowledge and technologies that are not available in its home country. In other words, the investing company seeks to draw on superior knowledge and technologies, rather than transferring knowledge and technologies from which the host country may benefit through spillovers.[8]

The empirical investigation of Chung and Alcácer (2002) reveals that the bulk of manufacturing FDI in the US took place in lower-tech industries and was located in states with relatively low R&D intensity. Yet, these authors provide evidence that asset seeking FDI has played a role in the US, though only in research-intensive industries. Moreover, they find that the asset seeking motive is not restricted to FDI from technically lagging source countries, but is also driving FDI from source countries that are similarly advanced as the US (see also Cantwell and Janne 1999).

The focus of the empirical literature on FDI in the US is on location choice, i.e., the determinants of FDI, rather than its effects on regional development.[9] If only implicitly, this strand of the literature tends to assume that FDI is an important mechanism to promote growth. For example, Friedman et al. (1996, p. 209) argue that policymakers wishing to foster economic development need to know about FDI determinants. As mentioned above, however, it cannot be taken for granted that a region attracting FDI will also derive benefits from it. Moreover, the relevant question in the present context is whether FDI-related benefits will go where they are needed most, i.e., to lagging US states trying to catch up with more advanced US states.

The literature on FDI determinants may offer some indirect evidence on the regional distribution of FDI-related benefits. For example, empirical findings put into doubt earlier hopes that FDI would help revitalize and reindustrialize relatively poor regions in the US. This is even though Casey (1998) observed that foreign investors shifted their attention somewhat from large industrial states such as California, New York, Texas, New Jersey or Illinois towards south-eastern states (notably, North Carolina, Georgia and Tennessee) in the 1980s. Several studies suggest that FDI added to the concentration of industrial activity within the US by locating in relatively advanced states and where agglomeration economies could be reaped

[7] Yet, Keller and Yeaple (2009) find FDI-related spillovers to be important for the US. The explanation they provide is that the relatively high average productivity of US firms masks a large amount of heterogeneity across US firms.

[8] Likewise, Mullen and Williams (2005) consider the possibility that foreign direct investors in the US may be more concerned with *receiving* technological spillovers from companies in the host region.

[9] In addition to studies mentioned in the text, examples of this strand of the literature include Hines (1996), Keller and Levinson (1999), as well as Coughlin and Segev (2000).

(Coughlin et al. 1991; Head et al. 1995; Friedman et al. 1996; Head et al. 1999; Bobonis and Shatz 2007). In this way, FDI may have contributed to the spatial density of economic activity which, according to Ciccone and Hall (1996), explains much of the variation of productivity across states. However, most studies focus on FDI in manufacturing and, thus, ignore the increasing role of FDI in services.[10]

By contrast, the effects of FDI on regional economic development in the US have received scant attention in the literature so far.[11] This is even though Greenstone and Moretti (2004) provide a most interesting analysis of the welfare implications of successfully bidding for large new plants at the county level. In contrast to Glickman and Woodward's (1989) above noted verdict, these authors reject the view that the provision of subsidies to attract investors reduces local residents' welfare. Their sample of 82 "Million Dollar Plants" includes foreign investors (notably automobile assemblers such as Volvo, BMW and Mercedes-Benz), but the sample clearly appears to be dominated by domestic US investors. Crain and Lee (1999) apply extreme-bounds analysis to assess the sensitivity of "numerous control variables" identified by earlier studies as potentially relevant to state economic performance: FDI is not considered at all! Apart from the aforementioned study of Torau and Goss (2004), we are aware of just one recent study specifically addressing the FDI-growth link at the level of US states:[12] Mullen and Williams (2005) estimate a neoclassical model of conditional convergence (Mankiw et al. 1992), extended by the FDI density as an additional determinant of the steady state income. In a fixed effects panel regression for the 48 contiguous US states and four five-year averages (1977–1997), they show different specifications of the FDI variable to have a significantly positive impact on income growth. This study suffers from implausible estimates for other model parameters, however. Most notably, the effect of population growth on per-capita income growth is estimated to be significantly positive, whereas it should be negative according to the underlying neoclassical growth model. In addition, it is not taken into account that the growth effects may depend on the characteristics of FDI. Finally, the elastic-

[10] Bobonis and Shatz (2007) provide a major exception. As noted by these authors, the majority of FDI in the US is outside manufacturing. In terms of stocks, total manufacturing accounted for just about one third of overall FDI in the US in 2005 (BEA online data on historical cost basis). This is why we follow Bobonis and Shatz in considering FDI in all sectors in the following. However, we account for the sectoral structure of FDI and test whether the growth impact of FDI depends on the ratio of FDI in manufacturing to FDI in other sectors.

[11] For the United Kingdom, Girma and Wakelin (2001) find that (i) FDI-induced spillovers in the electronics industry are mostly confined to the region where FDI is located (possibly due to lower transport and communication costs within regions), and (ii) spillovers are stronger in more developed regions (possibly because less developed regions lack technological absorptive capacity). Taken together, this suggests that FDI may widen regional disparity.

[12] In addition, Feliciano and Lipsey (1999) use state and industry-wise FDI data to assess whether foreign-owned subsidiaries pay higher wages than US firms, which they find to be the case, though not in manufacturing. Leichenko and Erickson (1997) find that FDI was positively associated with US states' export performance in 1980–1991. In concluding, these authors note that it would be interesting to know whether favorable export effects translated into higher regional economic growth and, particularly, into growth in employment. Gelan et al. (2007) show that inward FDI has improved the relative employment opportunities of skilled black workers in the manufacturing sector and, thus, reduced racial employment disparity in the US, but they do not consider the regional dimension.

ity of income growth with respect to FDI may differ between states with low and high income levels, or between states with low and high FDI densities.

3 APPROACH AND DATA

The present paper complements studies using the convergence regression approach by employing the distribution dynamics approach to assess the relationship between FDI and the economic performance of US states.[13] The convergence regression approach is usually based on the concept of conditional β convergence, which is rooted in a Solowian model of exogenous economic growth. This approach focuses on investigating the transition of a representative economy's actual per-capita income level towards its individual steady state per-capita income level. In this context, FDI may be regarded as one factor that conditions an economy's steady state income.

In contrast, the distribution dynamics approach is based on the concept of σ convergence. It focuses on investigating the dynamics of the entire distribution of incomes across economies. Following Bickenbach and Bode (2003), we extend this approach to include FDI as a factor that conditions the evolution of the distribution of income across US states. By estimating a larger number of transition probabilities rather than a single regression parameter, we account for differences in the effects of FDI on income between economies with low and high income levels, or between economies with low and high FDI densities.

Compared to the convergence regression approach, the distribution dynamics approach allows drawing inferences on a broader variety of issues related to the interplay between FDI and income growth (see below for details).[14] At the same time, the distribution dynamics approach straightforwardly concentrates on the variable of principal interest (here, FDI) and avoids imposing a restrictive functional form on the relationship between FDI and income growth. It is, however, not rooted explicitly in economic theory and does not establish unambiguously a causal relationship between FDI and income growth. It is nevertheless not necessarily inferior to the convergence regression approach in these respects. Causality is also an issue in the convergence regression approach, even if FDI is instrumented properly, because FDI is added in an ad hoc manner to convergence regression models rather than being derived consistently from the Solowian growth model.[15] We address endogeneity concerns at least tentatively in

[13] Magrini (2004) and Durlauf et al. (2005), among others, provide extensive evaluations of convergence regression and distribution dynamics approaches.

[14] In convergence regressions, the elasticity of income growth with respect to FDI is often assumed to be the same for all host economies. For instance, Mullen and Williams (2005) estimate a single elasticity of income growth with respect to FDI, which they assume to be the same for all US states. This limitation could only be mitigated by interacting other explanatory variables in the convergence regressions, including initial-year income, with FDI terms or indicator variables that group together states with similar FDI densities.

[15] See Levine and Renelt (1992) and Levine and Zervos (1993) for a critical discussion of the robustness of control variables in convergence regressions.

the appendix by showing that states with higher initial per-capita income do not generally attract more (or less) FDI than those with lower per-capita income.

This paper estimates separate Markov transition matrices for M subsamples of the 51 US states with differing FDI densities, and investigates to what extent the income growth and convergence behavior differs between these subsamples. Assuming that the distribution of per-capita income across US states follows a finite first-order Markov chain with stationary transition probabilities, and dividing the spectrum of possible per-capita incomes into N mutually exclusive and exhaustive income classes, the Markov chain for the mth subsample is characterized by the (NxN) Markovian transition matrix,

$$\mathbf{\Pi}_m = \begin{bmatrix} p_{11|m} & p_{12|m} & \cdots & p_{1N|m} \\ p_{21|m} & p_{22|m} & \cdots & p_{2N|m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1|m} & p_{N2|m} & \cdots & p_{NN|m} \end{bmatrix}, \tag{1}$$

$p_{ij|m} \geq 0 \; \forall \; i, j = 1, \ldots, N, \; \sum_{j=1}^{N} p_{ij|m} = 1, \; m = 1, \ldots, M$, which describes the dynamics of the Markovian process over time, and by the initial distribution $\mathbf{h}_m(0)$,

$$\mathbf{h}_m(0) = (h_{1|m}(0), h_{2|m}(0), \ldots, h_{N|m}(0)), \tag{2}$$

$h_{i|m}(0) \geq 0 \; \forall \; i = 1, \ldots, N, \; \sum_{i=1}^{N} h_{i|m}(0) = 1$.

The transition matrix, Π_m, reports, in each cell, the probability, $p_{ij|m}$, that a US state in the mth subsample will be in income class j at any time t+1, conditional on having been in income class i at time t. Starting from time 0, the income distribution will be $\mathbf{h}_m(k)=\mathbf{h}_m(0)\Pi_m{}^k$ after k transition periods. Provided the Markov chain is regular, this distribution converges to a limiting (or "ergodic") distribution, $\mathbf{h}_m$*,

$$\mathbf{h}_m{}^* = \lim_{k\to\infty} \mathbf{h}_m(0)\mathbf{\Pi}^k = diag\left(\lim_{k\to\infty} \mathbf{\Pi}_m^k\right), \tag{3}$$

which is independent of the initial distribution $\mathbf{h}_m(0)$. A Markov chain is regular if, for some positive integer x, all entries of the matrix Π^x are positive. The limiting distribution maps the information contained in the (NxN) transition matrix into a single (1xN) vector. It characterizes the steady state to which the distribution converges after a sufficient number of transition periods. Although the limiting distribution is purely hypothetical, it is frequently more informative than the transition matrix itself about the direction in which the income distribution is evolving during the sample period. The independence of the limiting distribution from the initial distribution is an important property in the context of the present paper (see below).

The transition matrices for the M subsamples of states with differing FDI intensities can be compared statistically by testing the hypothesis that they are equal to each other, i.e., H0: $\forall\, m$: $p_{ij|m} = p_{ij}$, $m = 1, \ldots, M$, $i, j = 1, \ldots, N$. p_{ij} denotes the probability of a transition from class i to class j in the US on aggregate. The (NxN) transition matrix $\Pi = \{p_{ij}\}$ is estimated from the entire sample of all 51 states. The appropriate likelihood ratio (LR) test statistic is

$$LR^{(M)} = 2\sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_{i|m}} n_{ij|m} \ln\frac{\hat{p}_{ij|m}}{\hat{p}_{ij}} \sim \text{asy } \chi^2 \left(\sum_{i=1}^{N}(a_i-1)(b_i-1)\right) \quad (4)$$

(Anderson and Goodman 1957; Bickenbach and Bode 2003). The hats (^) in equation (4) indicate estimated values; $n_{ij|m}$ denotes the absolute number of observed annual transitions from class i to class j within the m^{th} subsample; $A_{i|m}$ the set of non-zero transition probabilities in the i^{th} row of the transition matrix for the m^{th} subsample, Π_m; a_i the number of non-zero transition probabilities in the i^{th} row of the transition matrix from the entire sample, Π; and b_i the number of subsamples for which a positive number of empirical observations is available for the i^{th} row.

The LR test in (4) will not reject the null hypothesis if all states with similar initial income levels exhibit, on aggregate, similar growth prospects irrespective of their FDI densities. In this case, we conclude that all states converge to the same limiting (steady-state) income distribution, i.e., $\mathbf{h}^* = \mathbf{h}_m^*\ \forall\ m = 1, \ldots, M$. $\mathbf{h}^*$ denotes the limiting distribution for the entire sample of US states. This equality does not imply that all states have to grow at the same rate; richer states may still grow slower or faster than poorer states. It just implies that the FDI density makes no difference. The LR test will reject the null hypothesis, however, if states with similar initial income levels exhibit different growth prospects depending on their FDI densities. In this case, we conclude that the states converge to different limiting (steady-state) income distributions, i.e., $\mathbf{h}_m^* \neq \mathbf{h}_{m'}^*$, $m \neq m'$, for at least one pair of subsamples (m, m').

We draw three types of inferences from these estimates. First, comparing the limiting distributions across the M subsamples indicates whether a higher or a lower FDI density is more conducive to income growth. If a higher FDI density is more conducive to income growth, the limiting distributions for the subsamples with higher FDI densities will exhibit higher probabilities in high-income classes than those for the subsamples with lower FDI densities. The independence of the limiting from the initial distributions is important here. It allows drawing inferences on the differences between the subsamples in their steady-state income distributions that are independent of the actual income distributions. Second, we draw inferences from comparing the initial and limiting distributions of specific subsamples of states with similar FDI densities. This comparison indicates whether the subsample-specific income distributions tend to narrow or widen. And third, we compare these subsample-specific convergence patterns to the aggregate, national convergence pattern. This comparison indicates whether the convergence among states with similar FDI densities has been supportive of, or working against the convergence among all states.

For the present purpose, the transition probabilities from time t to t+1, p_{ij} and $p_{ij|m}$, are estimated from a panel of annual transitions of the logged relative per-capita personal income (PCPI) levels in the 51 US states over the period 1977 – 2005. The observed absolute per-capita income by state is demeaned by the national average at each point in time to control for national inflation, business cycles, and global or national shocks. The 1,428 observed annual transitions (28 years from 1977 to 2004; 51 states) are divided into $N = 6$ equally sized income classes such that the first income class comprises the 238 state-year observations with the lowest logged relative PCPI (≤ -0.20251), and the sixth income class the 238 state-year observations with the highest logged relative PCPI (> 0.088173). The mean per-capita income falls into the fourth class, which ranges from –0.06 to 0.010322. The observations for the final year of the transition, t+1, are divided into the same number of classes, using as upper bounds the upper bounds of the equally sized income classes for the initial year.

In addition, we divide the total population of the 51 states into $M = 3$ subsamples according to their FDI density, such that the first subsample comprises the 17 states with the lowest FDI density, and the third subsample the 17 states with the highest FDI density. The upper bounds of these subsamples depend on the indicator of the FDI density, which will be specified below. These subsamples are defined according to the average of the states' logged relative FDI densities in the first decade of the observation period (1977–1986). The states' annual FDI densities are divided by the contemporary national FDI density to control for inflation, cycles, and common shocks. We use only the first decade of the sample period for classifying states according to their FDI density to capture the *long-run* effects of FDI on the evolution of the income distribution.[16] The period of ten years is sufficiently long to ensure that the empirical results are independent of random variations in, and shocks to the FDI density in single years.

We measure the FDI density by two alternative quantitative indicators. The first indicator, subsequently labeled "density of FDI stocks", emphasizes the monetary dimension of FDI, given by the value of gross property, plant and equipment owned by foreign affiliates in all sectors. FDI stocks are normalized by the gross state product (GSP) to make the indicator independent of the absolute sizes of the states. The density of FDI stocks is the FDI indicator used most frequently in the literature (e.g., Leichenko and Erickson 1997; Bobonis and Shatz 2007). The second indicator, subsequently labeled "density of FDI employment", emphasizes the real dimension of FDI, given by the number of employees working full-time or part-time

[16] The results do not change much, however, if we define the FDI subsamples from average FDI densities over the whole period under study, 1977 – 2005.

in foreign affiliates in all sectors. FDI employment is normalized by the total employment in the respective state.[17]

We consider two alternative indicators of FDI density to take into account that the effects of FDI on the income distribution may depend on measurement. Keller and Yeaple (2009) argue that mismeasurement of FDI-related economic activity will bias the estimated FDI impact downwards. Measurement problems may concern FDI stocks in the first place, even though FDI stocks have been used extensively in the empirical literature on FDI effects. Relating to gross book values on a historical cost basis, they may be a flawed indicator of FDI-related activities such as production, sales, value added or employment that may promote economic growth in the host economy.[18]

And indeed, Figure 1 provides first indications that measurement matters for inward FDI in the US. The distribution of FDI across US states differs considerably between the two measures of FDI density. Only ten states, including the two Carolinas, Tennessee, Georgia and Louisiana in the south, Maine, Delaware, and West Virginia in the northeast, as well as Hawaii and Alaska are classified as having a high density in terms of both FDI stocks (Figure 1.a) and FDI employment (Figure 1.b).[19] The states located in a belt ranging from Wyoming and North Dakota in the north to Arizona in the south feature a high density in terms of FDI stocks but not in terms of FDI employment. By contrast, most of the New England states feature a high density in terms of FDI employment but not in terms of FDI stocks.

In addition to the *quantitative* measures of FDI density, *qualitative* or structural characteristics of FDI may impact significantly on its growth effects. Ideally, the quality of FDI would be captured by the degree to which FDI-related productivity effects spill over to local companies. Spillovers tend to be more pronounced if (backward and forward) linkages between foreign and local companies are relatively strong, and the fluctuation of workers is relatively high.[20] However, the data required for assessing the scope of such interactions between foreign- and domestically-owned firms in US states are not available. Therefore, we turn to two structural characteristics of FDI that may indicate the potential of spillovers at least tentatively, namely the sectoral affiliation of foreign-owned firms and the employment intensity of FDI.

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[17] All FDI-related data are available from the U.S. Bureau of Economic Analysis (BEA; http://www.bea.gov/). The data on gross state product (GSP) are also available from BEA. The data on employment by states are available from the Bureau of Labor Statistics (http://www.bls.gov/).

[18] There is at least some empirical evidence suggesting that FDI is not properly measured by stock data. Mayer-Foulkes and Nunnenkamp (2009) employ various measures of outward US FDI, including FDI stocks and employment of US affiliates, in a large number of host countries. They find that the growth effects of FDI tend to be understated, compared to almost all alternative measures of FDI, when using stock data. By contrast, the growth effects turn out to be particularly strong when using the employment data of affiliates.

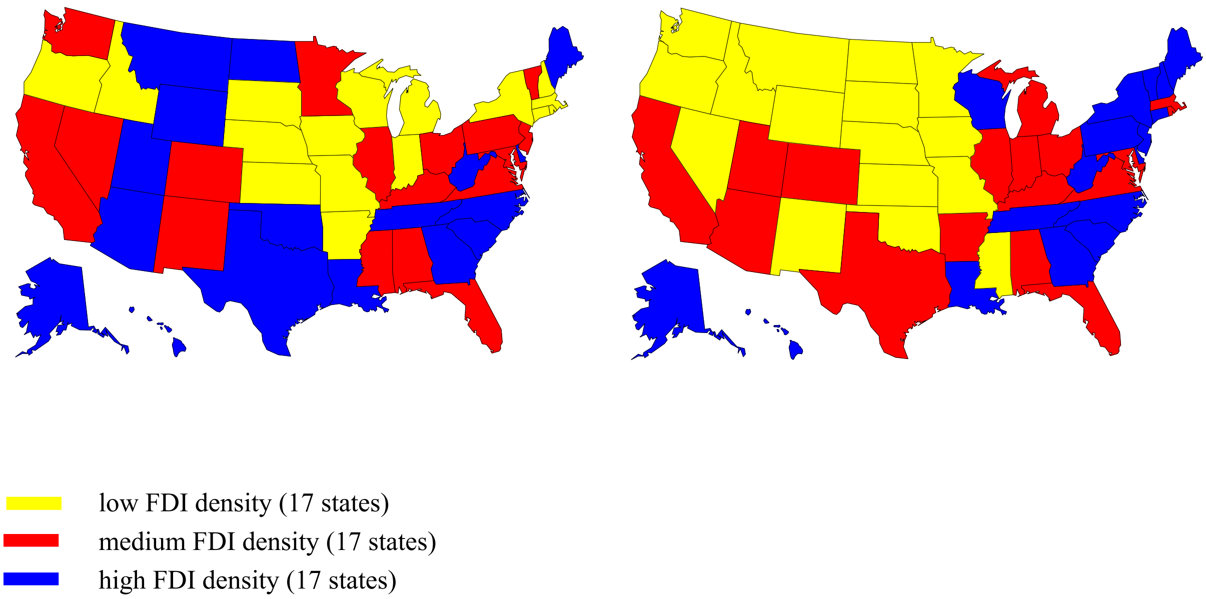
[19] The results presented in this paper do not change notably if Alaska, Hawaii and Washington, DC, are excluded from the analysis (see the Appendix).

[20] For example, an intensive use of local inputs by foreign-owned firms is widely expected to trigger technological and knowledge spillovers. The fluctuation of workers may benefit the local economy through human-capital externalities.

Figure 1: FDI densities in US states, 1977–1986

a. density of FDI stocks

b. density of FDI employment



The sectoral affiliation matters to the extent that the potential for productivity-enhancing spillovers differs across sectors. FDI-related transfers of technology and knowledge are frequently held to primarily occur in the manufacturing sector (e.g., Alfaro 2003). In contrast to the primary and tertiary sectors, the manufacturing sector is supposed to have a "broad range of linkage-intensive activities" (UNCTAD 2001, p. 138). This may create positive externalities and allow local producers to draw on a larger variety of inputs and, thereby, increase their productivity (Rodriguez-Clare 1996).[21] Hence, we consider the ratio of manufacturing to nonmanufacturing FDI ("manufacturing-nonmanufacturing ratio" for short), to be the first qualitative characteristic of FDI. We investigate whether US states with a higher manufacturing-nonmanufacturing ratio have a higher probability of staying or becoming rich. More precisely, this ratio relates FDI stocks (or FDI employment) in the manufacturing sector to FDI stocks (or FDI employment) in all other sectors (total economy minus manufacturing). This ratio is standardized by the contemporary national manufacturing-nonmanufacturing ratio, logged, and calculated as the average for the period 1977 – 1986.

The employment intensity of FDI matters to the extent that, compared to physical-capital-intensive FDI, labor- and human-capital-intensive FDI may have stronger productivity effects on the local economies by offering benefits from labor pooling and human-capital externalities. Hence, we consider the ratio of FDI stocks and FDI employment ("capital-labor ratio"

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[21] Aykut and Sayek (2007) suspect that technology and knowledge spillovers in manufacturing are most likely if FDI is motivated by efficiency-seeking reasons.

for short) to be the second qualitative characteristic of FDI. Again, this ratio is standardized by the contemporary national capital-labor ratio, logged, and averaged over the period 1977 – 1986.

Figure 2 depicts the assignment of the 51 US states to the respective two subsamples when considering below and above average values of the qualitative characteristics just described. The ratios of manufacturing to nonmanufacturing FDI (map a in terms of FDI stocks, and map b in terms of FDI employment), as well as the capital-labor ratio (map c) exhibit a clear-cut east-west divide. Foreign-owned firms tend to be more employment-intensive and more concentrated in manufacturing industries in most of the eastern states. This indicates that FDI in the manufacturing sector tends to be more employment-intensive than FDI in other sectors. This would explain that FDI has a high capital-labor ratio in states such as Alaska where foreign firms are predominantly engaged in resource-extracting industries. More surprisingly, the employment intensity of FDI is also low in states such as Hawaii and Florida where FDI in services related to tourism figures prominently. Figure 2 also indicates that the ratio of manufacturing to nonmanufacturing FDI hardly depends on whether it is measured in terms of FDI stocks or FDI employment (maps a and b). In the following, we will therefore use only the ratio in terms of FDI employment for investigating the income effects of the sectoral pattern of FDI.

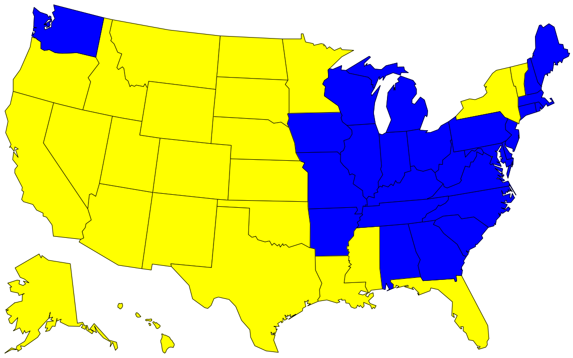
The relative impact of the two qualitative characteristics of FDI on income can be investigated in the framework used here by further dividing the subsamples of states with differing FDI densities. Specifically, we divide the subsamples of states with low and high FDI densities further into states with a low and a high manufacturing to nonmanufacturing ratio, or capital-labor ratio of FDI. Using the density of FDI stocks and the capital-labor ratio as an example, this results in four subsamples:

1. states with a below-average density of FDI stocks and a below-average capital-labor ratio;
2. states with a below-average density of FDI stocks and an above-average capital-labor ratio;
3. states with an above-average density of FDI stocks and a below-average capital-labor ratio;
4. states with an above-average density of FDI stocks and an above-average capital-labor ratio.

Similar subsamples are defined for the density of FDI employment, and for the ratio of FDI in manufacturing to FDI in nonmanufacturing. We prefer dividing the entire sample into only two (rather than three) subsamples for the FDI density in this step of the analysis to economize on the number of transition probabilities to be estimated.

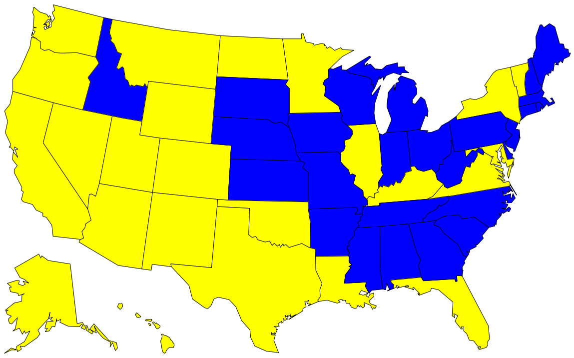
Figure 2: Manufacturing-nonmanufacturing ratios and capital-labor ratios of FDI in US states, 1977–1986

a. manufacturing-nonmanufacturing ratio of FDI (stocks)



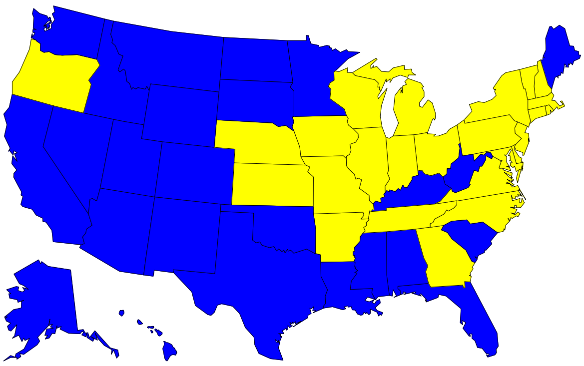
below-average manufact.-nonmanufact. ratio
above-average manufact.-nonmanufact. ratio

b. manufacturing-nonmanufacturing ratio of FDI (employment)



below-average manufact.-nonmanufact. ratio
above-average manufact.-nonmanufact. ratio

c. capital-labor ratio of FDI (all sectors)



below-average capital-labor ratio
above-average capital-labor ratio

4 RESULTS

4.1 FDI Density and Per-capita Income

To put the subsequent analysis of the effects of inward FDI on the evolution of the per-capita income distribution among the US states into perspective, Table 1 depicts the (6x6) Markovian transition matrix, Π in equation (1), for the entire sample of 1,428 observations (28 annual transitions 1977 – 2004 in the 51 US states). Table 1 also depicts the initial distribution, $\mathbf{h}(t)$ in equation (2), in terms of absolute and relative frequencies (columns labeled "initial distribution"), as well as the limiting distribution the Markov chain converges to ($\mathbf{h}^*$ in equation 3; row labeled "limiting").

The initial distribution is uniform by construction. Comparing the limiting to the initial distribution indicates that there has been a rather weak income convergence across the US states during the last about three decades: The limiting distribution shows somewhat higher probabilities in the middle income classes, and somewhat lower probabilities in the extreme classes 1 and 6. This result is perfectly in line with earlier results reported by Rey (2001), and Bickenbach and Bode (2003), among others.

Yet the limiting distribution differs only modestly from the initial distribution, which indicates that the income distribution across US states is already fairly close to its steady state. The estimated transition matrix offers more detailed insights into the mechanics of this convergence process. It shows that states with below-average income levels (classes 1 – 3) face a somewhat higher probability of moving up the income ladder than of moving down the income ladder. The opposite is true for states with relatively high income levels (classes 4 – 6).

Table 1 – Evolution of the income distribution across the 51 US states, 1977–2005

PCPI class	initial distribution		final distribution					
	N	%	1	2	3	4	5	6
1	238	0.167	0.891	0.105	0.004	0.000	0.000	0.000
2	238	0.167	0.105	0.811	0.080	0.004	0.000	0.000
3	238	0.167	0.004	0.063	0.828	0.105	0.000	0.000
4	238	0.167	0.000	0.000	0.097	0.824	0.080	0.000
5	238	0.167	0.000	0.000	0.000	0.084	0.866	0.050
6	238	0.167	0.000	0.000	0.000	0.000	0.067	0.933
limiting	1428	1.000	0.140	0.138	0.181	0.203	0.193	0.145

Density of FDI Stocks

The transition matrices estimated for the three subsamples of US states with low, medium, and high densities of FDI stocks are given in Table 2. The LR test of the hypothesis that these three transition matrices are equal to each other is clearly rejected at an error probability of virtually zero (LR = 57.0; 26 degrees of freedom).[22] The limiting distributions indicate that states with a low density of FDI stocks will tend to be *richer* in the long run than states with a high density of FDI stocks. The probability of ending up in one of the two highest income classes, 5 and 6, is estimated to be 0.438 (0.078 + 0.360; first, upper panel of Table 2) for states with a low density of FDI stocks, but only 0.129 (0.081 + 0.038; third, lowest panel of Table 2) for states with a high density of FDI stocks. Correspondingly, the probability of ending up in one of the three below-average income classes is only 0.35 for states with a low density of FDI stocks, but 0.8 for states with a high density of FDI stocks.

The initial distributions indicate that the states with a low density of FDI stocks were, on average, already richer from the start. The probability of starting from one of the two highest income classes is 0.323 (0.086 + 0.237; first panel of Table 2) for states with a low density of FDI stocks, but only 0.174 (0.09 + 0.084; third panel) for states with a high density of FDI stocks. However, the initial income gap is smaller than the gap in the limiting distribution. This indicates that states with lower density of FDI stocks have more favorable growth prospects than states with higher density of FDI stocks, even though the former are already richer to start with. We infer from this that FDI, if measured in terms of stocks, did not go along with faster overall income convergence among all US states during the last about three decades. If anything, FDI has been associated with less income convergence.

As noted in Section 3, caution is required with respect to causal inferences. States with lower income or less favorable growth prospects may have attracted higher FDI stocks. Arguably, higher FDI stocks may even have helped prevent still weaker income growth in states with unfavorable growth prospects to start with.[23] Robustness checks, discussed in the appendix, yield little evidence of reverse causality, however.

Density of FDI Employment

The transition matrices estimated for the three subsamples of US states with low, medium, and high densities of FDI employment are given in Table 3, which has the same shape as Table 2. The LR test rejects the hypothesis that these three transition matrices are equal to

[22] Robustness checks for various different numbers of PCPI classes and various different numbers of FDI density subsamples indicate that this result does not depend on the way we discretize income and FDI density. Table Table A1 in the appendix shows that the LR test of equality of the transition matrices for specific subsamples is not rejected at the 5% level for only one out of 36 specifications.

[23] We are grateful to an anonymous referee for pointing out this alternative interpretation.

each other at an error probability of only 6.4% (LR = 37.8; 26 degrees of freedom), thus slightly exceeding the conventional 5% threshold. Robustness checks for various specifica tions with different numbers of PCPI classes and FDI subsamples yield, however, error probabilities far below 5% (see lower panel of Table A1 in the appendix).[24] We conclude from these checks that the income dynamics differ significantly between US states with different densities of FDI employment.

Table 2: Evolution of the income distribution across the 51 US states, 1977–2005, by the density of FDI stocks

PCPI class	initial distribution		final distribution					
	N	%	1	2	3	4	5	6
			low density of FDI stocks 1977–1986 (<= –0.4305)					
1	48	0.101	0.875	0.125	0.000	0.000	0.000	0.000
2	40	0.084	0.150	0.700	0.150	0.000	0.000	0.000
3	124	0.261	0.000	0.040	0.847	0.113	0.000	0.000
4	110	0.231	0.000	0.000	0.118	0.809	0.073	0.000
5	41	0.086	0.000	0.000	0.000	0.195	0.683	0.122
6	113	0.237	0.000	0.000	0.000	0.000	0.027	0.973
limiting	476	1.000	0.071	0.059	0.220	0.210	0.078	0.360
			medium density of FDI stocks 1977–1986 (<= 0.12199)					
1	79	0.166	0.924	0.076	0.000	0.000	0.000	0.000
2	42	0.088	0.143	0.833	0.024	0.000	0.000	0.000
3	18	0.038	0.000	0.000	0.833	0.167	0.000	0.000
4	98	0.206	0.000	0.000	0.020	0.888	0.092	0.000
5	154	0.324	0.000	0.000	0.000	0.058	0.916	0.026
6	85	0.179	0.000	0.000	0.000	0.000	0.082	0.918
limiting	476	1.000	0.000	0.000	0.038	0.314	0.493	0.155
			high density of FDI stocks 1977–1986 (> 0.12199)					
1	111	0.233	0.874	0.117	0.009	0.000	0.000	0.000
2	156	0.328	0.083	0.833	0.077	0.006	0.000	0.000
3	96	0.202	0.010	0.104	0.802	0.083	0.000	0.000
4	30	0.063	0.000	0.000	0.267	0.667	0.067	0.000
5	43	0.090	0.000	0.000	0.000	0.070	0.860	0.070
6	40	0.084	0.000	0.000	0.000	0.000	0.150	0.850
limiting	476	1.000	0.230	0.317	0.249	0.085	0.081	0.038

[24] The error probabilities are larger than 5% for only five of the 36 specifications checked in the appendix. See the lower panel of Table A1.

Table 3: Evolution of the income distribution across the 51 US states, 1977–2005, by the density of FDI employment

PCPI class	initial distribution		final distribution					
	N	%	1	2	3	4	5	6
			low density of FDI employment 1977–1986 (<= –0.35044)					
1	92	0.193	0.848	0.141	0.011	0.000	0.000	0.000
2	90	0.189	0.156	0.744	0.089	0.011	0.000	0.000
3	115	0.242	0.009	0.070	0.809	0.113	0.000	0.000
4	65	0.137	0.000	0.000	0.215	0.677	0.108	0.000
5	73	0.153	0.000	0.000	0.000	0.110	0.877	0.014
6	41	0.086	0.000	0.000	0.000	0.000	0.073	0.927
limiting	476	1.000	0.209	0.190	0.271	0.152	0.150	0.028
			medium density of FDI employment 1977–1986 (<= 0.06721)					
1	79	0.166	0.937	0.063	0.000	0.000	0.000	0.000
2	54	0.113	0.093	0.852	0.056	0.000	0.000	0.000
3	55	0.116	0.000	0.073	0.800	0.127	0.000	0.000
4	112	0.235	0.000	0.000	0.054	0.875	0.071	0.000
5	104	0.218	0.000	0.000	0.000	0.077	0.885	0.038
6	72	0.151	0.000	0.000	0.000	0.000	0.069	0.931
limiting	476	1.000	0.191	0.131	0.100	0.237	0.220	0.122
			high density of FDI employment 1977–1986 (> 0.06721)					
1	67	0.141	0.896	0.104	0.000	0.000	0.000	0.000
2	94	0.197	0.064	0.851	0.085	0.000	0.000	0.000
3	68	0.143	0.000	0.044	0.882	0.074	0.000	0.000
4	61	0.128	0.000	0.000	0.049	0.885	0.066	0.000
5	61	0.128	0.000	0.000	0.000	0.066	0.820	0.115
6	125	0.263	0.000	0.000	0.000	0.000	0.064	0.936
limiting	476	1.000	0.042	0.069	0.133	0.199	0.199	0.357

The estimated relationship between FDI and income dynamics virtually turns into its opposite if the FDI density is measured in terms of employment shares of foreign affiliates rather than in terms of FDI stocks. The limiting distributions now indicate that states with a low density of FDI tend to be *poorer* in the long run than states with a high density of FDI. The probability of ending up in one of the three below-average income classes, 1 – 3, is estimated to about two third (0.674 = 0.209 + 0.190 + 0.271) for states with a low FDI employment density, but only about one fourth (0.244 = 0.042 + 0.069 + 0.133) for states with a high FDI employment density. And the initial distributions now indicate that the states with a higher FDI density were, on average, already richer from the start. The probability of starting from one of the two highest income classes is 0.391 (0.128 + 0.263; third panel of Table 3) for states with a high FDI employment density but only 0.239 (0.153 + 0.086; first panel) for states with a low FDI employment density. Moreover, the gaps between initial and limiting income distributions now indicate that states with higher FDI density have more favorable growth prospects than states with higher FDI density.[25] These striking differences corroborate Keller and Yeaple's (2009) point that measurement of FDI makes a big difference. As mentioned in Section 3, measurement problems may concern FDI stocks in the first place. It can thus not be ruled out that the results based on FDI stocks (Table 2) are biased downwards, similar to what Mayer-Foulkes and Nunnenkamp (2009) find for outward FDI by the US in a large number of host countries. Another possibility is that the income and growth effects of FDI depend crucially on qualitative characteristics of FDI, notably on whether FDI is physical capital-intensive or employment-intensive. This possibility is explored in the subsequent section.

In spite of these differences, the two indicators of FDI yield similar results in terms of the relationship between FDI and income convergence. Similar to Table 2, Table 3 reveals that the initial income gap between states with low and high FDI density is smaller than the gap in the limiting distribution. We infer from this that FDI, irrespective of whether it is measured in terms of stocks or employment, has been associated with weaker, rather than stronger, overall income convergence among all US states.

4.2 Qualitative Characteristics of FDI and Per-capita Income

Capital-labor Ratio of FDI

As discussed in Section 3, employment-intensive FDI may offer more favorable prospects for becoming or staying rich in the long-run, and for growing faster in the short and medium run than capital-intensive FDI. We use the aggregate capital-labor ratio of FDI in the US states to explore the importance of this qualitative characteristic of FDI. To this end, the subsamples of states with differing densities of FDI employment are further divided into subsamples of states with a below-average and an above-average capital-labor ratio of FDI. As noted in Section 3, we reduce the number of subsamples in terms of the density of FDI employment from three to two to be able to estimate the transition probabilities with a greater precision. For the same reason, we reduce the number of income classes from six to four. To save space, we will henceforth present only the initial and the limiting distributions of the estimated Markov chains in graphical terms.

Figure 3 depicts the initial and limiting distributions for the entire sample divided into four income classes (graph 0), and the corresponding distributions for the subsamples with low

[25] Robustness checks, discussed in the appendix, yield again little evidence of reverse causality.

densities of FDI employment (graphs a and b) and high densities of FDI employment (graphs c and d). Graphs a and c depict the distributions for states with below-average capital-labor ratios, graphs b and d those for states with above-average ratios. The distributions for the entire sample in graph 0 largely reproduce the main result of Table 1, namely that there has been a weak tendency towards income convergence across all US states. The estimated transition matrix for the subsample of states with a low density of FDI employment and a below-average capital-labor ratio (graph a) is non-ergodic (reducible). Consequently, a limiting distribution cannot be determined. This does, however, not invalidate the LR test of equality of all transition matrices.

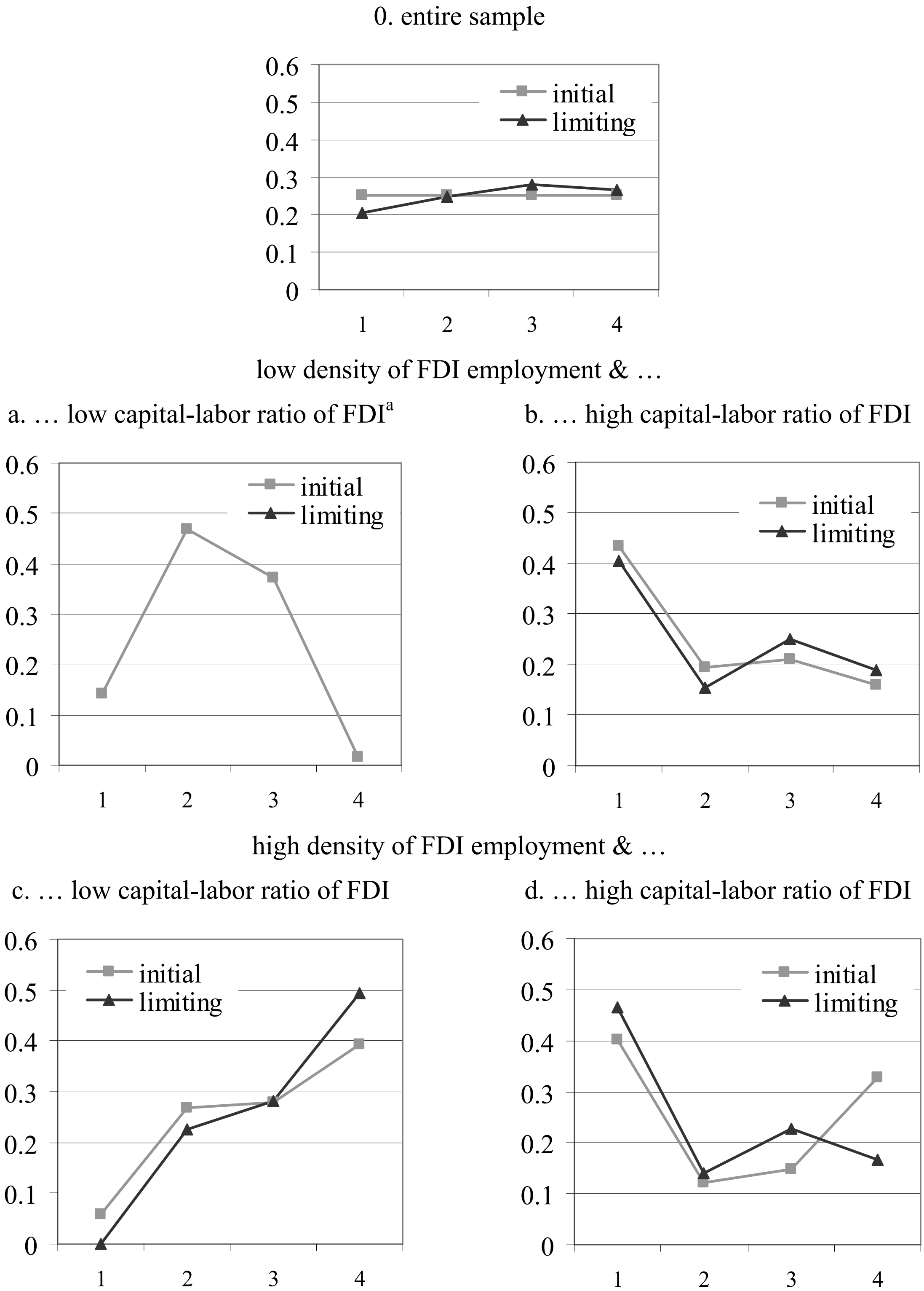
The LR test of the hypothesis that all four transition matrices for the combinations of FDI densities and capital-labor ratios are equal to each other is clearly rejected at an error probability of virtually zero (LR = 74; 18 degrees of freedom). This error probability is significantly lower than the error probability of the test comparing only the subsamples for different densities of FDI employment (6.4%; see Section 4.1). This suggests that the capital-labor ratio of FDI contributes some additional heterogeneity to the heterogeneity between states with low and high densities of FDI employment.

The limiting distributions for the three subsamples in graphs b – d indicate that the positive association of a high FDI density with the long-run income and growth prospects of states results mainly from employment-intensive FDI. By contrast, states with a high density of capital-intensive FDI (graph d) are even estimated to have slightly less favorable income and growth prospects than states with a low density of capital-intensive FDI (graph b). States with a high density of capital-intensive FDI face a higher probability of ending up in one of the two below-average income classes, 1 and 2, than states with a low density of capital-intensive FDI (0.605 versus 0.56). This implies that a high FDI density, in terms of the employment share of foreign-owned firms, is not sufficient for having particularly favorable long-run income and growth prospects. It is rather the combination of a high FDI density and a high employment intensity of foreign-owned firms that is associated with higher income and faster growth.

A comparison of the initial and the limiting distributions provides several insights. First, the income divergence of states with a high FDI density is driven only by states with a high employment intensity of FDI (graph c), which have the most favorable long-run income and growth prospects. Second, states with a high FDI density and a high capital intensity of FDI (graph d) have been falling back in the income distribution. While they had a fair chance of about one third (0.327) to be rich in the initial distribution, this chance drops to one sixth (0.167) in the limiting distribution.[26]

[26]Broadly similar patterns emerge if FDI stocks, instead of FDI employment, are used as an indicator of the FDI density: The long-run income and growth prospects are most favorable for states with a low density of FDI stocks and a high employment intensity of FDI, and least favorable for states with a high density of FDI stocks and a high capital intensity of FDI.

Figure 3: Evolution of the income distribution across the 51 US states, 1977–2005, by the density of FDI employment and the capital-labor ratio of FDI — initial and limiting distributions



[a] The limiting distribution does not exist because the Markov chain is not ergodic. The transition probabilities from and to the first, lowest income class are estimated to be zero.

Sectoral Composition of FDI

Next we assess the importance of our second qualitative characteristic of FDI, the sectoral pattern of FDI, for the states' long-run income and growth prospects. The discussion in Section 3 suggests that FDI in the manufacturing sector fosters income and growth to a greater extent than FDI in mining or the service sector. The probabilities of being rich in the long run should then be higher for the two subsamples with an above-average ratio of manufacturing to nonmanufacturing FDI (in terms of FDI employment).

Similar to Figure 3, Figure 4 depicts the initial and limiting distributions for the four subsamples divided simultaneously by the density of FDI employment and the manufacturing-nonmanufacturing ratio. The corresponding distributions for the entire sample are the same as those depicted in graph 0 of Figure 3.

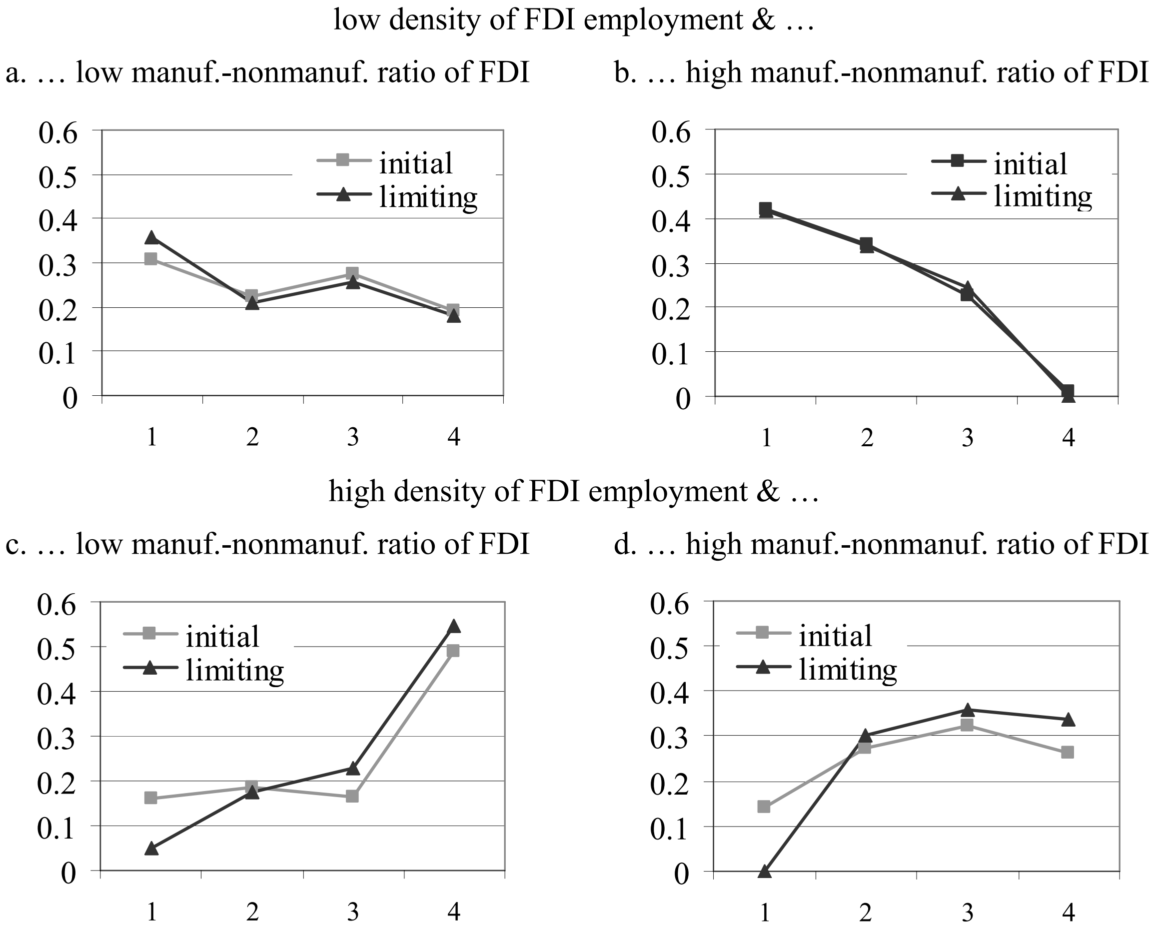
The LR test of the hypothesis that all four transition matrices for the combinations of the densities and sectoral patterns of FDI are equal to each other is clearly rejected at an error probability of virtually zero (LR = 42.4; 18 degrees of freedom). Again, this error probability is significantly lower than the error probability of the test comparing only the subsamples for different densities of FDI employment. Similar to the capital-labor ratio, the sectoral pattern of FDI appears to contribute some additional heterogeneity. However, additional tests not reported here indicate that the sectoral composition of FDI does not impact significantly on the income prospects of the states, if the differences in the FDI densities are not controlled for explicitly. In other words, the association of the sectoral pattern of FDI with the states' income and growth prospects is weak, compared to that of the density of FDI.

This conclusion is corroborated by the limiting and initial distributions depicted in Figure 4. They largely reproduce the result obtained for the density of FDI employment alone in the preceding section: A higher density of FDI employment goes along with better income and growth prospects. This result holds irrespective of the sectoral pattern of FDI. For a given density of FDI employment, a concentration of FDI on *nonmanufacturing sectors* (lower manufacturing-nonmanufacturing ratio; graphs a and c) appears to be associated with more favorable income prospects than a concentration of FDI on the *manufacturing sector*. This result conflicts with the view that FDI in manufacturing is most likely to enhance the productivity of local firms through economic spillovers. However, the robustness of this result is open to debate, as is shown in the appendix.[27] More substantive conclusions could be

[27] The finding that a higher density of FDI employment goes along with better the long-run income and growth prospects of US states can be shown to hold when separate estimations are performed for each of the two sectors (manufacturing and nonmanufacturing). The detailed results are available from the authors upon request.

expected from an analysis based on more disaggregated (industry-specific) FDI data, which are not available at the state level, however.

Figure 4: Evolution of the income distribution across the 51 US states, 1977–2005, by the density of FDI employment and the manufacturing-nonmanufacturing ratio of FDI — initial and limiting distributions



5 CONCLUSION

It is by various measures that the US represents the world's most attractive host country of FDI. It is the country with the largest inward FDI stocks and also the most favored location for affiliates of the top 100 multinational companies. Nevertheless, the economic impact of FDI in the US, and particularly its regional income and growth implications, has received only scant attention in the empirical literature. This is still more surprising in the light of the fierce competition for FDI among US states, which Glickman and Woodward (1989) dismissed as a "mad scramble for the crumbs" almost 20 years ago.

Our analysis contrasts sharply with such generalized verdicts. Applying a Markov chain approach and measuring FDI by our preferred measure, the employment share of foreign-owned firms, we find that states with a higher FDI density have a significantly greater chance of being *rich* in the long run. Yet FDI appears to be associated with weaker rather than stronger income convergence among US states. States with a higher density of FDI employment, which were, on average, already richer from the start, have diverged from the national average towards even higher income levels.

The finding that FDI is associated with less convergence among US states also holds when using FDI stocks as a measure of the density of FDI. However, states with a higher density of FDI stocks, which were, on average, already poorer from the start, have a significantly greater chance of being *poor* in the long run, and have diverged from the national average towards even lower income levels. This contrasting finding for the two different quantitative indicators of FDI corroborates Keller and Yeaple (2009) who argue that measurement of FDI makes a big difference. Especially in capital-abundant countries like the US, *capital* transfers through FDI may play a minor role for generating growth-enhancing economies of agglomeration among foreign-owned and local firms, compared to employment-related spillovers of human capital and knowledge.

Qualitative characteristics of FDI offer additional insights to this effect. In contrast to capital-intensive FDI, employment-intensive FDI has been positively associated with per-capita income growth during the last about three decades, and went along with a higher probability that the host state will be rich in the long run. It appears that employment-intensive FDI offers a greater potential for positive economies of agglomeration like labor pooling, knowledge spillovers, or human-capital externalities among foreign-owned firms and the local economy.

The sectoral composition of FDI is shown to be less important than the employment intensity. We find no compelling evidence supporting the view that FDI in the manufacturing sector is superior to FDI in other sectors. One possible explanation is that growth-enhancing spillovers and other agglomeration externalities are as strong in the services sector as they are supposed to be in the manufacturing sector. Another explanation is that efficiency-seeking FDI in the manufacturing sector, i.e., the type of FDI that Aykut and Sayek (2007) suspect to have particularly strong technology and knowledge spillovers, does not play a major role in the US. More detailed data would be required to assess the extent to which specific types of FDI, with different factor intensities and in different industries, generate positive agglomeration economies.

Our major findings are fairly robust to variations in the empirical setup. This invites two tentative policy conclusions. First, policymakers appear to be most interested in attracting FDI in the manufacturing sector, while they are often reluctant to accept foreign competition in services industries. According to our results, this form of selective treatment of inward FDI is not warranted. Second, the preference of policymakers for FDI that generates employment, rather than only adding to the local capital stock, appears reasonable. Indeed, the evidence for US states suggests that the benefits to be derived from employment-intensive FDI go beyond the first-round employment generation that policymakers typically have in mind.

Some caveats have to be kept in mind, however. Most obviously, it does not only depend on the benefits that a specific type of FDI is likely to deliver whether it makes economic sense to compete for inward FDI; it also depends on the costs involved in terms of foregone government revenues and outright subsidies. It remains to be seen whether the approach of Greenstone and Moretti (2004) can be transferred to specifically FDI-related contexts. This approach considers property values in the host region to reflect the *net* welfare effects of plant location, assuming that both the benefits and costs of luring a plant to a particular region enter into the price of land. Moreover, the present analysis invites further research in various other respects. The importance of measurement suggests considering additional dimensions of FDI such as production, sales and exports, in order to substantiate the point that FDI stocks may provide a misleading picture on the economic effects of FDI. Similarly, it would be desirable to account for other aspects of the heterogeneity of FDI. For instance, the investment and growth effects of greenfield FDI may differ from those of M&As (Wang and Wong 2009). Additional insights may be gained by differentiating market-seeking, efficiency-seeking and strategic-asset-seeking FDI, as well as FDI from different sources. However, accounting for FDI heterogeneity in these respects is subject to serious data constraints at the level of US states.

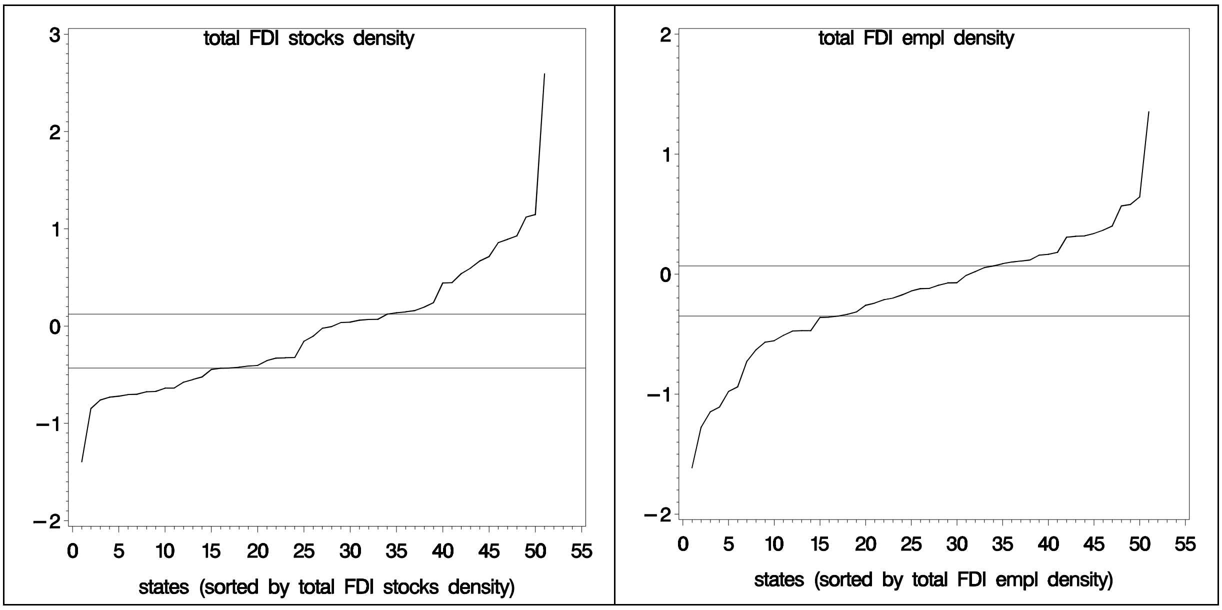
APPENDIX: ROBUSTNESS TESTS

This appendix investigates the robustness of the main results presented in Section 4 to the choices of the class and subsample bounds; to endogeneity of FDI densities with respect to income levels; to a violation of the assumptions of time homogeneity and time independence underlying the Markovian approach; and to including the non-contiguous states of Alaska and Hawaii as well as Washington, DC.

Class and subsample definitions

The inferences drawn from a Markov analysis are usually rather sensitive to the choices of the number of income classes and the location of the bounds between those classes (Magrini 2004). In addition, the inferences may be sensitive to the choice of the bounds between the subsamples. In fact, Figure A1 shows that the densities of FDI stocks or employment of several states are fairly close to the subsample bounds. For example, there is a concentration of states (consecutive numbers 15 – 20) at the boundary between low and medium density of FDI stocks. A slightly lower or higher boundary between these two subsamples may affect our results notably because it would shift several states to a different subsample.

Figure A1: Distribution of FDI stocks and employment densities across the 51 US states, average FDI densities over 1977–1986[a]



[a] Horizontal lines indicate the boundaries between the respective three subsamples of low, medium and high FDI densities. See Section 3 for the detailed definitions of FDI stocks and employment densities.

One way of reducing the arbitrariness of the choice of the bounds between the income classes would be using one of the formal criteria for determining the optimal number of classes proposed in the literature (Magrini 1999; Bulli 2001). These formal criteria are not used here because they usually suggest the optimum number of classes to be very high relative to the number of observations. The resulting high number of transition probabilities of the transition matrix for the entire sample could be estimated only imprecisely; this would apply still more so to the transition probabilities of the transition matrices for the subsamples. Another way of reducing arbitrary choices of the class bounds would be estimating continuous Markov chains (Quah 1997). This approach is not followed here because the number of observations is rather small in some of the subsamples for differing FDI densities, and because a statistical test for comparing the continuous transition processes across the subsamples is, to the best of our knowledge, not available.

Instead, we perform a series of additional estimations to investigate the robustness of our main results to the choice of the number of income classes and subsamples and, thus, to the location of the bounds between these classes and subsamples. Table A1 presents the results for estimations with 3 – 7 income classes and 3 – 7 subsamples of FDI density (employment or stocks). To save space, Table A1 reports only the error probabilities of the LR tests of equality of the transition matrices across the FDI subsamples. The tests for FDI stocks in the upper panel of Table A1 show that the results on the relationship between FDI and income reported in Section 4.1 are very robust against variations in the numbers of income classes or subsamples. The LR tests reject the hypothesis that the FDI stock density is irrelevant for the evolution of the income distribution among US states for 35 of the 36 specifications with different numbers of FDI subsamples and income classes. The respective sets of transition matrices and limiting distributions, which are not reported here for the sake of brevity, show similar patterns as those in Table 2: States with a higher density of FDI stocks have a lower probability of being rich in the long run.

The LR tests in the lower panel of Table A1 reject the hypothesis that FDI employment density is irrelevant for the evolution of the income distribution among US states for 31 of the 36 specifications with different numbers of FDI subsamples and income classes. One of the five "outliers" for which the error probability is above 5% is our baseline specification with three FDI subsamples and six income classes reported in Table 3. We infer from this that density of FDI employment makes a difference for the long-term growth prospects of US states. States with a higher density of FDI employment have a higher probability of being rich in the long run.

Likewise, the effects of the capital-labor ratio of FDI on the income distribution investigated in the first part of Section 4.2 are fairly robust against variations in the number of both income classes and subsamples (not shown here in detail). Only the effects of the sectoral composition of FDI investigated in the second part of Section 4.2 are somewhat sensitive to a variation in the number of subsamples. Some tests indicate that the sectoral composition may impact in a more complex way on the income and growth prospects of states with a high FDI density than suggested by the results in Section 4.2. More detailed information on the sectoral patterns of FDI is warranted to substantiate these results.

Table A1: Evolution of the per-capita income distribution across the 51 US states, 1977–2003, by initial densities of FDI stocks or employment 1997–1986: Probability values of LR tests on equality of Markov transition matrices across subsamples for different numbers of income classes and FDI subsamples

Number of PCPI classes	Number of FDI subsamples …					
	2	3	4	5	6	7
	… by density of FDI stocks					
2	0.003	0.000	0.000	0.000	0.000	0.000
3	0.020	0.000	0.018	0.000	0.001	0.000
4	0.039	0.000	0.000	0.000	0.000	0.000
5	0.005	0.000	0.000	0.002	0.000	0.000
6	0.089	0.000	0.000	0.000	0.000	0.000
7	0.045	0.001	0.000	0.008	0.000	0.000
	… by density of FDI employment					
2	0.020	0.002	0.002	0.005	0.000	0.008
3	0.006	0.302	0.004	0.331	0.000	0.020
4	0.006	0.001	0.001	0.000	0.000	0.000
5	0.014	0.004	0.019	0.001	0.000	0.000
6	0.069	0.064	0.015	0.070	0.000	0.002
7	0.002	0.018	0.000	0.000	0.000	0.000

Endogeneity of FDI density

While the Markovian analysis performed in this paper does, in general, not support causal inferences, it may raise endogeneity concerns insofar as the states' FDI densities may depend on these states' income levels. Indeed, there is a large literature on host-economy characteristics as major determinants of (particular types of) FDI. For instance, Lee and Mansfield (1996) have shown that the volume and composition of FDI by US based investors depend on the protection of property rights across various host countries. As concerns inward FDI in the US, Coughlin et al. (1991) find that foreign investors prefer, ceteris paribus, US states with higher per-capita income.

Endogeneity concerns may arise from two aspects: the overlap between the time periods used for defining FDI subsamples and for estimating transition probabilities, and reverse causality. Both aspects will be addressed below in more detail.

The overlap between the time period used for defining FDI subsamples (1977 to 1986) and that used for estimating the Markovian transition probabilities (1977 to 2003) may result in biased assignments of states to FDI subsamples as well as to biased estimates of transition probabilities.[28] Assignments of states to FDI subsamples will be biased, if some states are assigned to the group of states with high FDI densities not because they had high FDI employment densities to start with but because their high income levels or prosperous income growth during the period 1977 to 1986 attracted large amounts of FDI.[29] In addition, inflows of FDI during the period 1977 to 1986 may bias the estimated transition probabilities upwards by their effects on income levels. Even if FDI has no causal impact on states' long-run growth prospects, FDI inflows may increase per-capita income levels if they increase aggregate output and reduce unemployment.

We address this endogeneity concern by avoiding any overlaps between the time period used to define FDI subsamples and that used to estimate the transition probabilities. Table A2 summarizes, separately for FDI stocks (upper panel) and FDI employment (lower panel), the results of Markov chain estimations for different lengths of the time period used to define FDI subsamples (1 – 10 years). This time period, given in the first column of Table A2, is excluded from the time period used for estimating the transition probabilities. To save space, Table A2 reports only the results of the LR tests of equality of the transition matrices for three FDI subsamples and the probabilities in the tails (sums of the two lowest and the two highest income classes) of the limiting distributions for the subsamples of states with the lowest and the highest FDI density. The differences between the subsamples in terms of FDI stocks (upper panel of Table A2) lose somewhat in significance when the period used to define the FDI subsamples is very short or very long. We attribute these losses in significance to a trade off between the precision of the allocation of states to subsamples and the precision of the estimates of transition probabilities. The shorter the period used for defining subsamples, the stronger will be the influence of outliers on the definition of subsamples; and the longer this period, the lower the precision of the estimated transition probabilities due to a considerable loss of observations. Nevertheless, the limiting distributions corroborate the main results from our baseline specifications: States with lower initial densities of FDI stocks and higher initial densities of FDI employment tend to have a higher probability of being rich in the long run.

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[28] As discussed in Section 3, we prefer this overlap of ten years, which covers about one third of the entire sample period, in order to reduce the effects of short-term fluctuations in FDI densities on the classification of states. Moreover, we maximize the number of available transitions in this way in order to estimate the transition probabilities as reliably as possible.

[29] Likewise, some states may be assigned to the group of states with low FDI densities in our analysis because they lost FDI due to their low income levels or weak growth performances during the period 1977 to 1986.

Table A2: Evolution of the per-capita income distribution across the 51 US states, 1977–2003, by initial densities of FDI stocks or employment 1997–1986: Results for different lengths of time period for defining FDI subsamples[a]

Time period for definition of FDI subsamples	Test of equality across 3 FDI subsamples		Limiting distribution			
			Subsample low FDI density		Subsample high FDI density	
	LR	prob	poor[b]	rich[c]	poor[b]	rich[c]
			FDI stocks			
1977	32.4	0.117	0.146	0.502	0.502	0.224
1977–1978	51.7	0.001	0.150	0.476	0.372	0.280
1977–1980	37.0	0.012	0.142	0.459	0.387	0.269
1977–1982	38.2	0.008	0.082	0.655	0.428	0.143
1977–1984	30.7	0.059	0.088	0.467	0.555	0.163
1977–1986	29.5	0.079	0.117	0.367	0.366	0.231
			FDI employment			
1977	30.5	0.170	0.515	0.119	0.090	0.594
1977–1978	27.6	0.277	0.530	0.132	0.097	0.567
1977–1980	26.0	0.167	0.570	0.129	0.083	0.628
1977–1982	19.0	0.519	0.410	0.222	0.119	0.512
1977–1984	26.2	0.159	0.241	0.493	0.079	0.591
1977–1986	21.8	0.352	0.156	0.575	0.148	0.447

[a] The time periods used for defining FDI subsamples are excluded from those used to estimate the transition probabilities. [b] Sum of lowest income classes 1 and 2. [c] Sum of highest income classes 5 and 6.

The second endogeneity concern is reverse causality. Our finding that states with high densities of employment-intensive FDI tend to be richer in the long run may partly be due to foreign investors systematically preferring states with higher per-capita income for their employment-intensive investments. Likewise, our finding that states with high densities of capital-intensive FDI tend to be poorer in the long run may partly be due to foreign investors systematically preferring states with lower per-capita income for their capital-intensive investments. If per-capita income levels were causal for FDI densities, we should observe a tendency towards concentration of capital-intensive FDI in poorer states in the long run, and a tendency towards concentration of employment-intensive FDI in richer states.[30]

We address this reverse causality by testing if there is a systematic concentration of FDI stocks in poorer states in the long run, or of FDI employment in richer states. For this purpose, we simply interchange FDI density and per-capita income in our Markovian analysis. We define equally sized subsamples of states with different levels of per-capita income during

[30] This kind of sorting could also be expected to occur, if per-capita income and FDI densities depended on each other and were determined jointly in the long-run equilibrium, or if they jointly depended on third, unobserved variables.

the period 1977 – 1986. We then estimate the evolution of FDI densities separately for each subsample by Markov chains with (between two and seven) FDI density classes, which are equally sized in the entire sample. We evaluate by means of an LR test if these evolutions differ between states with different initial per-capita income levels.[31]

Table A3: Evolution of the distribution of densities of FDI stocks or employment across the 51 US states, 1977–2003, by initial per-capita income, 1997–1986: Probability values of LR tests on equality of Markov transition matrices across income subsamples for different numbers of FDI classes and income subsamples

Number of FDI classes	Number of subsamples by per-capita income 1977–1986					
	2	3	4	5	6	7
	error probabilities of LR tests					
FDI stocks						
2	0.086	0.558	0.004	0.488	0.125	0.005
3	0.008	0.001	0.002	0.009	0.040	0.014
4	0.039	0.068	0.008	0.295	0.170	0.007
5	0.125	0.366	0.015	0.240	0.520	0.098
6	0.032	0.024	0.036	0.406	0.233	0.166
7	0.128	0.318	0.155	0.457	0.163	0.219
FDI employment						
2	0.975	0.821	0.954	0.587	0.861	0.315
3	0.236	0.588	0.226	0.662	0.195	0.043
4	0.003	0.085	0.017	0.240	0.010	0.389
5	0.001	0.013	0.019	0.012	0.000	0.020
6	0.418	0.531	0.334	0.352	0.062	0.689
7	0.006	0.175	0.041	0.261	0.025	0.296

Table A3, which has the same shape as Table A1, depicts the error probabilities of the LR tests of equality of the transition matrices obtained from estimations for varying numbers of income subsamples and FDI density classes. The relationship between initial per-capita income and the subsequent evolution of FDI density turns out to be much weaker than the reverse relationship between initial FDI density and the subsequent evolution of per-capita income (see Table A1) for both of our FDI indicators, FDI stocks (upper panel) and FDI employment (lower panel). The evolution of FDI stocks differs significantly (at the 5% level) between income subsamples in only 15 of the 36 specifications, and the evolution of FDI

[31] Data availability limits the analysis of the evolutions of the densities of FDI stocks or employment to the period 1977 – 2003.

employment in only 13 of the 36 specifications.[32] Recall for comparison that the evolution of per-capita income differed significantly between FDI subsamples in almost all specifications.

Taken together, these findings suggest that the evidence for reverse causality is rather weak - even though there is some concentration of poorer states among the states with high density of FDI stocks (see Table 2), and some concentration of richer states among the states with high density of FDI employment (see Table 3). All this does not rule out that states at a particular level of per-capita income attract particular types of FDI. Yet, we find at least tentative evidence suggesting that causality may in fact run from FDI to per-capita income.

Time homogeneity and independence

Bickenbach and Bode (2003) emphasize that the Markovian approach rests on fairly restrictive assumptions. In particular, the transition probabilities are assumed to be constant over all transition periods (time homogeneity), and to be independent of the historical evolution of income, i.e., of the income levels at times before time t (time independence; or Markov property).

Applying the tests suggested in Bickenbach and Bode (2003), we could not reject the hypothesis that the Markov chain with six income classes is time-homogeneous over the sample period 1977–2004 (prob = 0.28). We could, however, reject the hypothesis that this Markov chain is time-independent (prob < 0.001). The usual procedure for retaining time independence is using longer transition periods (Bickenbach and Bode 2003). Therefore, we reestimated all transition matrices presented in Section 4 using biannual rather than annual transitions. The biannual transitions were calculated as changes of the (logged relative) per-capita incomes from the average of times t and t+1 to the average of times t+2 and t+3. Indeed, we cannot reject the hypothesis that the Markov chain for the biannual transitions is time-independent (prob = 0.59). At the same time, the aggregation of two consecutive observations in time reduces the number of observed transitions by more than half.[33]

Yet the main results arising from these biannual transitions are very similar to those arising from the annual transitions presented in Section 4. Figure A2 exemplifies this similarity by comparing the initial and limiting distributions estimated from the annual (left-hand side graphs) and the biannual transitions (right-hand side graphs) for the income and growth effects of the density of FDI employment investigated in Section 4.1. The only notable differ-

[32] Furthermore, the limiting distributions of those specifications that yield significant differences between income subsamples do not support unambiguous inferences on reverse causality. The specification for six FDI stocks classes and three income subsamples is supportive of reverse causality. The probability of having a high density of FDI stocks in the long run (FDI classes 5 and 6) is higher for poor states (0.469) than for rich states (0.317). By contrast, the specification for six FDI stocks classes and four income subsamples is not supportive of reverse causality. Here, the probability of having a high density of FDI stocks in the long run (FDI classes 5 and 6) is lower for poor states (0.441) than for rich states (0.493).

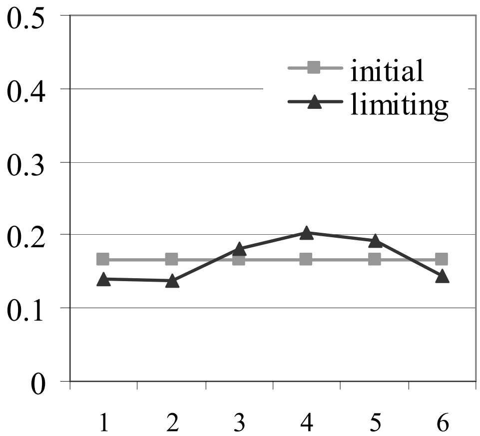
[33] The reason for presenting the time-dependent annual transitions in Section 4 is that the substantially larger number of observations facilitates more rigorous robustness tests.

ence is that the positive relationship between the higher density of FDI employment and the probability of being rich in the long run is even more pronounced for the biannual transitions. The tendency of the divergence of the low and high FDI density states into opposite directions from the national average is correspondingly estimated to be even stronger than for the annual transitions.

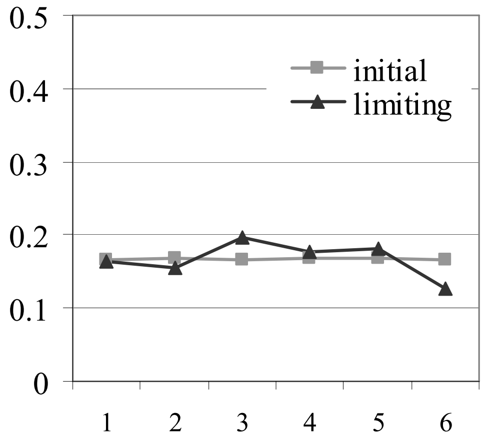
Figure A2: Evolution of the income distribution across the 51 US states, 1977–2005, by the density of FDI employment — initial and limiting distributions for annual and biannual transition periods

entire sample

a. annual transitions

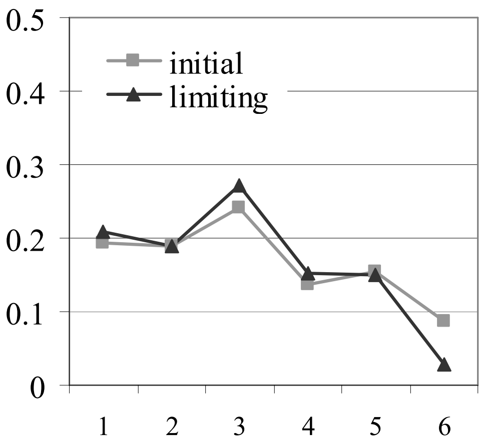


b. biannual transitions

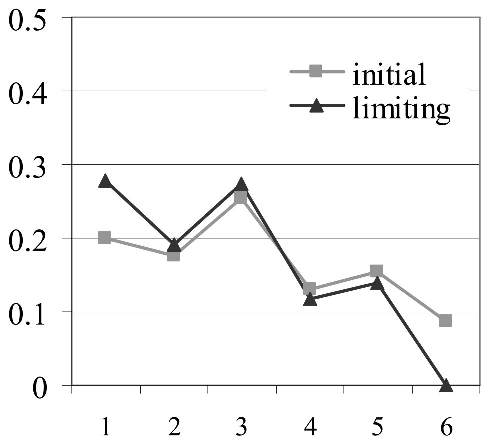


low density of FDI employment

a. annual transitions



b. biannual transitions

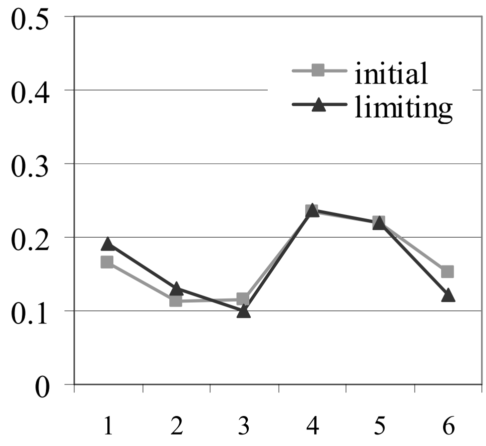


to be continued

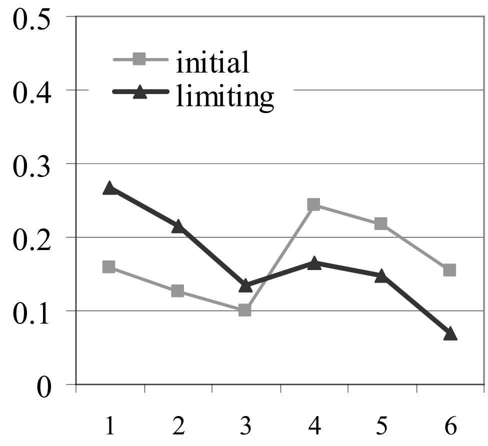
Figure A2 continued

medium density of FDI employment

a. annual transitions

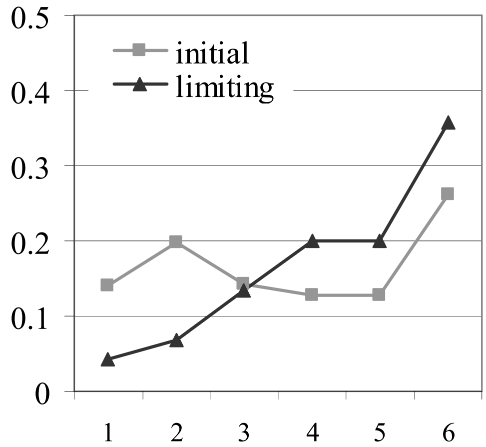


b. biannual transitions

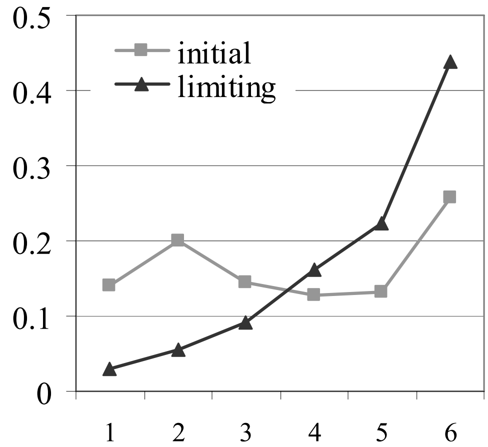


high density of FDI employment

a. annual transitions



b. biannual transitions



48 contiguous states

Finally, all estimations reported so far are based on data for all 51 US states. By contrast, various regression analyses on the location choice of foreign investors within the US and on the effects of FDI focus on the 48 contiguous states; see, among others, Chung and Alcácer (2002), Leichenko and Erickson (1997), Crain and Lee (1999), Garofalo and Yamarik (2002), Mullen and Williams (2005), and Bobonis and Shatz (2007). The exclusion of Alaska, Hawaii and Washington, DC, is typically justified by the exceptional nature of FDI in these states. For instance, Bobonis and Shatz (2007) note that Alaska attracted "outsize investments during the entire period", while Hawaii became an outlier in the 1990s. Moreover, the sectoral structure of FDI appears to be exceptional in these states, with FDI in Alaska being concentrated in resource extraction and FDI in Hawaii being concentrated in tourism.

Therefore, we investigated to what extent FDI located in Alaska, Hawaii and Washington, DC, affects the results reported in Section 4. We reestimated all transition matrices excluding these three states. The (unreported) estimations reveal that this modification does not affect the results to a notable extent. This finding is in line with Bobonis and Shatz (2007), whose regression results are robust to including the non-contiguous states.

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