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No. 1579 | January 2010

Web: www.ifw-kiel.de

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FDI and Income Inequality: Evidence from a Panel of US States

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Abstract:
This study employs state-level panel data to explore the relationship between inward foreign direct investment (FDI) and income inequality in the United States. Using panel cointegration techniques that allow for cross-sectional heterogeneity, cross-sectional dependence, and endogenous regressors, we find that the short-run effects of FDI on income inequality are insignificant or weakly significant and negative. In the long run, however, FDI exerts a significant and robust negative effect on income inequality in the United States. This result for the United States as a whole does not imply that FDI narrows income gaps in the long run in each individual state. There is considerable heterogeneity in the long-run effects of FDI on income inequality across states, with some states (21 out of 48 cases) exhibiting a positive relationship between FDI in income inequality.

Keywords: FDI; Inequality; Panel Cointegration; United States.

JEL classification: F21; D31; C23

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1. Introduction

The challenges that foreign direct investment (FDI) might involve for high-income countries such as the United States are typically discussed with respect to the domestic repercussions of foreign activities of US-based multinational enterprises (MNEs). In particular, the effects of offshoring and international sourcing on domestic labor demand and relative wages are subject to intense debate (e.g., Slaughter, 2000; Feenstra and Hanson, 1996).

However, the United States is not only the most important source of FDI but also tops the list of host countries of foreign-based MNEs.[1] US states compete aggressively for FDI inflows, especially for new manufacturing plants (e.g., Head et al., 1999). Indeed, recent empirical evidence suggests that inward FDI raises productivity and income even though US firms often produce at the technological frontier (e.g., Keller and Yeaple, 2009). Possible drawbacks of FDI attracted by US states, however, have received hardly any attention. This is in striking contrast to FDI in less advanced locations where it has been shown that FDI-induced growth effects typically went along with rising income inequality.

The United States may tolerate more inequality than most other host countries of FDI. Nevertheless, the case of FDI in the United States can offer relevant insights on whether public support of globalization is likely to wane in advanced economies. This could happen if FDI contributes to the trade-off between average income gains and widening income inequality even in economies that are widely perceived to be the major winners of globalization.

The effects of FDI on income distribution in advanced economies are theoretically ambiguous, and evidence is limited and inconclusive (Section 2). Against this background, we explore the relationship between inward FDI stocks and (several measures of) income inequality at the level of US states for the period 1977-2001. We employ panel cointegration techniques that allow for cross-sectional heterogeneity, cross-sectional dependence as well as endogenous regressors (Section 3). Perhaps surprisingly, we find that FDI significantly reduces income inequality in the United States in the long run. However, there is considerable heterogeneity across US states, with several states exhibiting a positive relationship between FDI and income equality (Section 4).

[1] While the United States held FDI stocks of US$ 3162 billion abroad in 2008, it hosted inward FDI stocks of US$ 2279 billion (UNCTAD 2009: 251).

2. Previous literature

Advanced economies such as the United States can derive benefits from inward FDI, even though many domestic firms produce at the technological frontier. Recent firm-level studies, notably Branstetter (2006) and Keller and Yeaple (2009), find positive spillovers from foreign to domestic firms. According to Keller and Yeaple, intra-industry spillovers stemming from FDI account for 14 per cent of productivity growth in US manufacturing. At the regional level, positive FDI effects on income and employment in US states appear to be fairly robust to different estimation approaches of empirical investigations (e.g., Mullen and Williams, 2005; Bode et al., 2009).[2]

Yet FDI may have "some undesirable effects upon the labour market" of host countries by leading to increasing wage inequality, as argued by Taylor and Driffield (2005: 243). Likewise, Figini and Görg (2006: 1) observe that FDI is often found to have a positive impact on growth and efficiency, but "what is generally neglected is the issue of equality." In North-South FDI models based on endowment driven comparative advantage, FDI can cause greater inequality by widening the wage gap between skilled and unskilled labor in the more advanced source country and the less advanced host country. The rising skill premium in both locations is because FDI-related outsourcing involves activities that are relatively skilled-labor intensive in the host country, though relatively unskilled-labor intensive in the source country (e.g., Feenstra and Hanson, 1997). As a consequence, the mix of production activities becomes more skill intensive in the North and the South.

Several empirical studies support the hypothesis of FDI being associated with greater inequality by raising the skill premium in developing host countries. The case of Mexico has received particular attention (e.g., Aitken et al., 1996; Feenstra and Hanson, 1997). Hanson (2003) concludes from a survey of the earlier literature that FDI raised the relative demand for skilled labor in Mexico. FDI benefited skilled workers more than unskilled workers in other developing countries as well, including Indonesia (e.g., Lipsey and Sjöholm, 2004).[3] Mah (2002) presents Johansen-type cointegration tests, based on annual Gini coefficients for 1975-1995, showing that FDI inflows were associated with greater income inequality in South Korea. Likewise, the simulation results obtained by Nunnenkamp et al. (2007) on the basis of a CGE model for Bolivia point to a trade-off between growth-promoting effects of FDI and a more unequal income distribution. Basu and Guariglia

[2] According to Ford et al. (2008), US states have to be well endowed with human capital to derive benefits from FDI.

[3] For an overview of this literature, see ODI (2002). Zhang and Zhang (2003) focus on regional inequality, showing that FDI contributed to the widening gap in labor productivity between Chinese provinces.

(2007) corroborate the trade-off between FDI-related growth promotion and rising inequality (in terms of schooling) for a large panel of 119 developing host countries in the period 1970-1999.[4]

While endowment driven FDI models provide important insights into the distributional effects of FDI in developing host countries, these models are less useful for explaining FDI and its consequences in advanced host countries such as the United States (e.g., Blonigen and Slaughter, 2001). A different strand of the theoretical literature departs from the observation that MNEs have firm-specific assets (e.g., technology and management skills), granting them a productivity advantage over domestic firms in the host country.[5] MNEs can then be regarded as "vehicles for introducing new technologies in the host economy and as 'role models' for indigenous firms", as argued by Figini and Görg (1999: 596).

In principle, new MNE models are better suited to make theoretical predictions concerning the effects of inward FDI on skill upgrading and wage inequality in advanced host countries. However, predictions are fairly complex depending on various factors such as country size, relative endowments, trade costs and FDI restrictions (e.g., Markusen and Venables, 1997). As a result, "both skill upgrading and its reverse are possible in these models" (Blonigen and Slaughter, 2001: 363). Placing technologically superior MNEs into the endogenous growth model developed by Aghion and Howitt (1998: chapter 8) gives rise to further non-linearities in the relationship between FDI and wage inequality in the host country (e.g., Figini and Görg, 1999, 2006; Taylor and Driffield, 2005). Domestic firms learn by imitating MNEs and adopting advanced technology, which leads to higher demand for skilled labor. At the same time, production workers acquire additional skills through learning by doing. Changes in relative wages are the outcome of complex interactions between skill improvement and shifts in the demand for skilled and unskilled labor.

Given the theoretical ambiguity, the impact of FDI on wage and income inequality in advanced host countries is essentially an empirical question. All the more surprisingly, empirical evidence is extremely scarce. Some indications exist that the distributional consequences of FDI in advanced host countries differ from those in developing host countries. Gopinath and Chen (2003) analyze time series data on FDI and wages for 15 advanced countries and 11 developing countries;

[4] The evidence from previous cross-country studies is more ambiguous. These studies are often based a small samples of developing countries. According to Tsai (1995: 479), the positive correlation between FDI and inequality "is more likely to reflect the geographical difference in equality than the perverse impact of FDI." Sylwester (2005) did not find a significant association between FDI and changes in income inequality across 29 developing countries. By contrast, the cross-country analysis of Choi (2006) covers a much larger sample and finds that Gini coefficients point to more pronounced income inequality where the ratio of FDI stocks to GDP is higher.
[5] For a summary of this literature, see Markusen (1995).

F-tests reveal that coefficients differ significantly between the two sets of host countries.[6] Similarly, the results presented by Figini and Görg (2006) suggest that pooling host countries at different levels of development is inappropriate. Using a panel of more than 100 countries for the period 1980-2002, Figini and Görg depict two different patterns in the relationship between inward FDI and wage inequality. Wage inequality increases with FDI in developing host countries; but this effect diminishes with further increases in FDI, which is in line with the non-linearity predicted by the model of Aghion and Howitt (1998). By contrast, inequality decreases with FDI in advanced host countries; non-linearity does not play a significant role here.

To the best of our knowledge, there are very few country-specific studies addressing the distributional consequences of FDI in advanced host countries. The focus is on wage disparity within manufacturing industries. Figini and Görg (1999) analyze the wage gap between white and blue collar workers in 17 Irish industries in 1979-1995. In line with Aghion and Howitt (1998), the Irish case reveals an inverted U-shaped relationship between MNE presence and wage inequality, i.e., inequality first increases with FDI, reaches a maximum, and decreases eventually. Taylor and Driffield (2005) follow a similar approach for the United Kingdom. Employing panel data for about 100 manufacturing industries over the period 1983-1992, FDI is shown to explain on average 11 per cent of wage inequality within industries. FDI has a significant impact on wage inequality, though at a decreasing rate over time, as domestic firms assimilate new technologies.

In contrast to the United Kingdom, Blonigen and Slaughter (2001) do not find any evidence that inward FDI has contributed to skill upgrading within US manufacturing industries in 1977-1994.[7] Rather, the boom of Japanese greenfield FDI in the 1980s was associated with lower relative demand for skilled labor. Figini and Görg (1999) suspect FDI not to be a major source of technological innovation in the United States. Similarly, Mullen and Williams (2005) as well as Bode and Nunnenkamp (2007) argue that affiliates of foreign-based MNEs operating in the technologically most advanced United States may be at the receiving end of technological and knowledge spillovers. However, the findings of Blonigen and Slaughter (2001) are also consistent with recent MNE models according to which affiliates abroad employ less skill intensive production techniques than the parent company at home. This is because parent companies provide skill

[6] Yet inward FDI is associated with higher labor shares in GNP in both sub-samples. While Gopinath and Chen (2003) report some evidence that FDI increased the wage gap between skilled and unskilled workers in developing countries, they do not address the wage gap in advanced host countries.

[7] While the distributional consequences of FDI in the United States have received little attention, Aitken et al. (1996) as well as Feliciano and Lipsey (2006) find that foreign firms pay higher average wages. Gelan et al. (2007) focus on racial employment disparity in the United States; they show that inward FDI has improved the relative employment opportunities of skilled black workers in the manufacturing sector. Bode and Nunnenkamp (2007), employing a Markov chain approach, find that FDI has tended to slow down rather than foster the income convergence among US states since the mid-1970s.

intensive headquarter services for the MNE as a whole. Taking further into account that the skill mix in US manufacturing has traditionally been shaped by US-based MNEs, an increasing presence of foreign affiliates may reduce the relative demand for skilled labor compared to the situation prior to the FDI boom.

Several limitations of the three country studies just summarized may provide another explanation for the mixed evidence on the distributional consequences of FDI in advanced host countries. First, the time dimension of the panel data is rather short, notably in the study of Taylor and Driffield (2005). Second, the analyses are restricted to the manufacturing sector, even though FDI in the services sector is quantitatively important and may have different distributional effects. In the case of the United States, the manufacturing sector accounted for just 35 per cent of total inward FDI stocks (on a historical cost basis) in 2008.[8] Third, studies on relative wages and labor shares provide an incomplete picture on inequality, ignoring "self-employment income, property income, profits, and executive compensation" (Lindert and Williamson, 2001: 34).[9] As specified in the next section, we attempt to overcome these shortcomings in our analysis of FDI and inequality at the US state level.

3. Empirical model and data

The analysis will examine the relationship between FDI and income inequality in the United States using panel cointegration estimators. Panel cointegration estimators are robust under cointegration to a variety of estimation problems that often plague empirical work, including omitted variables, endogeneity, and measurement errors (e.g., Banerjee, 1999; Baltagi and Kao, 2000; Pedroni, 2007). Moreover, panel cointegration methods can be implemented with shorter time periods than their time-series counterparts. In this section, we present the basic empirical model, discuss some econometric issues, and describe the data.

Following common practice in panel cointegration studies (e.g., Herzer, 2008), we consider a bivariate long-run relationship of the form

$$TopDecile_{it} = a_i + \delta_i t + b(FDI/GSP)_{it} + \varepsilon_{it}, \qquad (1)$$

[8] For details, see: http://www.bea.gov/scb/account_articles/international/iidguide.htm#FDIUS (accessed: December 2009).

[9] As Basu and Guariglia (2007) note, an FDI-induced increase in wage inequality is not necessarily associated with an increase in income inequality.

where the subscript i refers to one of the N cross- sectional units, $i = 1, 2, ..., N$; the subscript t refers to one of the T time points, $t = 1, 2, ..., T$; $TopDecile_{it}$ is a commonly used measure of income inequality in the United States — the percentage income share of the top 10% of income earners (see, e.g., Piketty and Saez, 2003; Frank, 2009); and $(FDI / GSP)_{it}$ is foreign direct investment in per cent of gross state product (GSP). Following Figini and Görg (2006), we use FDI stocks rather than FDI flows; stocks may capture long-run effects more effectively due to the accumulation of flows. The size of the long-run effect of FDI on income inequality is measured by the coefficient b, which can be interpreted as the long-run elasticity of income inequality with respect to the capital stock of foreign-owned firms. Finally, we include state-specific fixed effects, a_i, and state-specific time trends, $\delta_i t$, to control for any state-specific omitted factors that are relatively stable in the long run or evolve smoothly over time.

Equation (1) assumes a bivariate long-run relationship between permanent movements in the FDI-to-GSP ratio and permanent movements in the top-decile income share. Necessary conditions for this assumption to hold (and thus for our model to be a correct description of the data) are that both the individual time series for the top-decile income share and the individual time series for the FDI-to-GSP ratio are nonstationary or, more specifically, integrated of the same order, and that $TopDecile_{it}$ and $(FDI / GSP)_{it}$ form a cointegrated pair. A regression consisting of two cointegrated variables has a stationary error term, ε_{it} , in turn implying that no relevant integrated variables are omitted; any omitted nonstationary variable that is part of the cointegrating relationship would enter the error term, thereby producing nonstationary residuals and thus leading to a failure to detect cointegration. Therefore, it is important to examine the integration and cointegration properties of the data before the parameter b in Equation (1) is estimated.

Possible heterogeneity in the relationship between FDI and income inequality across US states represents a further econometric issue. US states differ widely in terms of size, income level, economic structure, government policies, and other characteristics. It would therefore be inappropriate to pool observations across cross-sectional units and thus to assume that the slope coefficients, or effects, of FDI are the same for all states, $b_i = b$. Specifically, the problem is that homogeneous pooled (within-dimension) estimators produce inconsistent and potentially misleading point estimates of the sample mean of the heterogeneous cointegrating vectors when the true slope coefficients are heterogeneous (e.g., Pesaran and Smith, 1995). For this reason, we use heterogeneous (between-dimension) estimators based on the mean group approach, which accounts for heterogeneous panels by estimating separate OLS regressions to obtain the individual slope estimates of b_i for each cross-sectional unit. The mean group estimator and its standard error are calculated as follows:

$$\hat{b} = \bar{b} = \frac{\sum_{i=1}^{N} \hat{b}_i}{N}, \tag{2}$$

$$se(\hat{b}) = \frac{\sigma(\hat{b}_i)}{\sqrt{N}} = \sqrt{\sum_{i=1}^{N} \frac{(\hat{b}_i - \bar{b})^2}{(N-1)}} \Bigg/ \sqrt{N}, \tag{3}$$

where the corresponding *t*-statistic is asymptotically distributed as a standard normal and exactly as a student-*t* with $N-1$ degrees of freedom if the underlying estimated b_i sample is normal.

Another issue is the potential cross-sectional dependence among the variables. Cross-sectional dependence may be the result of a common business cycle and other common factors, such as institutional, political, and social shocks, that affect all cross-sectional units in the panel. Especially inequality and FDI are likely to be in large part driven by a common business cycle and other unobserved common factors. Given that conventional panel techniques can lead to misleading inference in the presence of such dependence, we use recent advances in panel data econometrics to account for this issue. More specifically, our analysis is mainly based on the common correlated effects (CCE) mean group approach, which allows for cross-sectional dependencies that potentially arise from multiple unobserved common factors and permits the individual responses to these factors to differ across cross-sectional units (e.g., Pesaran, 2006).

Finally, we cannot completely exclude the possibility that inequality is a determinant of FDI. For example, in the United States the real wages of less-skilled workers have been falling both relative to those of more highly skilled workers and absolutely (e.g., Feenstra and Hanson, 1999; Handel and Gittleman, 2004). As a consequence, some MNEs could have located their low-skilled-labor intensive production processes in the United States to save costs. The empirical implication is that it is not only crucial to examine the time-series properties of the variables, to test whether the variables are cointegrated, and to control for cross-sectional heterogeneity and cross-sectional dependence, but it is also important to account for the potential endogeneity of FDI. In addition to the CCE mean group estimator, we therefore use the dynamic ordinary least squares (DOLS) mean group panel estimator of Pedroni (2001). This estimator is asymptotically unbiased and normally distributed even in the presence of endogenous regressors.

We now describe the data used in the empirical analysis. FDI stocks are measured by the gross book value in current dollars of property, plant and equipment of affiliates in all industries;

they are deflated by the producer price index for machinery and equipment (to convert them into real terms). FDI stocks are expressed as a percentage of nominal GSP deflated by the GDP price index (GSP in real terms). FDI and GSP data come from the Bureau of Economic Analysis (available at http://www.bea.gov/scb/account_articles/international/iidguide.htm#FDIUS and http://www.bea.gov/regional/gsp/), while the income inequality data are from Frank (2009) (available at http://www.shsu.edu/~eco_mwf/). Following Piketty and Saez (2003, 2006) and Frank (2009), we use the top-decile income share (in per cent) as our preferred measure of income inequality. Available income data do not allow accurate calculation of other inequality measures (e.g., Frank, 2009).[10] Nevertheless, we will examine the sensitivity of our results to alternative measures of income inequality such as the Atkinson index, Theil's entropy measure, and the standard Gini index. Details on the construction of these inequality measures are provided by Frank (2009).

The data we use cover the period 1977-2001, the longest period available for essentially all US states. We include all states with continuous time series, leading to a sample of 47 US states (excluding Alaska, Hawaii, and Montana, for which continuous data are not available) plus the District of Columbia. Thus, we consider a panel with 48 cross-sectional units and 25 time series observations per unit. In the figures in Appendix A1, we show the data for each of these units graphically. Visual inspection of the graphs indicates that both the top 10% income share and the FDI-to-GSP ratio increased between 1977 and 2001 in all states, which could suggest a positive link between FDI and income inequality. On the other hand, one must be cautious in drawing such a conclusion because there are several other (common or state-specific) factors that may influence both FDI and inequality, thereby inducing trends in the data.

Table 1 lists the US states (including the District of Columbia) along with the average values for $(FDI/GSP)_{it}$ and $TopDecile_{it}$. As can be seen, there are considerable differences in the values of these parameters across the states. Wyoming is the state with the largest FDI-to-GSP ratio, followed by West Virginia, Louisiana, and Delaware, while Nebraska ranks at the bottom of the FDI scale. The FDI-to-GSP ratio in West Virginia exceeds the corresponding ratio in Nebraska by more than 10-fold. The District of Columbia heads the list of US states in terms of income inequality (measured by the top 10% income share), followed by Florida, New York, and Connecticut. The states with the lowest income inequality indices are (in descending order) Maine,

[10] Compiling a standardized top income shares dataset for 13 developed countries, Leigh (2007) finds that there is a strong and significant relationship between top income shares and broader inequality measures such as the Gini coefficient. He concludes that top income shares may be a useful substitute for other measures of inequality when alternative income distribution measures are of low quality, or unavailable.

Indiana, Iowa, and West Virginia. The top-decile income share in the District of Columbia is about 30 per cent greater than that in West Virginia.

Table 1

Summary statistics

	Average of $(FDI/GSP)_{it}$	Average of $TopDecile_{it}$		Average of $(FDI/GSP)_{it}$	Average of $TopDecile_{it}$
Alabama	8.34	35.71	Nebraska	2.15	35.91
Arizona	6.01	36.76	Nevada	9.06	40.30
Arkansas	4.35	35.80	New Hampshire	5.02	35.70
California	6.88	39.74	New Jersey	6.88	38.28
Colorado	5.93	37.15	New Mexico	8.40	35.88
Connecticut	4.37	40.86	New York	5.38	41.22
Delaware	13.98	35.68	North Carolina	7.64	35.62
D. of Columbia	5.47	42.89	North Dakota	8.44	34.50
Florida	5.40	41.31	Ohio	6.27	34.39
Georgia	7.74	37.19	Oklahoma	7.15	36.63
Idaho	3.60	35.29	Oregon	4.89	35.44
Illinois	5.94	37.75	Pennsylvania	5.18	35.95
Indiana	7.23	33.98	Rhode Island	5.12	35.76
Iowa	4.22	33.81	South Carolina	13.25	34.77
Kansas	5.07	35.74	South Dakota	3.16	36.87
Kentucky	9.80	35.21	Tennessee	7.85	36.84
Louisiana	16.37	37.29	Texas	10.72	39.76
Maine	9.06	34.06	Utah	9.98	34.83
Maryland	4.24	35.56	Vermont	5.81	34.58
Massachusetts	4.23	38.15	Virginia	5.53	35.66
Michigan	5.56	34.61	Washington	5.08	35.75
Minnesota	5.85	35.90	West Virginia	16.95	32.71
Mississippi	5.53	35.95	Wisconsin	4.18	34.11
Missouri	4.51	36.00	Wyoming	23.03	37.31

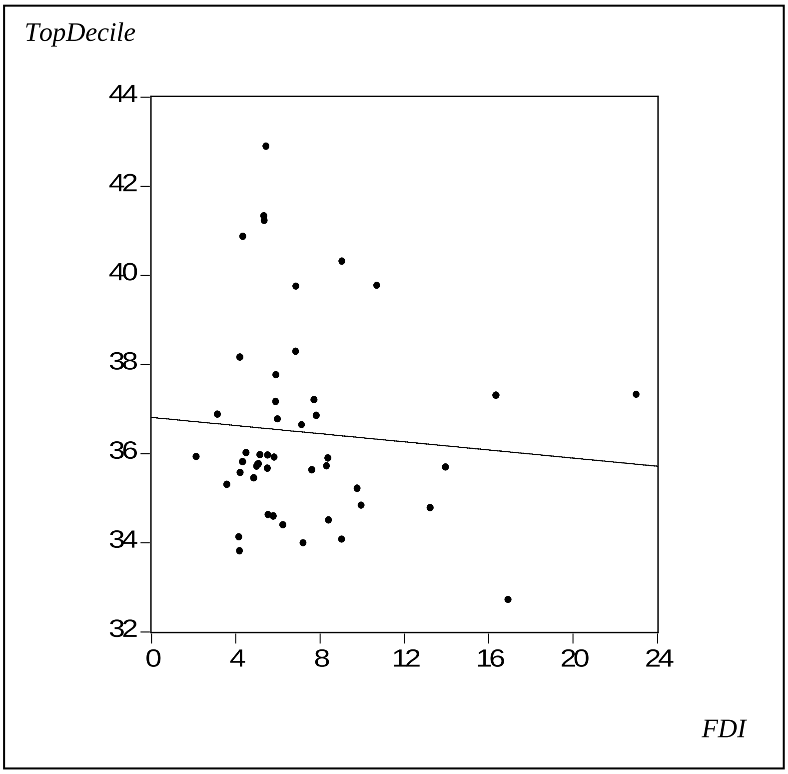
Figure 1 shows the scatter plot of the average top-decile income share versus the average FDI-to-GSP ratio for the 48 states (including the District of Columbia) in our sample along with the regression line. The slope of the regression line is slightly negative, which could suggest that FDI is associated with less income inequality. In the next section, we examine this relationship in more detail using panel cointegration techniques.

4. Empirical analysis

The pre-tests for unit roots and cointegration, which are reported in the Appendix, suggest that the variables are nonstationary and cointegrated, as assumed in Equation (1). In this section, we provide estimates of the long-run or cointegrating relationship between FDI and income inequality and test the robustness of the estimates. We also examine the short-run effects of FDI on income inequality and investigate the degree of heterogeneity in the effects of FDI on income inequality across US states.

Figure 1

Scatter plot of the top-decile income share versus the FDI-to-GDP ratio



In order to estimate the long-run effect of FDI on income inequality in the United States, we first use the common correlated effects (CCE) mean group estimator of Pesaran (2006). This estimator is consistent in the presence of cross-sectional dependencies that potentially arise from multiple unobserved common factors and involves augmenting the basic regression with cross-section averages of the dependent and explanatory variables as proxies for the unobserved common factors. An attractive feature of the CCE mean group estimator is that it permits the individual US states to respond differently to the common time effects as reflected by the state-specific coefficients on the cross-sectionally averaged variables. Another advantage of the CCE approach is that it yields consistent estimates also when the regressors are correlated with the common factors. In addition, Kapetanios et al. (2009) have shown that the CCE estimator is consistent regardless of whether the common factors are stationary or nonstationary. The cross-sectionally augmented cointegrating regression for the *i*th cross-section is given by

$$TopDecile_{it} = a_i + \delta_i t + b_i\,(FDI\,/\,GSP)_{it} + g_{1i}\overline{TopDecile_t} + g_{2i}\overline{(FDI\,/\,GSP)_t} + e_{it}\,, \tag{4}$$

where $\overline{TopDecile_t} = N^{-1}\sum_i^N TopDecile_{it}$ and $\overline{(FDI\,/\,GSP)_t} = N^{-1}\sum_i^N (FDI\,/\,GSP)_{it}$ are the cross-sectional averages of $TopDecile_{it}$ and $(FDI\,/\,GSP)_{it}$.

The result of the CCE mean group estimation procedure is presented in the first column of Table 2 where, for brevity, we report only the estimated *b* coefficients. The CCE mean group estimate for *b* is statistically significant (at the 5% level) and negative. More precisely, the elasticity of the top 10% income share with respect to the FDI-to-GSP ratio is estimated to be -0.032, implying that a one percentage point increase in the FDI-to-GSP ratio reduces the top 10% income share by 0.032 percentage points. Thus, we find that FDI lowers income inequality in general or on average in the United States.[11]

Table 2

Estimates of the long-run effect, *b*, of $(FDI/GSP)_{it}$ on $TopDecile_{it}$

CCE mean group estimator (Pesaran, 2006)	DOLS mean group estimator (Pedroni, 2001)
-0.032*	-0.048**
(-2.37)	(-3.15)

Notes: *t*-statistics in parenthesis. ** (*) indicate significance at the 1% (5%) level. The DOLS regressions were estimated with one lead and one lag.

The CCE estimator is intended for the case in which the regressors are exogenous. To account for the possible endogeneity of FDI we also use the DOLS mean group panel estimator of Pedroni (2001), which is asymptotically unbiased and normally distributed even in the presence of endogenous regressors (e.g., Stock and Watson, 1993). The DOLS regression, carried out separately for each state, is given by

$$TopDecile_{it} = a_i + \delta_i t + b_i(FDI\,/\,GDP)_{it} + \sum_{j=-k}^{k}\Phi_{ij}\Delta(FDI\,/\,GSP)_{it-j} + \varepsilon_{it}\,, \tag{5}$$

where Φ_{ij} are coefficients of current, lead and lag differences, which account for possible serial correlation and endogeneity of the regressor(s), thus yielding unbiased estimates. To account for certain forms of cross-sectional dependence, we apply the DOLS procedure to time-demeaned data;

[11] Interestingly, using a sample of Mexican states, Jensen and Rosas (2007) also find that increased FDI inflows are associated with a decrease in income inequality. However, their results are based on simple cross-sectional regressions with only 32 observations and should therefore be viewed with caution.

that is, in place of $TopDecile_{it}$ and $(FDI/GSP)_{it}$, we employ $TopDecile'_{it} = TopDecile_{it} - \overline{TopDecile_t}$, and $(FDI/GSP)'_{it} = (FDI/GSP)_{it} - \overline{(FDI/GSP)_t}$.

The DOLS point estimate of the long-run effect of FDI on the top 10% income share is presented in the second column of Table 2. As the CCE mean group estimator and the DOLS mean group estimator produce almost identical results, it can be ruled out that the observed negative relationship between FDI and income inequality is due to possible endogeneity of FDI (apart from the fact that there is no good theoretical reason to expect a decrease in FDI as a result of an increase in income inequality). However, a problem with the use of time-demeaned data is that it requires the cross-sectional dependence to be driven by a single common source and the cross-sectional units to respond in a similar fashion. Otherwise, the cross-sectional dependence cannot be eliminated effectively. Since it is reasonable to assume that US states respond in a heterogeneous fashion and that there are multiple dependencies, we continue our robustness analysis with the CCE mean group estimator.

Table 3

Parameter estimates using alternative measures of inequality

Atkinson index	Theil entropy index	Gini index
-0.00059**	-0.00104*	-0.00012*
(-2.94)	(-2.14)	(-2.17)

Notes: t-statistics in parenthesis. ** (*) indicate significance at the 1% (5%) level.

Specifically, we examine whether the negative long-run relationship between FDI and income inequality is robust to alternative measures of inequality. To this end, we re-estimate the CCE model using the Atkinson index (with an inequality aversion parameter of ε = 0.5), the Theil inequality measure, and the standard Gini index in place of the top-decile income share. The results are presented in Table 3. Regardless of which inequality measure is used, the long-run relationship between FDI and income inequality remains negative and statistically significant.

Next, we examine whether there are differences between the long-run and short-run effects of FDI on income inequality. To this end, we enter the residuals from the individual CCE long-run relations,

$$ec_{it} = TopDecile_{it} - \hat{a}_i - \hat{\delta}_i t - \hat{b}_i (FDI/GDP)_{it}, \tag{6}$$

as error correction terms into a panel error correction model (ECM) of the form

$$\Delta TopDecile_{it} = c_i + \alpha_i ec_{it-1} + \sum_{j=0}^{2} \varphi_{2ij} \Delta(FDI/GSP)_{it-j} + \sum_{j=1}^{2} \varphi_{1ij} \Delta TopDecile_{it-j} + v_{it}, \tag{7}$$

where the error correction terms contain the long-term elasticities, and the short-run relationship is described by the variables in first differences. To allow for possible cross-section dependence in the errors, v_{it}, we (again) compute the CCE mean group estimator by regressing $\Delta TopDecile_{it}$ on ec_{it-1}, the first differences of $(FDI/GSP)_{it}$ up to lag order two, the lagged first differences of $TopDecile_{it}$ also up to lag order two, the associated cross-section averages, $\overline{\Delta TopDecile_t}$, $\overline{ec_{t-1}}$, $\overline{\Delta(FDI/GSP)_t}$, $\overline{\Delta(FDI/GSP)_{t-1}}$, $\overline{\Delta(FDI/GSP)_{t-2}}$, $\overline{\Delta TopDecile_{t-1}}$, $\overline{\Delta TopDecile_{t-2}}$, and individual intercepts. Note that we choose two lags since a lag length of one is certainly insufficient to fully capture the short-run dynamics of the model, while a lag length of three might be too long given the short sample period.

The results are presented in Table 4. As expected, the lagged error correction term is negative and highly significant, from which it can be concluded that the variables are cointegrated and that the top-decile income share is endogenous in the long run. In the short run, however, FDI appears to have no or weakly significant effects on income inequality. The coefficients on $\Delta(FDI/GSP)_{it}$ and $\Delta(FDI/GSP)_{it-2}$, though negative, are both insignificant, while the coefficient on $\Delta(FDI/GSP)_{it-1}$ (also negative) is significant only at the 10 % level. This implies that positive and negative effects largely offset each other in the short run, leading to net effects that are not significant at the conventional 5% level. The overall inequality-reducing effect of FDI thus appears to be primarily a long-run phenomenon.

Table 4

Panel error correction model

	Coefficients	*t*-statistics
ec_{it-1}	-0.713**	-10.75
$\Delta(FDI/GSP)_{it}$	-0.061	-0.09
$\Delta(FDI/GSP)_{it-1}$	-0.033^{+}	-1.78
$\Delta(FDI/GSP)_{it-2}$	-0.027	-1.22
$\Delta TopDecile_{it-1}$	0.045	1.56
$\Delta TopDecile_{it-2}$	-0.070	-1.40

Notes: *t*-statistics in parenthesis. ** (+) indicate significance at the 1% (10%) level.

Summarizing, we find the short-run effects of FDI on income inequality to be insignificant or weakly significant, whereas, in the long run, FDI exerts a significant and robust negative effect on income inequality in the United States. However, this negative long-run effect for the United States as a whole is an average of the individual state effects and may therefore mask important differences across states. As pointed out in Section 3, the effects of FDI on income inequality may be highly heterogeneous, due to cross-state differences in income levels, policies, and various other characteristics.

In order to examine the heterogeneity in the long-run effects of FDI on income inequality across states, we plot the individual CCE estimates of the coefficients on $(FDI/GSP)_{it}$ in Figure 2. These estimates should be interpreted with caution given the relatively short time dimension of our data. Yet it can be safely concluded that there is considerable heterogeneity in the long-run effects of FDI on income inequality across states. The coefficients range from *minus* 0.82 in Pennsylvania to *plus* 0.76 in Connecticut, indicating that, although the long-run effect of FDI on income inequality is negative in general or on average in the United States, FDI does not have a negative long-run effect on inequality in all states. More specifically, we find that an increase in FDI is associated with a decrease in inequality in 27 states: Alabama, California, Colorado, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kentucky, Maine, Michigan, Minnesota, Mississippi, Missouri, New Jersey, New York, North Dakota, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Utah, Virginia, and Wisconsin. On the other hand, an increase in FDI is associated with an increase in inequality in 21 cases: Arizona, Arkansas, Connecticut, District of Columbia, Kansas, Louisiana, Maryland, Massachusetts, Nebraska, Nevada, New Hampshire, New Mexico, North Carolina, Ohio, Oklahoma, Tennessee, Texas, Vermont, Washington, West Virginia, and Wyoming. But even within the two groups with negative and positive effects, the individual state estimates show considerable heterogeneity. For example, the point estimates suggest that FDI plays an important role in reducing inequality in Pennsylvania, South Dakota, New York, and Wisconsin. In some states such as Maine and Ohio, both the positive and negative effects are close to 0. In striking contrast, FDI has a strong inequality-increasing effect in Connecticut, Arkansas, Massachusetts and Nebraska. Especially these four outliers with strong positive effects call for a tentative explanation.

All four states where FDI has led to greater inequality have in common that MNEs played a minor role until recently.[12] Three of them ranked at the very bottom in terms of the FDI-to-GSP ratio in 1982-1986.[13] This ratio increased to 7-8 per cent in Arkansas, Connecticut and Massachusetts only at the end of the period of observation (1997-2001).[14] Greater inequality thus

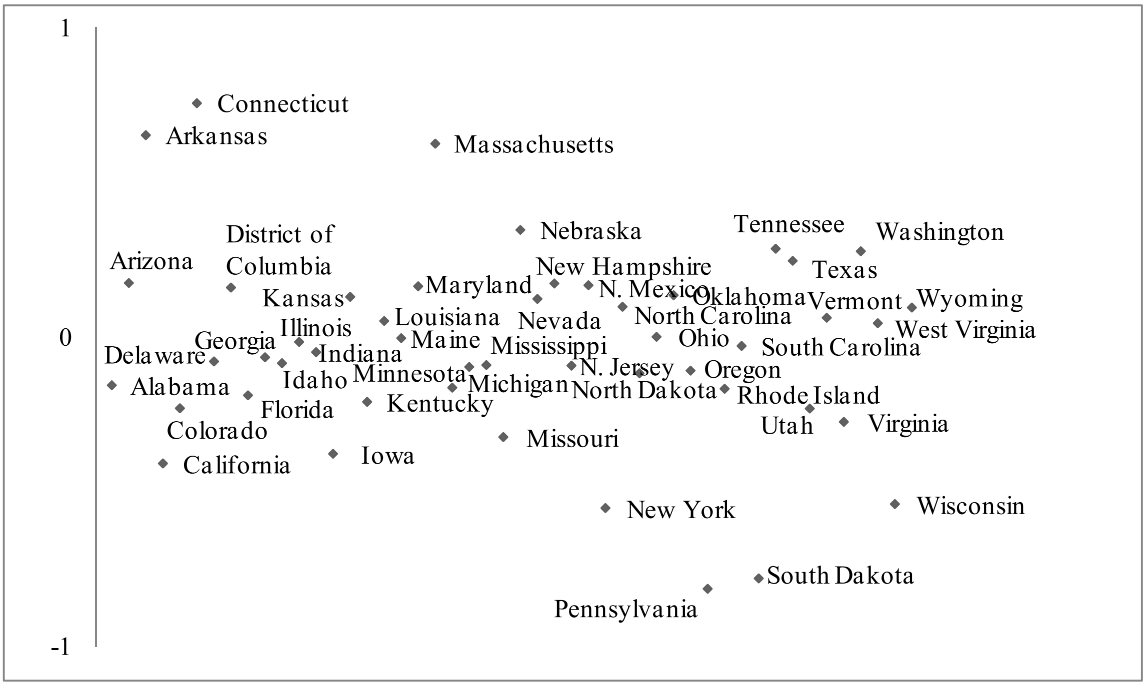
[12] Admittedly, the same is true for South Dakota.
[13] The exception was Arkansas, which belonged to the bottom quintile though.
[14] Nebraska remained the taillight with 4.3 per cent.

appears to be in line with Figini and Görg (1999), who argue that FDI tends to increase inequality when MNE presence is weak and recent. Similarly, Jensen and Rosas (2007) argue that FDI in Mexico has widened income inequality in the south which was considerably less exposed to FDI inflows than the northern states bordering the United States.

While the ratio of FDI stocks to GSP was rather low, MNEs drew relatively strongly on local labor in the four states where FDI added to inequality.[15] The number of workers employed by MNEs per unit of property, plant and equipment was considerably higher in Arkansas, Connecticut, Massachusetts and Nebraska than the corresponding median for all US states.[16] At the same time, the supply of skills was either particularly poor (Arkansas) or increased by less than the median for all US states.[17] Assuming that MNEs demand predominantly skilled labor, the interplay between supply and demand may thus have given rise to (wage) inequality along the lines suggested in Section 2.[18]

Figure 2

Individual state CCE estimates of the long-run effect of FDI on income inequality



[15] The Bureau of Economic Analysis (BEA) reports the employment of foreign affiliates at the level of US states, in addition to the gross book value of property, plant and equipment (available at http://www.bea.gov/scb/account_articles/international/iidguide.htm#FDIUS). Detailed calculations are not reported here for brevity, but are available on request.

[16] This was particularly true at the beginning of the period under consideration. In 1977-1981, for instance, foreign affiliates in Arkansas, Connecticut and Massachusetts employed more than twice as many workers per unit of property, plant and equipment as elsewhere in the United States.

[17] As a proxy, we use the share of state population with a high school diploma or higher and its change between 1980 and 2001.

[18] Note that BEA does not distinguish between skilled and unskilled employment by foreign affiliates at the state level.

5. Conclusion

Income inequality has widened in both developed and developing countries over the past two decades of deepening globalization. It is open to debate, however, whether foreign direct investment as one of the driving forces of globalization has contributed to larger income gaps. Previous empirical findings are inconclusive even though there is a considerable literature on the effects of inward FDI on inequality in developing countries. Furthermore, there are very few country-specific studies addressing the distributional consequences of FDI in advanced host economies.

Utilizing state-level panel data for 48 states (including the District of Columbia) over the period 1977-2001, we investigated the relationship between inward FDI and income inequality in the United States. Specifically, we employed panel cointegration techniques that allow for cross-sectional heterogeneity, cross-sectional dependence as well as endogenous regressors. Our results indicate that the short-run effects of FDI on income inequality are insignificant, or weakly significant and negative. In the long run, FDI exerts a significant and robust negative effect on income inequality in the United States. All the same, there is considerable heterogeneity in the long-run effects of FDI on income inequality across states. In some states, it even appears that FDI has contributed considerably to widening income gaps.

The experience of the United States invites the conclusion that policymakers trying to lure FDI must not fear that access to foreign technology and knowledge generally comes at the cost of deepening social divides where multinational enterprises locate. However, trade-offs between productivity gains and greater income disparity cannot be ruled out under all circumstances. It remains open to question what exactly might explain varying effects across US states. One possibility to be pursued in future research relates to non-linearities resulting from technological adaptation by local firms and learning-by-doing of local workers — along the lines suggested by Aghion and Howitt (1998). Accordingly, inequality-increasing effects of inward FDI are more likely as long as MNE presence is weak and recent. But other possible factors to explain the varying effects of FDI deserve scrutiny as well. Such factors include the economic development and structure of host regions, government policies, as well as the composition and type of FDI attracted by specific regions.

Appendix A1. Key variables by state over the sample period

Figure A.1

Top-decile income share by state over the period 1977-2001, $TopDecile_{it}$

Notes: The states from the left to the right are: Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming

Figure A.2

FDI-to-GSP ratio by state over the period 1977-2001, $(FDI/GSP)_{it}$

Notes: The states from the left to the right are: Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming

Appendix A2. Panel unit root tests

To examine the unit root properties of $TopDecile_{it}$ and $(FDI/GSP)_{it}$, we first use the panel unit root test of Levin, Lin, and Chu (2002) (LLC). This test is based on the following ADF-type regression:

$$\Delta x_{it} = z_{it}\gamma_i + \rho x_{it-1} + \sum_{j=1}^{k_i} \varphi_{ij}\Delta x_{it-j} + \varepsilon_{it}, \qquad i = 1, 2, ..., N, \quad t = 1, 2, ..., T, \tag{A.1}$$

where k_i is the lag length, z_{it} is a vector of deterministic terms, such as fixed effects or fixed effects plus individual trends, and γ_i is the corresponding vector of coefficients. As can be seen from Equation (A.1), the LLC unit root test statistic is a within-dimension-based statistic that pools the autoregressive coefficients across the cross-section units during the unit root test and thus restricts the first-order autoregressive parameters to be the same for all states, $\rho_i = \rho$. Accordingly, the null hypothesis is that all time series have a unit root, $H_0 : \rho = 0$, while the alternative hypothesis is that no series contains a unit root, $H_1 : \rho = \rho_i < 0$, that is, all are (trend) stationary. To conduct the LLC test statistic, the following steps are performed: First, the residuals, $\hat{e}_{it}$, are calculated from individual regressions of Δx_{it} on its lagged values (and on z_{it}), $\Delta x_{it} = \sum_{j=1}^{k_i} \theta_{1ij}\Delta x_{it-j} + z_{it}\gamma_i + e_{it}$. Second, x_{it-1} is regressed on the lagged values of Δx_{it} (and on z_{it}) to obtain $\hat{v}_{it-1}$, that is, the residuals of this regression, $\Delta x_{it-1} = \sum_{j=1}^{k_i} \theta_{2ij}\Delta x_{it-j} + z_{it}\gamma_i + \upsilon_{it-1}$. In the third step, $\hat{e}_{it}$ is regressed on $\hat{v}_{it-1}$, $\hat{e}_{it} = \delta\hat{v}_{it-1} + \xi_{it}$. The standard error, $\hat{\sigma}^2_{ei}$, of this regression is then used to normalize the residuals $\hat{e}_{it}$ and $\hat{v}_{it-1}$ (to control for heterogeneity in the variances of the series), $\tilde{e}_{it} = \hat{e}_{it} / \hat{\sigma}^2_{ei}$, $\tilde{v}_{it-1} = \hat{v}_{it-1} / \hat{\sigma}^2_{ei}$. Finally, ρ is estimated from a regression of $\tilde{e}_{it}$ on $\tilde{v}_{it-1}$, $\tilde{e}_{it} = \rho\tilde{v}_{it-1} + \xi_{it}$. The conventional *t*-statistic for the autoregressive coefficient ρ has a standard normal limiting distribution if the underlying model does not include fixed effects and individual time trends (z_{it}). Otherwise, this statistic has to be corrected using the first and second moments tabulated by Levin et al. (2002) and the ratio of the long-run variance to the short-run variance, which accounts for the nuisance parameters present in the specification. The limiting distribution of this corrected statistic is normal as $N \to \infty$ and $T \to \infty$.

However, the LLC test procedure assumes cross-sectional independence and thus may lead to spurious inferences if the errors, ε_{it}, are not independent across *i*. Therefore, we also use the cross-sectionally augmented IPS or CIPS panel unit root test proposed by Pesaran (2007). This test allows for cross-sectional dependence by augmenting the standard ADF regression with the cross-section averages of lagged levels and first-differences of the individual series. It is based on the between dimension approach and therefore involves the estimation of separate cross-sectionally augmented ADF (CADF) regressions for each state, thereby allowing for different autoregressive parameters for each panel member. Formally, the CADF regression model is given by

$$\Delta x_{it} = z_{it}\gamma_i + \rho_i x_{it-1} + \sum_{j=1}^{k_i} \varphi_{ij} \Delta x_{it-j} + \alpha_i \bar{x}_{t-1} + \sum_{j=0}^{k_i} \eta_{ij} \Delta \bar{x}_{t-j} + v_{it}, \tag{A.2}$$

where $\bar{x}_t$ is the cross-section mean of x_{it}, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$. The null hypothesis is that each series contains a unit root, $H_0 : \rho_i = 0$ for all *i*, while the alternative hypothesis is that at least one of the individual series in the panel is (trend) stationary, $H_1 : \rho_i < 0$ for at least one *i*. To test the null hypothesis against the alternative hypothesis, the CIPS statistic is calculated as the average of the individual CADF statistics:

$$CIPS = N^{-1}\sum_{i=1}^{N_i} t_i, \tag{A.3}$$

where t_i is the OLS *t*-ratio of ρ_i in the above CADF regression. Critical values are tabulated by Pesaran (2007).

Table A1 reports the test results for the variables in levels and in first differences. Both the LLC and the CIPS test statistics are unable to reject the null hypothesis that $TopDecile_{it}$ and $(FDI/GSP)_{it}$ have a unit root in levels. Since the unit root hypothesis can be rejected for the first differences, it can be concluded that the variables are integrated of the same order, *I*(1), which is the necessary condition for cointegration in a bivariate context.

Table A.1

Panel unit root tests

Variables	Deterministic terms	LLC statistics	CIPS statistics
Levels			
$TopDecile_{it}$	c, t	2.709	-2.261
$(FDI/GSP)_{it}$	c, t	2.430	-1.540
First differences			
$\Delta TopDecile_{it}$	C	-8.208**	-3.806**
$\Delta(FDI/GSP)_{it}$	C	-16.069**	-3.123**

Notes: c (t) indicates that we allow for different intercepts (and time trends) for each country. The number of lags was determined by the Schwarz criterion with a maximum of five lags. The relevant 1% (5%) critical value for the CIPS statistics is -2.76 (-2.62) with an intercept and a linear trend. The relevant 1% (5%) critical value for the CIPS statistics is -2.25 (-2.11) with an intercept. ** denote significance at the 1% level.

Appendix A3. Panel cointegration tests

To test for cointegration between $TopDecile_{it}$ and $(FDI/GSP)_{it}$ we first use the Larsson et al. (2001) approach, which is based on Johansen's (1988) maximum likelihood estimation procedure. Like the Johansen time series cointegration test, the Larsson et al. panel cointegration test treats all variables as potentially endogenous, thus avoiding the potential normalization problems inherent in residual-based cointegration tests. Specifically, the Larsson et al. procedure involves estimating the Johansen vector error-correction model for each state separately:

$$\Delta y_{it} = \Pi_i\, y_{it-1} + \sum_{i=1}^{k_i} \Gamma_{ik} \Delta y_{it-k} + z_{it}\gamma_i + \varepsilon_{it}\,, \tag{A.4}$$

where y_{it} is a $p \times 1$ vector of endogenous variables ($y_{it} = [TopDecile_{it}, (FDI/GSP)_{it}]'$; p is the number of variables) and Π_i is the long-run matrix of order $p \times p$. If Π_i is of reduced rank, $r_i < p$, it is possible to let $\Pi_i = \alpha_i \beta_i$, where β_i is a $p \times r_i$ matrix, the r_i columns of which represent the cointegrating vectors, and α_i is a $p \times r_i$ matrix whose p rows represent the error correction coefficients. The null hypothesis is that all of the N states in the panel have a common cointegrating rank, i.e. at most r (possibly heterogeneous) cointegrating relationships among the p variables: $H_0 : rank(\Pi_i) = r_i \leq r$ for all $i = 1, \ldots, N$. The alternative hypothesis is that all the cross-sections have a higher rank: H_1: $rank(\Pi_i) = p$ for all $i = 1, \ldots, N$. To test H_0 against H_1, a panel cointegration rank trace-test statistic is computed by calculating the average of the individual trace statistics, $LR_{iT}\{H(r)|H(p)\}$:

$$\overline{LR}_{NT}\{H(r)|H(p)\} = \frac{1}{N}\sum_{i=1}^{N} LR_{iT}\{H(r)|H(p)\}, \tag{A.5}$$

and then standardizing it as follows:

$$\Psi_{\overline{LR}}\{H(r)|H(p)\} = \frac{\sqrt{N}\left(\overline{LR}_{NT}\{H(r)|H(p)\} - E(Z_k)\right)}{\sqrt{Var(Z_k)}} \Rightarrow N(0,1). \tag{A.6}$$

The mean $E(Z_k)$ and variance $Var(Z_k)$ of the asymptotic trace statistic are tabulated by Breitung (2005) for the model (with an intercept and a trend) we use. However, a well known problem is that the Johansen trace statistics tend to over-reject the null hypothesis in small samples. To avoid the Larsson et al. test also overestimating the cointegrating rank, we compute the standardized panel trace statistics based on small-sample corrected state-specific trace statistics. Specifically, we use the small-sample correction factor suggested by Reinsel and Ahn (1992) to adjust the individual trace statistics as follows:

$$LR_{iT}\{H(r)|H(p)\} \times \left[\frac{T - k_i \times p}{T}\right]. \tag{A.7}$$

The Larsson et al. approach, however, does not take into account potential error cross-sectional dependence, which could bias the results. To test for cointegration in the presence of possible cross-sectional dependence we use the two-step procedure suggested by Holly et al. (2009). In the first step, we apply the common correlated effects (CCE) estimator of Pesaran (2006) to the static cointegrating regression. As discussed in Section 4, this estimator allows for cross-section dependencies that potentially arise from multiple unobserved common factors by augmenting the cointegrating regression with the cross-section averages of the dependent variable and the observed regressors as proxies for the unobserved factors. In the second step, we compute the CIPS statistic for the residuals from the individual CCE long-run relations,

$\hat{\mu} = TopDecile_{it} - \hat{\delta}_i t - \hat{b}_i (FDI/GSP)_{it}$, including an intercept. In doing so, we account for unobserved common factors that could be correlated with the observed regressors in both steps.

The results of these tests are presented in Table A2. For completeness, we also report the standard panel and group ADF and PP test statistics suggested by Pedroni (1999, 2004). As can be seen, all tests suggest that $TopDecile_{it}$ and $(FDI/GSP)_{it}$ are cointegrated. The standardized trace statistics clearly support the presence of one cointegrating vector. Also, the CIPS, the ADF, and the PP statistics reject the null hypothesis of no cointegration at the 1% level, implying that there exists a long-run relationship between FDI and income inequality, as assumed in Equation (1).

Table A.2

Panel cointegration tests

	Cointegration rank	
	r = 0	*r* = 1
Panel trace statistics	3.582**	-2.067
CIPS statistic	-2.909**	
Panel ADF statistic	-10.168**	
Group ADF statistic	-6.633**	
Panel PP statistic	-7.206**	
Group PP statistic	-4.103**	

Notes: ** indicate a rejection of the null hypothesis of no cointegration at the 1% level. The panel trace statistics, the ADF statistics, and the PP statistics are asymptotically normally distributed. The relevant 1% critical value for the CIPS statistics is -2.25. The number of lags was determined by the Schwarz criterion with a maximum number of five lags. The panel statistics pool the autoregressive coefficients across different countries during the unit root test on the residuals of the static cointegrating regressions, whereas the group statistics are based on averaging the individually estimated autoregressive coefficients for each country. The panel ADF statistic is analogous to the LLC panel unit root test. The group ADF statistic is analogous to the panel unit root test of Im et al. (2003). The PP statistics are panel versions of the Phillips-Perron (PP) *t*-statistics.

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