Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Income inequality and FDI: evidence with Turkish data

Meltem Ucal, Alfred Albert Haug & Mehmet Hüseyin Bilgin

To cite this article: Meltem Ucal, Alfred Albert Haug & Mehmet Hüseyin Bilgin (2016) Income inequality and FDI: evidence with Turkish data, Applied Economics, 48:11, 1030-1045, DOI: 10.1080/00036846.2015.1093081

To link to this article: https://doi.org/10.1080/00036846.2015.1093081

APPLIED ECONOMICS, 2016
VOL. 48, NO. 11, 1030–1045
http://dx.doi.org/10.1080/00036846.2015.1093081

Income inequality and FDI: evidence with Turkish data

Meltem Ucal[a], Alfred Albert Haug[b] and Mehmet Hüseyin Bilgin[c]

[a]Department of Economics, Faculty of Economics, Administrative and Social Sciences, Kadir Has University, Istanbul, Turkey; [b]Department of Economics, University of Otago, Dunedin, New Zealand; [c]Department of International Relations, Faculty of Political Sciences, Istanbul Medeniyet University, Istanbul, Turkey

ABSTRACT

This article explores how foreign direct investment (FDI) and other determinants impact income inequality in Turkey in the short- and long-run. We apply the nonlinear auto-regressive distributed lag (ARDL) modelling approach, which is suitable for small samples. The data for the study cover the years from 1970 to 2008. The empirical results indicate the existence of a co-integration relationship among the variables with asymmetric adjustment of the income distribution in the short- and long-run. The negative impact of FDI on the Gini coefficient, decreasing income inequality, is statistically significant in the short- and long-run, though with a quantitatively small impact in both cases. In the short run, GDP growth increases inequality initially, an effect that is reversed in the next period, increases in domestic gross capital formation decreases inequality, and increases in the literacy rate have very minor adverse effects on income equality. However, in the long run these variables have no statistically significant effects on the Gini coefficient. A reduction in the population growth rate reduces inequality in the short run but has no effect in the long run, whereas an increase in the rate reduces inequality in the long run but has no effect in the short run.

KEYWORDS
Income inequality; FDI; nonlinear ARDL estimation; Turkey

JEL CLASSIFICATION
D31; F21; C22

I. Introduction

In recent decades, there have been numerous investigations into the relationship between income inequality and other variables. The literature indicates that income and wage inequality have been rising in many countries since the 1970s. There is supporting evidence, for both developed and developing countries, for an increase in inequality (e.g. Diwan and Walton 1997). A crucial question is whether and what role international trade has played in changes to income distributions.[1] We discuss in the next section the mixed empirical evidence found for the role of foreign direct investment (FDI) in affecting income distributions. The relationship between FDI and income inequality has potentially important implications for economic policy.

Herzer, Hühne, and Nunnenkamp (2014) point out that there are only a few empirical studies that look at FDI and income inequality for low to middle income countries, such as Turkey. Furthermore, Turkey has been included in a few panel studies along with other countries. However, while panels increase the overall number of observations, it may be preferable to consider countries separately if sufficiently long time-series data are available.[2] Countries differ, for example in cultural norms, institutions and social welfare programmes for which it may be difficult to control for in panels.[3] We add to the literature on FDI and income inequality by analysing the relationship between FDI and income inequality in Turkey. Turkey has seen a significant increase in FDI inflows during the past decade. In fact, FDI inflows to Turkey reached about 10 billion US

CONTACT Alfred Albert Haug alfred.haug@otago.ac.nz

[1]Related to the issue of FDI and income inequality is the relationship between trade liberalization and inequality. See Anderson, Tang, and Wood (2006), Gourdon (2007) and Munshi (2008) for examples of empirical research. Anderson et al. find that globalization tends to narrow the gap between developed and developing countries in the wages of less-skilled workers, but to widen the wage gap within developed countries between highly skilled and less-skilled workers.

[2]Examples of panel studies on FDI and inequality that include Turkey are Im and McLaren (2015) for income inequality and Figini and Görg (2011) for wage inequality.

[3]Favero, Giavazzi, and Perego (2011) make this point in regard to panels for fiscal policy analysis.

dollars in 2005, compared with only 2.8 billion dollars in 2004. This figure increased to around 20 billion dollars in 2006 and about 22 billion dollars in 2007. However, between the years 1980 and 2000, the total amount over the entire period was only around 15 billion dollars.

The Gini index of inequality (SWIID 2012) in 2004 was 42.5 in Turkey. It reached a value of 65.3 in that year for South Africa, at the higher end. The index in 2004 was 45.8 for Mexico, 41.6 for China, 40.5 for Russia, 37.2 for the United States, 34.5 for the United Kingdom, 31.0 for Taiwan, 30.9 for South Korea, 27.8 for Germany and 22.6 for Sweden to give just a few examples for comparison purposes. Other alternative measures of inequality have been suggested in the literature (Atkinson and Brandolini 2009). However, the Gini index is the only measure that is available for Turkey over our full sample period. Also, it is the most commonly used measure in studies on income inequality and FDI.

Rising income inequality seems to have been observed in Turkey. Bircan (2007) states that income and wage inequality are high in Turkey. We investigate how FDI inflows affect domestic income inequality by using the nonlinear auto-regressive distributed lag (NARDL) modelling approach to co-integration. The NARDL method can be applied regardless of whether variables have a unit root or are covariance stationary. Furthermore, the method corrects for endogeneity and serial correlation and allows for possibly asymmetric (i.e. nonlinear) adjustments of income inequality to movements in other variables. In other words, increases and decreases in other variables are allowed to affect income inequality differently.

The remaining sections are organized as follows. Section II presents an overview of related previous studies. Section III explains the econometric methodology and data used for examining the relationship between FDI inflows and domestic income inequality in Turkey. Section IV analyses the relationship for the short- and long-run by using NARDL modelling and presents empirical results. Section V evaluates our findings and concludes.

II. Literature review

There is a growing interest in examining the relationship between FDI and income inequality lately. Choi (2006) states that, with the recent increase in FDI, concerns about the effects of FDI on income inequality have heightened. In this section, we present the results of some recent closely related studies which analyse the relationship between income inequality and FDI. We should mention that theories regarding the impact of FDI show that FDI may increase or decrease income inequality.

Choi (2006) analyses the relationship between FDI and income inequality within countries using pooled Gini coefficients for 119 countries from 1993 to 2002. The author attempts to determine whether FDI affects domestic income inequality. Choi finds that income inequality increases as FDI stocks (as a percentage of GDP) increase. On the other hand, Figini and Görg (2011) analyse the relationship between FDI and wage inequality by using a panel of more than 100 countries for the period 1980–2002. The authors argue that the effects of FDI differ according to the level of development. The results are that wage inequality decreases with FDI stocks in developed countries, however for developing countries, 'wage inequality increases with FDI stocks but this effect diminishes with further increases in FDI', which qualifies the findings of Choi.

Another group of the panel studies examines the relationship between FDI, income inequality and economic growth specifically. For instance, Basu and Guariglia (2007) examine the interactions between FDI, inequality and growth, both from an empirical and a theoretical point of view. They use a panel of 119 developing countries and observe that FDI promotes both inequality and growth.

A problem with pooled data or panel studies is that individual country effects of FDI on income inequality may differ substantially or even cancel each other to some degree, and not be captured by fixed or random effects. In other words, it may be a missing variables problem. For this reason, individual country studies or regional groups with similar levels of development may be preferable. Herzer and Nunnenkamp (2013) examine the effects of inward and outward FDI on income inequality in Europe by using panel co-integration techniques and unbalanced panel regressions. The results show that, on average, both inward and outward FDI have a negative long-run effect on income inequality.[4] Furthermore, teVelde (2003) analyses FDI and income inequality for Latin America experiences. The author reviews results with different data sources and states that 'all findings support the conclusion that in most countries the relative position of skilled workers has improved over much of the late 1980s and early 1990s'. Moreover, teVelde mentions that not all types of workers necessarily gain from FDI to the same extent. In another study on Latin America, Herzer, Hühne, and Nunnenkamp (2014) investigate the long-run impact of FDI on income inequality in five Latin American host countries by applying country-specific and panel co-integration techniques. They find, except for Uruguay, that FDI contributes to widening income gaps in all individual sample countries.

Jensen and Rosas (2007) examine the relationship between investments of multinational corporations (FDI) and income inequality in Mexico. They use an instrumental variables approach and find that increased FDI inflows are associated with a decrease in income inequality within Mexico's 32 states. On the other hand, Tang and Selvanathan (2005) examine the relationship for China between FDI inflows and regional income inequality using data for the period 1978–2002 at national, rural and urban levels. They find that FDI inflows are one of the main factors that have led to increasing regional income inequality at the national level, as well as in rural and urban regions of China.

Finally, Bircan's (2007) investigates the effects of FDI in Turkey on the manufacturing sector in terms of wages and productivity. Models are estimated to demonstrate the impact of plant-level foreign equity participation on wages. The results indicate that 'foreign plants pay on average higher wages to their workers, and both production and nonproduction workers benefit from foreign ownership'.

III. Empirical modelling and econometric methodology

Theoretical aspects of modelling income inequality

The conventional Heckscher–Ohlin model of international trade considers two countries that are identical, except for their resource endowments. If emerging countries are deemed relatively abundant in unskilled labour, and the opposite is true for developed countries, then FDI should be concentrated in activities that use less-skilled labour intensively in emerging economies, according to standard trade theory.[5] Then, FDI should lead to an increase in the demand for low-skilled labour and drive up wages of the low-skilled workers relative to the wages of the skilled workers in the emerging economy. Therefore, income inequality will decline in the emerging economy as FDI increases. However, when the restrictive assumptions of the Heckscher–Ohlin type model are relaxed, the effects of FDI on the income distribution can be negative, leading to more inequality. For example, Feenstra and Hanson (1996, 1997) present a model, along with empirical evidence to support it, where FDI increases the relative wage of the skilled workers in the emerging economy (Mexico) as well as in the developed economy (the United States). The activities related to FDI in their model employ relatively large amounts of unskilled labour from the perspective of the developed country. However, from the perspective of the emerging country, the labour used in FDI activities in relatively large amounts is skilled labour and not unskilled labour, comparing skilled and unskilled labour within the Mexican labour market.

Another example of relaxing the assumptions of the standard Heckscher–Ohlin type model is to allow for production functions (technologies) that differ across countries (e.g. Grossman and Helpman 1991). FDI can have adverse effects on income inequality in such a model. Further, technological change may be skill-biased (Wang and Blomstrom 1992) and increase the relative wage of skilled workers. Also, FDI can be seen as a vehicle

[4]Hanousek, Kočenda, and Maurel (2011) survey the literature on direct and spillover effects of FDI and conduct a meta-analysis for transition economies going from a command to a market system in central and eastern Europe, the Balkans and the Commonwealth of Independent States. They find that the weakening of FDI effects over time found in several studies is due to a publication bias in these studies. See also Herzer, Klasen, and Nowak-Lehman (2008) on FDI and economic growth in general.

[5]The Stolper–Samuelson theorem predicts that trade (and FDI) would take advantage of the relatively abundant factor of production, which is low-skilled labour in the emerging economy (see, e.g. Lee and Vivarelli 2006).

for bringing new technologies into a country, with spillover effects when imitation by local firms occurs (Piva 2003). FDI can also lead to intra- and inter-industry technology upgrading (Kinoshita 2000). If these new technologies require relatively more skilled than unskilled labour, relative wages of skilled labour increase along with FDI (teVelde 2003). Figini and Görg (2011) also consider FDI as a vehicle to introduce new technology into a country, such as FDI carried out by multinational firms. They use the endogenous growth model of Aghion and Howitt (1998). A new technological innovation in that model leads to increases in wage inequality at the early stage because firms use skilled labour to implement the new technology. However, at later stages less skilled labour is used when the new technology has been implemented and more wage equality is the result.[6]

Various other theoretical models and explanations of the relationship between FDI and income inequality have been proposed in the literature. For example, FDI can cause crowding out of domestic production (Aitken and Harrison 1999) and investment (Berg and Taylor 2001). Moreover, the employment effects of FDI may be country- and sector-specific (Lee and Vivarelli 2006). Here, FDI affects the income distribution via relative wages. Overall, on a theoretical level the direct and indirect effects of FDI could improve or worsen income inequality.

The empirical model

The links between income inequality and FDI are multifaceted. In the econometric analysis, we do not only use FDI as a determinant of income inequality. A nonlinear model will be used to test the hypothesis of causality and study the long-run relationship for Turkey. We explore the effects of the following variables on income inequality:

$$GINI = f(FDI, GDPGR, GFC, INF, KOFPOL, LR, POPGR, TRADE) \tag{1}$$

Inequality is measured by the Gini index (*GINI*), and *FDI* is the stock of FDI in Turkey, expressed as a percentage of GDP. *GDPGR* is the growth rate of the real GDP calculated from changes in natural logarithms and expressed in US dollars based on period-average exchange rates. Economic growth increases the income ‘pie’ in a country but the increase may or may not benefit all members of society. Also, there may be reverse causality from the income distribution to economic growth, depending on the level of development of a country, and more inequality could either help or hinder economic growth. *GFC* is gross domestic fixed capital formation as a percentage of GDP. FDI competes with domestic capital for domestic workers, which may possibly push up domestic wages and down the income to capital and therefore should be included as a control variable to capture the influence of domestic capital formation (investment) on the distribution of income (e.g. Berg and Taylor 2001, and Im and McLaren 2015). *INF* is the annual inflation rate, based on the GDP deflator. It is a measure of the stance of monetary policy and economic conditions in general. Economic uncertainty and high inflation affect financial markets and income from them and therefore the income distribution. *KOFPOL* is the political stability index that we will explain in the data section in more detail. *LR* is the annual adult literacy rate in per cent and *POPGR* is the annual population growth rate. The literacy rate is a broad measure of education levels, or human capital, which reflects basic skill levels and therefore is related to returns to education and income. *TRADE* measures trade flows and trade openness. It is the sum of exports and imports as a percentage of GDP. In this study, we take into account only the macroeconomic factors that affect the Gini coefficient, with a particular emphasis on FDI.

The choice of variables is motivated by related studies on inequality and *FDI*. Figini and Görg (2011) use a Gini coefficient, though specific to manufacturing wages, and as an alternative a measure related to the UTIP Theil index (discussed in Section IV) in a panel study with 103 countries from 1980 to 2002. They regress either the inequality index on inward FDI stocks (as a percentage of GDP), GDP per capita, education (students enrolled in secondary schools, or, alternatively, people

[6]A related literature, surveyed by Ostry, Berg, and Tsangarides (2014), debates at what point inequality becomes harmful to economic growth and swamps any positive effects of inequality on growth that stem from providing rewards for effort and innovation.

holding a secondary degree, each as a percentage of the population) and *TRADE* defined in the same way as earlier. Similar variables are employed in the study by Basu and Guariglia (2007) in a panel of 119 countries with nonoverlapping 5-year averages from 1970 to 1999. They regress a Gini coefficient for the population aged 15 years and over on FDI inflows (as a present of GDP), GDP growth, investment/GDP, education (the average years of secondary education of those aged 25 years and over) and *TRADE*. Instead of investment, we use gross domestic capital formation because investment data are not available. To capture human capital, we use the literacy rate instead of other schooling data, for the same reason. In addition, Basu and Guariglia used the monetary aggregate *M2* (*M2*/GDP). It is a measure of financial liquidity in the economy. We will explore this measure as part of our robustness analysis in the empirical section, along with the exchange rate.

We employ the Gini coefficient as the dependent variable and explore whether it is co-integrated with other variables. Co-integration in our model is based on the Gini index having a unit root along with some or all of the other variables in the model. Herzer and Nunnenkamp (2013) state that Gini coefficients cannot strictly be a pure unit-root process because Gini indices are bounded from below and above and a true unit-root process would cross any bound with probability 1. However, in the relevant range in small samples, unit-root behaviour may approximate the unknown true data generating process much better than a near-unit-root process with very high persistence. Gini coefficients are likely affected by permanent shocks to factors such as tastes, time preferences and government policies, which lead to unit-root behaviour. In a unit-root process, shocks have permanent effects, in contrast to, say, a mean-reverting stationary process where they have only temporary effects. Guest and Swift (2008) found that the Gini coefficients are stationary in first differences and are therefore $I(1)$ for all countries in their study. Similarly, Chintrakarn, Herzer, and Nunnenkamp (2012) state that Gini coefficients are integrated and co-integrated with other variables (determinants) for the United States.

The econometric methodology

First, we focus on examining the time-series properties of our data before estimating the model of inequality in Equation 1. We analyse the data for a unit root in the levels and also for a unit root in the first differences, that is we test for $I(1)$ and $I(2)$. Next, we examine the long-run relationship of income inequality with its determinants. The residual-based co-integration tests are sensitive to the specification of the test regression and the tests can lead to conflicting results, especially when there are more than two $I(1)$ variables in the analysis. The model of income inequality is estimated within the context of recent developments in econometric methodologies, particularly with respect to co-integration analysis and error-correction models (ECMs) that allow estimation of both the short-run and long-run dynamics. We will apply a nonlinear co-integration analysis but will first discuss the linear analysis for ease of exposition.

The linear ARDL model and FM-OLS

In order to estimate the co-integration relationship and the associated long-run coefficients we use two different estimation methods: the auto-regressive distributed lag (ARDL) approach to co-integration (Pesaran and Shin 1998) and the fully modified ordinary least squares (FM-OLS) method of Phillips and Hansen (1990). Both methods correct for endogeneity and serial correlation in co-integrating regressions, thereby providing asymptotically unbiased and asymptotically (fully efficient) normally distributed estimates of the co-integrating coefficients. These methodologies have proven to produce reliable estimates in small samples and provide a cross-check for the robustness of the results.[7] The advantage of the ARDL method is that it can be applied regardless of whether variables are $I(0)$ or $I(1)$, whereas FM-OLS relies on variables that are $I(1)$. Moreover, it is generally the case that the time span of the period considered for the empirical analysis is of crucial importance when studying long-run relationships, such as co-integration. The frequency of observation is of lesser importance (Haug 2002). In other words, moving from annual

[7]The time period that we look at is not very long but these methodologies are the best available in this case. See Pesaran and Shin (1998) for more information. In particular, the ARDL method applied here uses simulations for proper inference in small samples.

to quarterly data would certainly increase the sample size but it would likely not help much in terms of getting better estimates for the long-run coefficients that we are most interested in.

In what follows we briefly explain these two methodologies. Assume that the long-run formulation of the co-integration regression is

$$y_i = \mu + \delta t + \theta' x_t + v_t \quad (2)$$

where $\Delta x_t = e_t$ and $\xi_t = (v_t, e_t')'$ follows a general linear stationary process. In this case the ordinary least squares (OLS) estimators of δ and θ are consistent, but in general the asymptotic distribution of the OLS estimator of θ involves the unit-root distribution as well as a second-order bias in the presence of the contemporaneous correlation that may exist between v_t and e_t. Therefore, the finite sample performance of the OLS estimator is poor, and in addition nuisance parameter dependences make inference on θ using the usual t-test in the OLS regression of Equation 2 invalid. To overcome these problems, Phillips and Hansen have suggested the FM-OLS estimation procedure that asymptotically takes account of these correlations in a semi-parametric manner. FM-OLS assumes that v_t and e_t in Equation 2 follow a general correlated linear-stationary process:

$$v_t = A_1(L)u_t \quad \text{and} \quad e_t = A_2(L)\varepsilon_t \quad (3)$$

where $\xi_t = (v_t, e_t')'$ are serially uncorrelated random variables with zero means and a constant variance. Assuming $A_1(L)$ and $A_2(L)$ are invertible, FM-OLS takes into account the presence of a constant term and possible correlation between the error term and the differences of the regressors.

The use of the ARDL estimation procedure is directly comparable to the semi-parametric FM-OLS approach to the estimation of co-integrating relationships. Pesaran and Shin proved that OLS estimators of the ARDL model lead to consistent short-run parameter estimates and to super-consistent long-run parameter estimates. Therefore, standard asymptotic normal theory applies for carrying out statistical inference with the OLS parameter estimates, that is usual F- and t-tests can be used. However, due to the asymptotic nature of the model, it is necessary to explore how well the ARDL methodology performs in typical small samples. Pesaran and Shin have carried out a Monte Carlo study with samples of size T = (50, 100, 250). They also compare the ARDL approach to the FM-OLS method of Phillips and Hansen, which is the closest competitor for inference with $I(1)$ variables. They compare biases of the two estimators, and size and power properties of associated t-statistics in Monte Carlo simulations. They find that the bias is generally smaller for the ARDL estimates than for the FM-OLS estimates. Similarly, empirical test sizes are much closer to their nominal values for the ARDL method as compared with the FM-OLS method. In addition, the ARDL method leads to tests with higher power than the FM-OLS method, as far as power comparisons are feasible. However, Pesaran and Shin point out that their Monte Carlo comparison of the two methods is not 'comprehensive' because the data generating process used by them favours the ARDL method. For this reason, we will apply nonlinear versions of both methods, ARDL and FM-OLS, in our empirical analysis. If the results of the two methods are close to each other, we can be quite confident that the results are fairly reliable and robust.

We consider the following general ARDL (p, m) model:

$$\Delta y_i = \beta_0 + \pi_{yy} y_{t-1} + \pi_{yx} x_{t-1} + \sum_{i=1}^{p} \vartheta_i \Delta y_{t-i} + \sum_{j=0}^{m-1} \phi \Delta x_{t-j} + \mu_t \quad (4)$$

Here, π_{yy} and π_{yx} are long-run multipliers and β_0 is the drift. Lagged values of Δy_t and current and lagged values of Δx_t are used to model the short-run dynamic system. As a starting point for the ARDL approach, one estimates Equation 4 in order to examine first if there is a long-run relationship among the variables by carrying out an F-test. In cases where independent variables are integrated of order 0 or 1, the null hypothesis of no long-run relationship can be rejected if the F-statistic exceeds the upper critical value. Conversely, it cannot be rejected when the test statistic is below the lower critical value. In the second step, when there is a long-run relationship between variables, an error-correction representation exists. The ECM estimation result shows the speed of the adjustment back to the long-run equilibrium after a short-run shock.

The nonlinear ARDL (NARDL) model

Shin, Yu, and Greenwood-Nimmo (2014) develop a relatively simple method for modelling, in a coherent way, both short- and long-run asymmetry in the ARDL framework, which they call the non-linear ARDL or NARDL. They define the partial sums x_t^+ and x_t^- in the following way:

$$x_t^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0)$$

and

$$x_t^- = \sum_{j=1}^{t} \min(\Delta x_j, 0)$$

so that Equation 4 can be rewritten, as shown by Shin, Yu, and Greenwood-Nimmo (2014), in the following way:

$$\Delta y_i = \alpha_0 + \pi_{yy} y_{t-1} + \pi_{yx}^+ x_{t-1}^+ + \pi_{yx}^- x_{t-1}^- + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \sum_{j=0}^{m-1} (\phi^+ \Delta x_{t-j}^+ + \phi^- \Delta x_{t-j}^-) + \zeta_t \quad (5)$$

which is the NARDL model. The parameters π_{yx}^+ and π_{yx}^- capture the long-run co-integrating relationship between y_t and the positive movements of the variables in the x_t vector, denoted x_t^+, and the negative movements of the variables in the x_t vector, denoted x_t^-. The variables y_t, x_t^+ and x_t^- form the long-run equilibrium or co-integrating relationship. The asymmetric error-correction part of the model consists of the two remaining terms involving the summations, aside from the random errors ζ_t. Shin, Yu, and Greenwood-Nimmo (2014) prove that this NARDL model can be estimated consistently by ordinary least squares. Also, the bounds testing procedure of the ARDL model can be applied as well to the NARDL model, regardless of whether the regressors are $I(0)$, $I(1)$ or mutually co-integrated. They carried out a Monte Carlo study and show that the critical values from Pesaran, Shin, and Smith (2001) are generally appropriate, but they recommend selecting the critical values based on the number of variables included prior to the decomposition into the partial sums. Furthermore, long-run symmetry where $\pi_{yx}^+ = \pi_{yx}^-$ and short-run symmetry where $\sum_{j=0}^{m-1} \phi^+ = \sum_{j=0}^{m-1} \phi^-$ can be tested with standard Wald tests. They suggest following the general-to-specific approach for testing these symmetry hypotheses.

IV. Data and empirical results

This section presents data sources and variable definitions, along with the empirical results for the relationship of income inequality (the Gini index or coefficient) and *FDI*, controlling for the influences of *GDPGR, GFC, INF, KOFPOL, LR, POPGR* and *TRADE*. As our focus is on Turkey, for which data availability is somewhat limited, we undertake a time-series analysis with annual data for the period from 1970 to 2008.

Data

The Gini index (*GINI*) of inequality in equalized household disposable income, post-tax and post-transfers was obtained from the SWIID (2012; Standardized World Income Inequality Database, version 3.1) of Solt (2009) and TURKSTAT (2007). Alternative measures of income inequality for Turkey are available but the time periods are too short to be useful for regressions. The University of Texas Income Inequality Project (UTIP; http://utip.gov.utexas.edu/about.html) developed an alternative inequality Theil index using wage and employment statistics for the manufacturing sector but it has data for Turkey only for the period from 1980 to 2001. On the other hand, their estimated household income inequality (EHII) data set for Turkey has gaps and is continuously available only till the year 2000. Also, Atkinson and Brandolini (2009) discuss the difficulties associated with measuring income inequality. The Gini coefficient is commonly used in studies related to FDI. For example, Herzer and Nunnenkamp (2013) use it in a panel with eight European countries from 1980 to 2000, and Herzer, Hühne, and Nunnenkamp (2014) in a panel with Latin American countries from 1980 to 2011.

The Turkish FDI stocks of inward FDI into Turkey are from Lane and Milesi-Ferretti (2007), with updates from www.philiplane.org/EWN.html. Figure 1 provides data, from the same source, for Mainland China, South Korea and Taiwan, for the inward FDI stocks as a percentage of GDP for comparison. Turkey is similar to Taiwan and the graph for South Korea shows similarities as well, except for the period

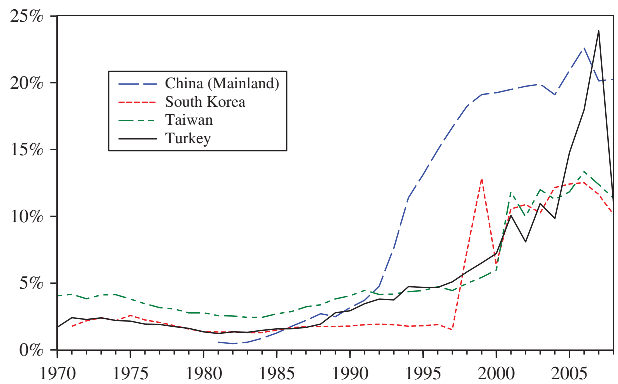

Figure 1. Inward FDI stocks as a percentage of GDP.

1989–1997 and the spike in 1999 when South Korea differed to a greater degree. China's experience is similar until 1992 but after that date China saw a steep increase in FDI until 1999 that is not matched by the other countries. After 1999, FDI levelled off to stay at around 20%, whereas the other countries levelled off at around 12%, aside from a spike for Turkey in 2006 and 2007, reaching Chinese levels.

Turkey has experienced several military coups or interventions in our sample period. This suggests including a measure of political and economic stability in our analysis. Unfortunately, the World Bank's Worldwide Governance Indicators are only available from 1996, initially biannually, and from 2002 annually. One indicator measures 'political stability and absence of violence'. However, such a short sample period gives us insufficient degrees of freedom to run meaningful regressions. Therefore, we use instead *KOFPOL*, which is the *KOF* political globalization index from Dreher (2006), with updates from Dreher, Gaston, and Martens (2008). We treat it as an indicator of political stability in Turkey because it is a proxy for external political engagement (Dreher 2006, fn. 6, p. 1093), which we would expect to decrease at times of military interventions. It is based on embassies in Turkey, Turkish membership in international organizations, participation in UN Security Council missions and international treaties in place. This index started to fall continuously from 1977 to reach a low in 1982 and then gradually increased again to go above the 1977 level in 1988. This coincides with a military takeover in Turkey in 1980. On the other hand, the index did not fall by much around the date of the 1997 intervention by the military (without seizing power) and soon afterwards resumed its increase.

The real GDP growth rate (*GDPGR*) in constant US dollars and the GDP deflator are from the World Bank, as are *GFC, POPGR*, exports and imports as a percentage of GDP (*TRADE*), the monetary aggregate *M2* as a percentage of GDP and (from 1974) FDI net inflows (instead of stocks) as a percentage of GDP. The adult literacy rate was retrieved from the World Bank and TURKSTAT (2007). The average annual US dollar exchange rate for the Turkish lira is from Lane and Milesi-Ferretti.

Empirical results

The NARDL approach has the advantage that it does not require pretesting of the regressors for the presence of unit roots, a problem that afflicts other approaches to the estimation of long-run relations, such as the FM-OLS approach of Phillips and Hansen (see Pesaran 1997). This can be particularly an issue when the unit-root test results are mixed, as they will turn out to be in our case. In any event, we study first the integrating order of all the variables by applying standard unit-root tests. Unit-root tests allow us to classify each series as being stationary or having one or more unit roots. The NARDL (and ARDL) approach allows for at most one unit root only.

The augmented Dickey–Fuller (ADF) and Phillips–Peron (PP) tests are tests for the null hypothesis of a unit root against the alternative hypothesis of a stationary process around a constant mean or deterministic time trend. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test considers instead the null hypothesis of stationarity versus the alternative hypothesis of a unit root. The ADF and PP test results in Table A1 show that all variables are nonstationary in levels and stationary in first differences (i.e. have a unit root), except for possibly GDP growth (*GDPGR*). Both tests indicate that GDP growth is likely stationary in levels, that is, is integrated of order zero, denoted as *I*(0). The KPSS results corroborate these findings for all variables with the following exceptions. The KPSS test indicates that *GINI, GFC, INF, KOFPOL* and *LR* are possibly stationary in levels for a 5% significance level, which is contradicted by the ADF and PP tests. However, the KPSS test results are borderline cases and at the 10% level of significance the null of stationarity is rejected for four out of the five cases in favour of a unit root. Further, the KPSS test indicates two unit roots for *M2*, but we rely on the ADF and PP results that clearly reject two unit roots. The only other cases of test conflict are for the first differences of *FDI* and *POPGR*, where the ADF test does not reject the null hypothesis, indicating two unit roots or *I*(2). The ADF test may lack power, especially in small samples like ours. A test developed by Elliott, Rothenberg, and Stock (1996), using the same kernel and bandwidth procedure as for the PP test, is a modified version of the Dickey–Fuller *t*-test that has substantially improved power (but may have some size disadvantages) in small samples. This test clearly rejects *I*(2) in favour of *I*(1) for *POPGR*, with a test statistic value of 37.8, and for *FDI* with a value of 5.57 as well. Also, it is possible that the presence of structural breaks leads to a spurious finding of either *I*(0), *I*(1) or I(2) behaviour, depending on where in the sample the break occurs (Leybourne, Mills, and Newbold 1998). For this reason, we employ next a unit-root test that considers up to two breaks. Due to events in the Turkish economy, such as financial crises in 1994, 1999 and 2001, the potential presence of structural breaks is a concern.

The standard unit-root tests that we used cannot identify structural breaks. Lee and Strazicich (2003) propose a unit-root test that is valid when there are possibly two structural breaks present in the sample. It is a two-break minimum Lagrange multiplier (LM) unit-root test in which the alternative hypothesis definitely implies the series is trend stationary (Glyyn, Nelson, and Reetu 2007). A unique feature of this test is that it considers up to possibly two breaks under the null hypothesis of a unit root and under the alternative hypothesis of a trend-stationary process. In other words, a unit-root process with up to two breaks is tested against a trend-stationary process with up to two breaks. The null and alternative hypotheses are treated symmetrically in regard to breaks. This is an advantage over other break tests for unit roots that allow only a break under the alternative hypothesis. Lee and Strazicich show that the two-break LM unit-root test statistic, which is estimated according to the LM principle, will not spuriously reject the null hypothesis of a unit root.

Table A1 reports results for the unit-root *t*-statistics in the presence of breaks, along with the dates of breaks. We consider two models, one with two breaks in the constant term only, the other with two breaks each in the constant and deterministic time trend. In the model with a trend, we report a significant break if at least one break is significant, either in the constant term or in the trend term. Once we allow for two breaks, the Gini index is still *I*(1), as is the literacy rate (*LR)*, but *INF* seem to be *I*(0). *TRADE* and *FXRATE* are either *I*(0) or *I*(1), depending on whether the break is in the constant only or in the constant and trend, respectively. The results for the order of integration for *FDI* and *POPGR* are the same as with the ADF without breaks previously but the test of Elliott *et al.* and the PP test earlier clearly indicated one unit root for *FDI* and *POPGR* instead of two. These mixed results illustrate the need for a method such as NARDL where it is unnecessary to pretest for the order of integration as long as it is either *I*(0) or *I*(1). Moreover, the NARDL approach will tell whether there is a linear combination of the variables in our model that is stationary, that is co-integrated. Also, it allows for testing symmetry in the short and/or long run. If there is short- and long-run symmetry, the NARDL model reduces to the ARDL model.

We would like to emphasize that in regard to breaks, we are interested whether the linear NARDL function in Equation 5 shows evidence of structural change, that is whether the relationship is stable over time, regardless of how the individual time series behave. It is possible that the co-movement of variables compensates for breaks in individual series when one models an error-correction process with a long-run equilibrium (the co-integrating relationship). In order to assess the structural stability of the NARDL model, we will examine the residuals from the NARDL regression with the CUSUM and CUSUM of squares tests.

We start the NARDL analysis with a model selection procedure for choosing the variables to include in the model. The goal is to keep the NARDL model parsimonious. We use Akaike's information criterion (AIC), which tends to over-parameterize the model but it minimizes problems due to potentially omitted variables and helps to reduce residual serial correlation that would interfere with our subsequent analysis.[8] This allows us to reduce the model to the following variables:

[8]See Anderson, Athanasopoulos, and Vahid (2007) for this argument.

$$GINI = f(FDI, GDPGR, GFC, LR, POPGR) \quad (6)$$

The variables *INF, KOFPOL* and *TRADE* are therefore excluded. We also used usual Wald tests for the exclusion of each variable in turn and reached the same conclusion that they do not contribute in a significant way (at the usual 5% significance level) to the variations in *GINI*. The next step is to test for symmetry by allowing for each of these variables to have asymmetric effects on *GINI* and then test the hypothesis that the coefficients of x_t^+ and x_t^- are equal. In order not to overload the regressions with too many parameters to be estimated, we do this for each variable in Equation 6 in turn by including the calculated partial sums for it. Then we apply the usual Wald test for symmetry. We uncover statistically significant asymmetric effects for the partial sums of the variables *GFC* and *POPGR*, denoted as GFC^+, *GFC-*, $POPGR^+$ and *POPGR-* and therefore will include them in our NARDL model for further analysis. We also test for short-run symmetry and for long-run symmetry and reject both hypotheses for each variable.

Next, we test for the existence of a long-run relationship. The ARDL and NARDL approaches to co-integration involve the comparison of the *F*-statistics against the appropriate critical values, as explained in Pesaran and Pesaran (1997) and Pesaran, Shin, and Smith (2001).[9] They report two sets of critical values that provide critical value bounds for all classifications of the regressors into purely *I*(1), purely *I*(0) or mutually co-integrated. One type of critical value assumes that all variables are *I*(0) and the other type assumes they are all *I*(1). If the computed *F*-statistic is higher than the upper bound of the critical value, then the null hypothesis of no co-integration is rejected.

The *F*-statistic with income inequality as the dependent variable is *F*(*GINI*|*FDI, GDPGR, GFC, LR, POPGR*) = 4.13. This leads us to conclude that the null hypothesis of no co-integration is rejected. The 5% critical values from Pesaran, Shin, and Smith (2001) are 2.39 for *I*(0) and 3.38 for *I*(1), using $k = 5$ (instead of 7) and therefore not counting the extra variables introduced with the partial sums, as recommended by Shin, Yu, and Greenwood-Nimmo (2014). The null hypothesis of no co-integration can be rejected even at the 2.5% significance level. Results for the long-run model estimated by using NARDL and FM-OLS (with the partial sum terms replacing *GFC* and *POPGR*) are presented in Table 1.[10]

We discuss the short-run and long-run results in Table 1 for each variable in turn. Increased flows of FDI could have a positive effect or negative effect on the Gini coefficient, thereby increasing or decreasing income inequality, respectively. Our estimated coefficients of the short-run adjustment dynamics have a statically significant negative effect on *GINI* and therefore FDI reduces income inequality in the short run. The long-run relationship for both methods, NARDL and FM-OLS, show that FDI has a negative effect as well. Both short-run and long-run

Table 1. Estimated coefficients of the NARDL short-run error-correction process and the long-run (co-integrating) relationship.

Dependent variable: *GINI*

	Regressor	Coefficient	SE	*t*-Statistics (*p*-values)
A. NARDL estimates	$\Delta GINI$ (−1)	−0.33	0.10	−3.19 **(0.007)**
	ΔFDI	−0.003	0.001	−2.45 **(0.03)**
	ΔFDI (−1)	−0.007	0.001	−5.37 (0.0001)
	$\Delta GDPGR$	0.001	0.0002	6.23 (0.0001)
	$\Delta GDPGR$ (−1)	−0.0009	0.0002	−4.89 (0.0002)
	ΔGFC^+	−0.002	0.0005	−3.37 (0.005)
	ΔGFC^-	−0.004	0.0006	−6.21 (0.0001)
	ΔGFC^- (−1)	−0.005	0.0008	−5.53 (0.0001)
	ΔLR	0.0007	0.0002	2.89 (0.01)
	ΔLR (−1)	−0.0009	0.0002	−3.83 (0.002)
	$\Delta POPGR^+$	0.17	0.11	1.53 (0.15)
	$\Delta POPGR^-$	−0.05	0.02	−2.84 (0.01)
	ECM (−1)	−0.35	0.04	−8.86 (0.0001)
B. Long-run NARDL estimates	Constant	0.27	0.18	1.46 (0.17)
	FDI	−0.02	0.008	−2.98 (0.01)
	GDPGR	0.01	0.005	2.04 (0.06)
	GFC^+	−0.004	0.002	−1.80 (0.09)
	GFC^-	0.001	0.0008	1.52 (0.15)
	LR	0.003	0.002	1.46 (0.17)
	$POPGR^+$	−0.77	0.08	−9.44 (0.0001)
	$POPGR^-$	−0.13	0.08	−1.67 (0.17)
C. Long-run FM-OLS estimates	Constant	0.55	0.05	11.5 (0.0001)
	FDI	−0.003	0.0005	−4.96 (0.0001)
	GDPGR	−0.0002	0.0003	−0.68 (0.50)
	GFC^+	0.001	0.001	0.97 (0.34)
	GFC^-	−0.0007	0.0005	−1.43 (0.16)
	LR	0.0001	0.0005	0.22 (0.83)
	$POPGR^+$	−0.73	0.06	−12.5 (0.0001)
	$POPGR^-$	0.03	0.05	1.44 (0.16)

Notes: *p*-Values equal to or smaller than 0.05 are marked in bold.
FM-OLS was estimated with Bartlett weights and Andrews' automatic bandwidth selection.
See Table A2 for other diagnostic statistics for the NARDL model supporting the results of Table 1.

[9]The ambiguities in the order of integration of the variables lend support to the use of the NARDL bounds approach rather than one of the alternative co-integration tests.
[10]No indications of multicollinearity were found in the model.

effects have p-values of 0.03 or smaller. The short-run effect of an increase in the FDI stock of 1% of GDP is to reduce the *GINI* index by 0.33 units from year to year. On the other hand, the magnitude of the effect in the long run is quite small: if FDI stocks go up by 1% of GDP, then the Gini coefficient is reduced by 0.02 units for the NARDL estimates and by 0.003 units for the FM-OLS estimates, for the Gini index defined on a scale from 0 to 100. The long-run effect, while statistically significant, is economically rather small. The short-run effect is not very large either.

GDP growth has initially a small positive effect on *GINI*, thus increasing income inequality, in the short run that is reversed in the next period. There is a similarly small positive effect in the long run. This effect is statically significant in the short run but not in the long run, using a 5% significance level. Domestic gross fixed capital formation reduces income inequality statistically significantly in the short run but not in the long run. The effects are asymmetric with decreases in capital formation more severely affecting the income distribution than increases, though overall the effects are again not very large in magnitude. Increases in the literacy rate have quantitatively very small effects that are only statistically significant in the short run. The effect is to increase income inequality. This indicates that improvements in education in general do not benefit all income groups equally and have led to less equal incomes, however, the effect is so small that it has little effect on GINI.

Population growth has asymmetric effects in the short run and in the long run. In the short run, decreases in population growth reduce income inequality but increases in the growth rate have no statistically significant effects on inequality. On the other hand, in the long run increases in population growth rates lead to reductions in income inequality, whereas decreases in population growth have no long-run statistically significant effects on *GINI*. The long-run coefficient estimate can be interpreted as the long-run cumulative effect of a 1% increase in population growth on the Gini coefficient. It is −0.77 for the NARDL estimate and −0.73 for the FM-OLS estimate, which is very similar in magnitude and turns out to be the largest of the long-run coefficient estimates, in absolute terms. With each estimation method, the estimate is highly statistically significant.

The *ECM* coefficient demonstrates how quickly or slowly variables go back to equilibrium and it should have a statistically significant coefficient with a negative sign. The error-correction term, *ECM* (−1), therefore measures the speed of adjustment to restore equilibrium in the dynamic model. It appears with a negative sign and is highly statistically significant, ensuring that long-run equilibrium can be attained. The coefficient of *ECM* (−1) is equal to −0.35 for the short-run model and implies that deviations from the long-term inequality are corrected by about one-third each year. Diagnostic tests in Table A2 for serial correlation and normality support the model as specified. In addition, we used the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUM of squares) of the standardized recursive residuals of the NARDL regression for analysing the stability of the model. The plots of both the CUSUM and the CUSUM of squares in Figures 2 and 3 are within the 95% confidence bands and these statistics verify the stability of the

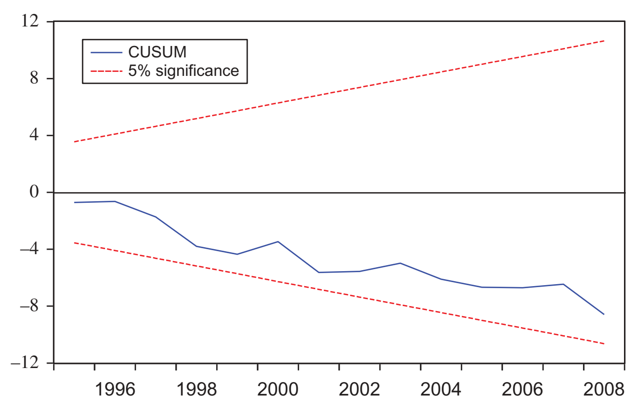

Figure 2. CUSUM of the NARDL model.

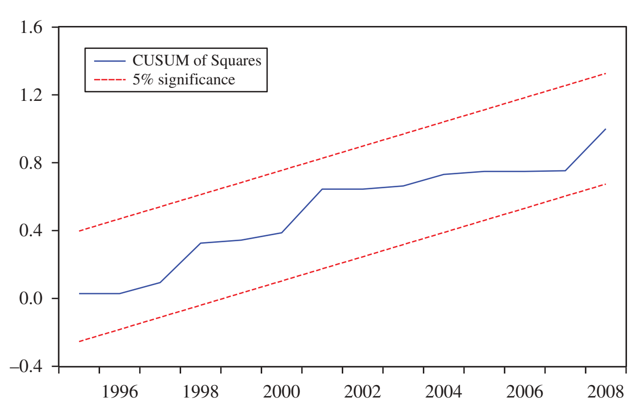

Figure 3. CUSUM of squares of the NARDL model.

NARDL model coefficients for income inequality for Turkey.

As a further check of the robustness of our results, we include in turn the US dollar exchange rate (FXRATE) and the *M2* to GDP ratio in the NARDL model. These variables do not enter the model statistically significantly. Also, using FDI flows instead of stocks does not affect the qualitative results either.

Our empirical findings for FDI are consistent with those of Figini and Görg (2011), who study wage inequality, whereas we study inequality for all income based on the Gini coefficient. They find for developing countries that wage inequality increases with FDI but for developed countries wage inequality decreases when FDI increases.

Placing Turkey as a middle-income country, between developing and developed countries, makes our results consistent with that of Figini and Görg's. Our empirical results are also consistent with those of Jensen and Rosas (2007) for Mexico, finding that FDI reduces inequality, though in our case the magnitude of this effect is rather small. On a theoretical level, these empirical results fit in with standard trade theory of the Heckscher–Ohlin type that predicts that FDI decreases inequality in emerging economies. They also fit in with the theory of Aghion and Howitt (1998) if one argues that Turkey is at a stage beyond the early implementation of new technologies.

V. Conclusion

In the literature, there are only a few empirical studies analysing the relationship between FDI and income inequality for low- to middle-income countries and none exists for Turkey, as far as we know. We apply nonlinear ARDL methods to investigate the short-run and long-run relationships among inequality and FDI in Turkey. We show that the error-correction coefficient, which determines the speed of adjustment, indicates that deviations from long-term inequality are corrected by approximately 35% in each of the following years. The model passes various diagnostic and stability tests and we provide empirical evidence for asymmetric adjustments of the distribution of income in the short run and long run in response to domestic capital formation and population growth rate changes.

Results show that increasing FDI stocks in Turkey have led to reductions in income inequality in the short run and in the long run, however, the quantitative effects turn out to be relatively small though statistically significant and symmetric. The largest effects on income inequality come from population growth: population growth rate increases lead to statistically significant reduction in income inequality in the long run. Reductions in the population growth rate have, however, no statically significant effects on inequality in the long run. These effects are exactly reversed in the short run, with reductions in the rate reducing inequality and increases having no effects. On the other hand, an increase in the literacy rate has no long-run statistically significant effects on inequality but has very small adverse effects in the short run. The implications of our results for economic policy are as follows. FDI has no adverse effects on the distribution of incomes in Turkey but instead reduces inequality though not by much. Therefore, FDI is not a tool for changing the distribution of incomes.

A future study is planned to assess income inequality for urban and rural incomes in Turkey. In this regard, other factors of income inequality components will be included, such as environmental, political, governmental and regional factors. For this purpose, we would like to design a questionnaire for measuring changes in rural and urban incomes.

Acknowledgements

The authors thank, without implicating, the editor and referees of this journal for many helpful and constructive comments on an earlier version of this article that did not consider nonlinearities.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Aghion, P., and P. Howitt. 1998. *Endogenous Growth Theory*. Cambridge, MA: MIT Press.

Aitken, B., and A. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review* 89: 605–618. doi:10.1257/aer.89.3.605.

Anderson, E., P. J. G. Tang, and A. Wood. 2006. “Globalization, Co-Operation Costs, and Wage Inequalities.” *Oxford Economic Papers* 58: 569–595. doi:10.1093/oep/gpl011.

Anderson, H. M., G. Athanasopoulos, and F. Vahid. 2007. “Nonlinear Autoregressive Leading Indicator Models of Output in G-7 Countries.” *Journal of Applied Econometrics* 22: 63–87. doi:10.1002/(ISSN)1099-1255.

Atkinson, A. B., and A. Brandolini, 2009. *On Analyzing the World Distribution of Income*. Bank of Italy, Working Paper No. 701. Accessed July 15, 2015. https://www.bancaditalia.it/pubblicazioni/temi-discussione/2009/2009-0701/index.html

Basu, P., and A. Guariglia. 2007. “Foreign Direct Investment, Inequality, and Growth.” *Journal of Macroeconomics* 29: 824–839. doi:10.1016/j.jmacro.2006.02.004.

Berg, J., and L. Taylor. 2001. “External Liberalization, Economic Performance, and Social Policy.” In *External Liberalization, Economic Performance, and Social Policy*, edited by Taylor, L., 11–55. Oxford: Oxford University Press.

Bircan, C., 2007. “The Effects of Foreign Direct Investment on Wage Inequality in Developing Countries: A Case Study of Turkey.” Honors Thesis in Economics. Accessed May 3, 2008. http://www.williams.edu/Economics/Honors/2007/Bircan_thesis.doc

Chintrakarn, P., D. Herzer, and P. Nunnenkamp. 2012. “FDI and Income Inequality: Evidence from a Panel of US States.” *Economic Inquiry* 50: 788–801. doi:10.1111/ecin.2012.50.issue-3.

Choi, C. 2006. “Does Foreign Direct Investment Affect Domestic Income Inequality?” *Applied Economics Letters* 13: 811–814.

Diwan, I., and M. Walton. 1997. “How International Exchange, Technology, and Institutions Affect Workers: An Introduction.” *The World Bank Economic Review* 11: 1–15. doi:10.1093/wber/11.1.1.

Dreher, A. 2006. “Does Globalization Affect Growth? Evidence from a New Index of Globalization.” *Applied Economics* 38: 1091–1110. doi:10.1080/00036840500392078.

Dreher, A., N. Gaston, and P. Martens. 2008. *Measuring Globalization: Gauging Its Consequence*. New York: Springer.

Elliott, G., T. J. Rothenberg, and J. H. Stock. 1996. “Efficient Tests for an Autoregressive Unit Root.” *Econometrica* 64: 813–836. doi:10.2307/2171846.

Favero, C., F. Giavazzi, and J. Perego, 2011. *Country Heterogeneity and International Evidence on Effects of Fiscal Policy*. Boston, MA: National Bureau of Economic Research, Working Paper No. 17272. Accessed July 15, 2015. http://www.nber.org/papers/w17272

Feenstra, R. C., and G. H. Hanson. 1996. “Foreign Investment, Outsourcing, and Relative Wages.” In *Political Economy of Trade Policy: Essays in Honor of Jagdish Bhagwati*, edited by Feenstra, R. C., G. M. Grossman, and D. A. Irwin, 89–127. Cambridge, MA: MIT Press.

Feenstra, R. C., and G. H. Hanson. 1997. “Foreign Direct Investment and Relative Wages: Evidence from Mexico’s Maquiladoras.” *Journal of International Economics* 42: 371–393. doi:10.1016/S0022-1996(96)01475-4.

Figini, P., and H. Görg. 2011. “Does Foreign Direct Investment Affect Wage Inequality? An Empirical Investigation.” *The World Economy* 34: 1455–1475. doi:10.1111/j.1467-9701.2011.01397.x.

Glyyn, J., P. Nelson, and V. Reetu. 2007. “Unit-Root Tests and Structural Breaks: A Survey with Applications.” *Journal of Quantitative Methods for Economics and Business Administration* 3: 63–79.

Gourdon, J., 2007. “Trade and Wage Inequality in Developing Countries: South–South Trade Matters.” MPRA. Accessed June 3, 2008. http://mpra.ub.uni-muenchen.de/4177/1/ MPRA_paper_4177.pdf

Grossman, G. M., and E. Helpman. 1991. *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.

Guest, R., and R. Swift. 2008. “Fertility, Income Inequality, and Labor Productivity.” *Oxford Economic Papers* 60: 97–618.

Hanousek, J., E. Kočenda, and M. Maurel. 2011. “Direct and Indirect Effects of FDI in Emerging European Markets: A Survey and Meta-Analysis.” *Economic Systems* 35: 301–322. doi:10.1016/j.ecosys.2010.11.006.

Haug, A. A. 2002. “Temporal Aggregation and the Power of Cointegration Tests: A Monte Carlo Study.” *Oxford Bulletin of Economics and Statistics* 64: 399–412. doi:10.1111/obes.2002.64.issue-4.

Herzer, D., P. Hühne, and P. Nunnenkamp. 2014. “FDI and Income Inequality: Evidence from Latin American Economies.” *Review of Development Economics* 18: 778–793. doi:10.1111/rode.2014.18.issue-4.

Herzer, D., S. Klasen, and F. Nowak-Lehman. 2008. “In Search of FDI-Led Growth in Developing Countries: The Way Forward.” *Economic Modelling* 25: 793–810. doi:10.1016/j.econmod.2007.11.005.

Herzer, D., and P. Nunnenkamp. 2013. “Inward and Outward FDI and Income Inequality: Evidence from Europe.” *Review of World Economics* 149: 395–422. doi:10.1007/s10290-013-0148-3.

Im, H., and J. McLaren (2015). “Does Foreign Direct Investment Raise Income Inequality in Developing Countries?” A new instrumental variables approach. Manuscript.

Jensen, N. M., and G. Rosas. 2007. “Foreign Direct Investment and Income Inequality in Mexico, 1990-2000.” *International Organization* 61: 467–487. doi:10.1017/S0020818307070178.

Kinoshita, Y., 2000. *R&D and Technology Spillovers via FDI: Innovation and Absorptive Capacity*. William Davidson Institute Working Paper Series, 349. Ann Arbor, MI: William Davidson Institute at the University of Michigan Business School. Accessed July 15, 2015. http://deepblue.lib.umich.edu/bitstream/handle/2027.42/39733/wp349.pdf?sequence=3

Lane, P. R., and G. M. Milesi-Ferretti. 2007. “The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970–2004.” *Journal of International Economics* 73: 223–250. doi:10.1016/j.jinteco.2007.02.003.

Lee, E., and M. Vivarelli 2006. "The Social Impact of Globalization in the Developing Countries." IZA DP No. 1925. Accessed January 30, 2014. http://ftp.iza.org/dp1925.pdf 10.1111/j.1564-913X.2006.tb00016.x.

Lee, J., and M. C. Strazicich. 2003. "Minimum Lagrange Multiplier Unit-Root Test with Two Structural Breaks." *Review of Economics and Statistics* 85: 1082–1089. doi:10.1162/003465303772815961.

Leybourne, S. J., T. C. Mills, and P. Newbold. 1998. "Spurious Rejections by Dickey–Fuller Tests in the Presence of a Break under the Null." *Journal of Econometrics* 87: 191–203. doi:10.1016/S0304-4076(98)00014-1.

Munshi, F., 2008. "Does Openness Reduce Wage Inequality in Developing Countries? A Panel Data Analysis." Accessed May 1, 2008. http://gupea.ub.gu.se/dspace/bitstream/2077/2665/3/gunwpe0241corr.pdf

Ostry, J. D., A. Berg, and C. G. Tsangarides, 2014. "Redistribution, Inequality, and Growth." IMF Staff Discussion Note, SDN/14/02.

Pesaran, M. H. 1997. "The Role of Economic Theory in Modeling the Long Run." *Economic Journal* 107: 178–191. doi:10.1111/1468-0297.00151.

Pesaran, M. H., and B. Pesaran. 1997. *Working with Microfit 4: Interactive Econometric Analysis*. Oxford: Oxford University Press.

Pesaran, M. H., and Y. Shin, 1998. "An Autoregressive Distributed-Lag Modeling Approach to Cointegration Analysis." *Econometrics and economic theory in 20th century. The Ragnar Frisch Centennial Symposium*, edited by Strom, S. Cambridge: Cambridge University Press, 371–413.

Pesaran, M. H., Y. Shin, and R. J. Smith. 2001. "Bounds Testing Approaches to the Analysis of Level Relationships." *Journal of Applied Econometrics* 16: 289–326. doi:10.1002/(ISSN)1099-1255.

Phillips, P. C. B., and B. Hansen. 1990. "Statistical Inference in Instrumental Variables Regression with I(1) Processes." *Review of Economic Studies* 57: 99–125. doi:10.2307/2297545.

Piva, M., 2003. "The Impact of Technology Transfer on Employment and Income Distribution in Developing Countries: A Survey of Theoretical Models and Empirical Studies." International Labour Office, Policy Integration Department, International Policy Group, Working Paper n.15, Geneva.

Shin, Y., B. Yu, and M. J. Greenwood-Nimmo. 2014. "Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework." In *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*, edited by Horrace, W. C. and R. C. Sickles, 281–314. New York, NY: Springer Science & Business Media.

Solt, F. 2009. "Standardizing the World Income Inequality Database." *Social Science Quarterly* 90: 231–242. doi:10.1111/ssqu.2009.90.issue-2.

SWIID, 2012. "The Standardized World Income Inequality Database, Version 3.1." Accessed May 22, 2008. https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/11992

Tang, S., and S. Selvanathan, 2005. "Foreign Direct Investment and Regional Income Inequality in China." Accessed May 16, 2008. http://www.uib.es/congres/ecopub/ecineq/papers/245tang.doc

teVelde, D. W., 2003. "Foreign Direct Investment and Income Inequality in Latin America Experiences and Policy Implications." Overseas Development Institute. Accessed May 16, 2008. http://www.odi.org.uk/IEDG/Meetings/FDI_feb2003/fdi_la_dwtv.pdf

TURKSTAT, 2007. "Turkish Statistical Institute." Accessed May 22, 2008. http://www.turkstat.gov.tr/PreTablo.do?alt_id=1013.

Wang, J. Y., and M. Blomstrom. 1992. "Foreign Investment and Technology Transfer: A Simple Model." *European Economic Review* 36: 137–155. doi:10.1016/0014-2921(92)90021-N.

Appendix

Table A1. Unit-root test results.

							Lee-Strazicich (2003) break test[a]		
Variables	ADF statistic	5% Critical value	PP statistic	5% Critical value	KPSS statistic	5% Critical value	*t*-Statistic	First break	Second break
GINI	−2.44	−3.54	−1.83	−3.52	0.141	0.146	−4.13 (−1.94)	1980* (1979*)	1997* (1996*)
ΔGINI	−4.60*	−2.94	−4.60*	−2.94	0.09	0.463	−6.40* (−5.81*)	1983* (1983)	1996* (1997)
FDI	1.51	−3.57	−2.70	−3.53	0.17*	0.146	−1.34 (−5.24)	1993 (1986)	2002 (2004*)
ΔFDI	1.67*	−2.96	−6.47*	−2.94	0.41	0.463	−2.65 (−32.1*)	1993 (2000*)	2005 (2005*)
GDPGR	−6.18	−2.94	−6.18*	−2.94	0.04	0.146	−6.95* (−6.59*)	1998* (1979*)	2005* (2004)
ΔGDPGR	−3.80*	−1.95	−11.7*	−1.95	0.08	0.463	−11.4* (−10.4*)	1979* (1998)	1988* (2004)
GFC	−1.94	−3.53	−1.94	−3.53	0.12	0.146	−3.50 (−5.08)	1985 (1985*)	2000* (1999*)
ΔGFC	−5.37*	−2.94	−5.33*	−2.94	0.11	0.463	−3.94* (−41.0*)	1993 (2000*)	2005 (2005*)
INF	−2.31	−3.53	−2.31	−3.53	0.137	0.146	−4.94* (−3.16*)	1996 (1998*)	1999 (2001)
ΔINF	−5.69*	−2.95	−6.85*	−2.94	0.14	0.463	−7.99* (−7.42*)	1997* (1979)	2000* (1982)
KOFPOL	−3.45	−3.56	−2.10	−3.53	0.09	0.146	−2.32 (−4.55)	1987* (1986*)	1990* (1996*)
ΔKOFPOL	−7.45*	−2.94	−7.41*	−2.94	0.10	0.463	−7.87* (−9.39*)	1977 (1982*)	1994 (1993*)
LR	−3.36	−3.54	−3.10	−3.53	0.12	0.146	−2.74 (−4.02)	1985 (1991)	1991 (2001)
ΔLR	−4.82*	−2.95	−6.01*	−2.94	0.06	0.463	−6.24* −6.71*	1975 (1991)	1992 (2000)
POPGR	−2.12	−3.57	−2.24	−3.53	0.154*	0.146	−2.71 (−1.05)	1985* (1983)	1995* (1986)
ΔPOPGR	−1.98	−2.96	−2.96*	−2.94	0.18	0.463	−2.06 (−1.65)	1977* (1984*)	1983* (1993)
TRADE	−3.49	−3.54	−2.91	−3.53	0.18*	0.146	−4.52* (−4.60)	1979 (1981)	1996* (1993*)
ΔTRADE	−5.45*	−2.94	−6.19*	−2.94	0.04	0.463	−5.64* (−6.41*)	1978 (1996*)	1989 (1999*)
FXRATE	−0.94	−3.57	−1.45	−3.53	0.24*	0.146	−6.68* (−2.57)	1996* (1997)	2002* (2005*)
ΔFXRATE	−21.8*	−2.96	−3.08*	−2.94	0.22	0.463	−3.89* (−8.09*)	1988 (1999*)	2002* (2002*)
M2	−3.28	−3.53	−3.16	−3.53	0.18*	0.146	−2.20 (−4.47)	1993 (1979*)	2004 (1998*)
ΔM2	−4.79*	−2.95	−10.8*	−2.94	0.50*	0.463	−10.5* (−10.9*)	1981 (1997*)	2002* (2002*)

Notes: The lags for the ADF test are selected with Akaike's criterion. The PP test is based on a quadratic kernel and Andrews' automatic bandwidth. The critical values for both tests are from EViews 8 and are based on response surface estimates. The KPSS test uses a Bartlett kernel and Andrews' automatic bandwidth. The level tests include a deterministic time trend, except for *GDPGR*. This time trend cancels out in the first differences.

*Rejection of the relevant null hypothesis at the 5% significance level.

[a]The first entry in the cell is the break model with two breaks in each, in the intercept and in the trend; the second entry in the cell, in parentheses, is the crash model with two breaks in the intercept only.

Table A2. NARDL estimates.

Dependent variable: *GINI*			
Variables	Coefficient	SE	*t*-Statistics (*p*-value)
α	0.09	0.10	0.94 (0.36)
GINI (−1)	0.31	0.15	2.09 (0.06)
GINI (−2)	0.34	0.11	3.13 (0.007)
FDI	−0.003	0.001	−2.19 (0.046)
FDI (−1)	−0.01	0.003	−4.11 (0.001)
FDI (−2)	−0.007	0.0003	2.59 (0.02)
GDPGR	0.001	0.0002	5.27 (0.0001)
GDPGR (−1)	0.002	0.0002	6.23 (0.0001)
GDPGR (−2)	0.0009	0.0004	2.38 (0.03)
GFC^{+}	−0.001	0.0003	−4.57 (0.0004)
GFC^{-}	−0.004	0.0006)	−5.72 (0.0001)
GFC^{-} (−1)	−0.0005	0.0007	−0.62 (0.55)
GFC^{-} (−2)	0.005	0.001	4.47 (0.0003)
LR	0.0007	0.0004	1.88 (0.08)
LR (−1)	−0.0007	0.0003	−2.14 (0.05)
LR (−2)	0.0009	0.0002	3.96 (0.001)
$POPGR^{+}$	0.16	0.16	1.03 (0.32)
$POPGR^{+}$ (−1)	−0.43	0.14	−3.15 (0.007)
$POPGR^{-}$	−0.05	0.01	−3.98 (0.001)
R^2	0.99	*F*-statistics	116.5 (p = 0.0001)

Notes: R^2 adjusted 0.98; *Q*-statistic (12) 9.40 (p = 0.67). Jarque–Bera normality test 3.69 (p = 0.16).