POLITIK EKONOMIK KURAM

Research Article

FDI-Inequality Nexus and the Role of Absorptive Capacity: A Finite Mixture Modeling Approach*

Bengi SARSILMAZ[1]

[1] Doktora Öğrencisi, Hacettepe Üniversitesi, bengi.sarsilmaz@gmail.com ORCID: 0000-0001-5197-7717

Abstract: The FDI-income inequality nexus is indetermined in theory, with several opposing mechanisms proposed. Empirical studies also produce mixed results. It might suggest a heterogeneous response of income inequality to FDI inflows conditional on distinct characteristics in recipient countries. While fixed or random effects modeling addresses unobserved country-specific characteristics in panel applications, recent studies introduce observable factors like absorptive capacity for explaining conflicting results and employ threshold panel regression models based on outcomes (supervised learning). Different from the previous studies, this study takes a distinct empirical strategy by adopting a finite mixture model (FMM) as an unsupervised model-based clustering technique to scrutinize distributional heterogeneity in this nexus. The study then questions the role of absorptive capacity as a conditioning factor with varying effects on the inequality of FDI. To this end, we construct a country-wise absorptive capacity index that, to the best of our knowledge, has not been developed before in the context of FDI-inequality linkage. Our empirical results, based on panel data from 26 developing countries between 2004-2019, explain the varying effects of FDI on inequality across three clusters. FDI improves income inequality in the first cluster, while it does not significantly affect in the second and deteriorates in the third cluster. A notable finding is the spatial proximity between clusters, as all transition economies are in the first cluster, where FDI contributes to income distribution. Furthermore, this study reveals that a country's high absorptive capacity, especially its high-level human capital, prevents its negative impact of FDI on distribution.

Keywords: Finite-Mixture Model, Foreign Direct Investment, Income Inequality, Absorptive Capacity, Panel Data
Jel Codes: C18, E25, F21

Doğrudan Yabancı Yatırım-Gelir Eşitsizliği Bağlamı ve Özümseme Kapasitesinin Rolü: Bir Sonlu Karışım Model Yaklaşımı

Öz: Literatürde Doğrudan Yabancı Yatırımların (DYY) gelir dağılımı eşitsizliği üzerindeki etkisi ile ilişkili birkaç karşıt mekanizma öne sürülmekte ve bu mekanizmalar DYY-gelir dağılımı eşitsizliği bağıntısını teorik zeminde belirsiz kılmaktadır. Bununla birlikte, ampirik çalışmalar da birbiriyle çelişen sonuçlar üretmektedir. Bu durum, alıcı ülkelerin kendilerine özgü farklı özelliklerinden kaynaklı olarak DYY'lere karşı gelir eşitsizliğinin heterojen bir tepkisi ile açıklanabilir. Sabit veya rassal etkiler modellemesi, panel uygulamalarında gözlemlenmeyen ülkeye özgü özellikleri ele alırken, son çalışmalar, çelişkili sonuçları açıklamak için özümseme kapasitesi gibi gözlemlenebilir faktörleri ele almakta ve sonuçlara (denetimli öğrenme) dayalı eşik panel regresyon modellerini kullanmaktadır. Bu çalışma, önceki çalışmalardan farklı olarak DYY- gelir dağılımı eşitsizliği bağıntısını denetimsiz bir model tabanlı kümeleme tekniği olan sonlu karışım modeli (SKM) ile inceleyerek farklı bir ampirik strateji ortaya koymaktadır. Ek olarak, bu çalışma DYY'nin eşitsizlik üzerindeki değişen etkilerinde koşul faktör olarak özümseme kapasitesinin rolünü de sorgulamaktadır. Bu amaçla, bu çalışmada daha önce DYY-eşitsizlik bağıntısı çerçevesinde geliştirilmemiş, ülke bazında bir özümseme kapasitesi endeksi oluşturuyoruz. 2004-2019 döneminde 26 gelişmekte olan ülkenin panel verilerine dayanan ampirik sonuçlarımız DYY'nin gelir eşitsizliği üzerindeki etkisini üç farklı ülke kümesine göre açıklamaktadır. DYY, birinci kümede

Atıf: Sarsılmaz B. (2023). FDI-Inequality Nexus and the Role of Absorptive Capacity: A Finite Mixture Modeling Approach, *Politik Ekonomik Kuram, 7*(2), 215-236. https://doi.org/10.30586/pek.1322531

Geliş Tarihi: 04.07.2023
Kabul Tarihi: 06.09.2023

* Bu çalışma "The Impact of Absorptive Capasity on the Linkage Between Foreign Direct Investment and Income Inequality" başlıklı doktora tez çalışmasından türetilmiştir.

gelir eşitsizliğini iyileştirirken, ikinci kümede önemli ölçüde etkilememekte ve üçüncü kümede kötüleştirmektedir. Çalışmada dikkat çekici bir bulgu ise tüm geçiş ekonomilerinin DYY'lerin gelir dağılımına katkıda bulunduğu ilk kümede yer alması gibi kümeler içerisinde mekânsal yakınlıkların bulunmasıdır. Ayrıca, bu çalışma bir ülkenin yüksek özümseme kapasitesinin özellikle de yüksek düzeydeki beşerî sermayesinin, DYY'lerin gelir dağılımı üzerindeki olumsuz etkisini önlediğini ortaya koymaktadır.

Anahtar Kelimeler: Sonlu Karışım Modeli, Doğrudan Yabancı Yatırım, Gelir Dağılımı Eşitsizliği, Özümseme Kapasitesi, Panel Veri
Jel Kodları: C18, E25, F21

1. Introduction

Despite many efforts to reduce global income inequality to a desirable level, it has remained high since the 1990s. Along with a rise in global integration over the last decades, inequitable wealth distribution continues to pose a growing concern not only for economic injustice but also for the well-being of society (Antràs, de Gortari and Itskhoki, 2017; Lee, Lee, and Lien, 2020). Therefore, many studies have been conducted to examine the factors contributing to income inequality, such as economic growth (Kuznets, 1955), population growth (Deaton and Paxon, 1997; Firebaugh 1999), unemployment (Mocan 1999), inflation (Blank and Blinder 1986; Blejer and Guerrero, 1990), trade openness (Reuveny and Li, 2003), and urbanization (Kanbur and Zhuang, 2014).

A significant increase in international capital mobility and multinational businesses has sparked academic interest in investigating the role of foreign direct investment (FDI) in explaining income inequality. However, the FDI-income inequality nexus seems conceptually unclear in the theoretical literature. On the one hand, some studies argue that FDI inflow leads to an increase in labor productivity and, thus, real wages. This, in turn, makes closer the incomes of capital owners and labor, resulting in equal income distribution in the host country (Mundell, 1957). Some other studies, on the other hand, propose that multinational companies enhance the demand for skilled labor in host countries due to outsourcing activities (Feenstra and Hanson, 1997) or skill-driven technological changes (Findlay, 1978; Wang, 1990; Wang and Blomström, 1992), thereby boosting the wages of the skilled or causing unemployment for the unskilled, consequently widening the gap in income inequality. Further, another strand of the literature explains this nexus within the context of the transition to a new technological paradigm (Aghion and Howitt, 1998, 262) and argues that the relationship between FDI inflow and income inequality is non-linear. Based on this paradigm, technological transfers through FDI increase inequality in the short run as a learning process and reduces it over the long term as a process of skill upgrading. This pattern is an alternative explanation of the Kuznets curve (1955) relating income inequality to the level of GDP[1].

In line with the opposing theoretical views, empirical studies produce mixed results. Although the majority of empirical studies document that FDI widens income inequality (Tsai, 1995; Gopinath and Chen, 2003; Basu and Guariglia, 2007; Mahutga and Bandelj, 2008; Herzer, Hühne, and Nunnenkamp, 2014; Suanes, 2016), some studies find that FDI reduces income inequality (Jensen and Rosas, 2007; Jalilian and Weiss, 2022) while others find no significant link (Alderson and Nielsen, 1999; Milanovic, 2005; Sylwester, 2005; Franco and Gerussi, 2013). Further, another line of research finds evidence of an inverted U-shaped pattern (Figini and Görg, 1999; Herzer and Nunnenkamp, 2012; Ucal, Haug, and Bilgin, 2016).

1Kuznets theory explains income inequality in the context of economic development based on a rural-to-urban transition. He considers a dual economy with two income groups: Capital and labor owners. Income inequality between these two groups rises in the early stages of industrialization, then falls in the later stages.

Consequently, some studies consider country-specific characteristics to address heterogeneity in the response of inequality to FDI (Mihaylova, 2015; Tsaurai, 2020). Threshold regression is a commonly used method for this purpose (Wu and Hsu, 2012; Yeboua, 2019; Huynh, 2021). This method chooses a threshold for the conditioning factor to split the sample into different subgroups. The main concern of this supervised methodology is that it relies on subjective decisions on the choice of threshold for the conditioning factor (Wang and Lee, 2021).

This study revisits the FDI-inequality link to account for distributional heterogeneity with a focus on the role of absorptive capacity, employing panel data from 26 developing countries over the 2004-2019 period. Contrary to the previous studies, the study takes a distinct empirical strategy by adopting Finite Mixture Modeling as an unsupervised model-based clustering [2] technique to scrutinize distributional heterogeneity in the linkage between income inequality and FDI.[3] Before FMM analysis, however, the study takes into account cross-sectional dependency in the model by augmented mean group estimation technique (AMG) since common global shocks due to political and financial events and unobserved factors may lead to the co-movement of income inequality across countries (Acemoglu and Robinson, 2002; Bumann and Lensink, 2016; Sayed and Peng, 2021). FMM is a data-driven methodology that endogenously identifies clusters based on the similarity of the conditional distributions of income inequality and thus avoids the arbitrary choice of threshold problem encountered in previous studies (Ouédraogo, Sawadogo, R. and Sawadogo H., 2020; Wang and Lee, 2021). FMM allows us to capture varying effects of FDI on inequality across the clusters and hence enables us to investigate the question of whether the absorptive capacity of countries plays a prominent role in assigning the membership for countries where FDI has a favorable or adverse effect on inequality.

Absorptive capacity[4] refers a host country's ability to learn and apply new external technology from a developed foreign country (Dahlman and Nelson, 1995). There are important reasons why absorptive capacity might explain the membership of the clusters. On one hand, a host country's robust absorptive capacity might enhance its ability to attract more FDI by creating a favorable investment environment and increasing FDI efficiency (Wu and Hsu, 2012). On the other hand, some absorptive capacity indicators, such as financial depth and attainment of secondary and tertiary education, can act as driving forces of income inequality (Dabla-Norris et al., 2015). Because there is no agreement on how to measure absorptive capacity, previous studies have used proxy variables such as school enrollment rates (Mihaylova, 2015; Khan and Nawaz, 2019; Yeboua, 2019), information and communication technologies (Tsaurai, 2020), air transport, electricity consumption (Wu and Hsu, 2012), financial indicators (private credit, bank deposits) (Majeed, 2017; Lee, Lee, and Cheng, 2022), and, institutional quality and governance indicators (Huynh, 2021; Le. et al., 2021). In each study, the absorptive capacity is viewed from a different standpoint, and the empirical results vary accordingly. Further, although some firm-based studies construct an absorptive capacity index, to the best of our knowledge, a country-wise absorptive capacity index has not yet been

2 Among unsupervised clustering techniques, finite mixture models (FMM) are increasingly preferred over heuristic approaches (K-means, hierarchical agglomerative methods and etc.) This inclination primarily arises from FMM's solid foundation in a well-defined mathematical framework, which is investigated using well-established statistical methodologies (Marriott, 1974). Unlike heuristic clustering methods that lack an underlying statistical model, FMM presents a systematic and formal approach to address issues like determining cluster numbers and evaluating model validity (Figueiredo and Jain, 2002). Furthermore, this approach offers advantages when confronted with real-world scenarios. For instance, when clusters overlap or are in close proximity, the assumption of equal variances across clusters, as employed in heuristics, may not hold in practice (Vermunt, 2011). Moreover, under the assumption of multivariate normal components, mixture model-based clustering is sensitive to outliers (McLachlan, 2009). To compare the performance of these two methods, both scenarios involving overlapping clusters and outliers were tested, revealing FMM's empirical superiority (Luoma, 2019).

3As an exception, a study by Wang and Lee (2020) uses FMM to explain the FDI-inequality nexus by country risk. Wang and Lee employ a country risk measure that reflects institutional quality and documents that it affects the probability of class membership. However, we find no evidence that our measure of the institution has such an effect. It might be because our measure is different in that we focus on the indicators referring to the effectiveness of the government in implementing regulations regarding the institutions instead of the government's role in political matters.

4An extensive overview of the absorptive capacity concept is presented in the literature review section.

developed using a formal method in the context of the FDI-income inequality nexus.[5] We construct an absorptive capacity index for each country in the sample over time, using principal component analysis (PCA) that transforms a large number of original variables into a set of factors or components (Sharma, 1996; Meyers, Gamst, and Guarino, 2013).To this end, we include twelve variables derived from the relevant literature under four components: human capital, financial development, governance/institutional quality, and infrastructure development.[6]

Our results point to the presence of three clusters for the countries in the sample with the opposing impacts of FDI on inequality. FDI improves income inequality in the first cluster, while it does not significantly affect in the second and deteriorates in the third cluster. In addition, there are certain spatial proximities between the countries in these clusters. One of the main findings is that all transition economies are inclined to be part of a first cluster where FDI contributes to income equalization. As for the role of absorptive capacity, both the absorptive capacity index and its subcomponents significantly affect the FDI-inequality nexus. Concretely speaking, while absorptive capacity itself does not lead to an income-equalizing effect of FDI, it contributes significantly to avoiding the inequality-widening effect of FDI. Especially human capital, a key component of the absorptive capacity index, has been identified as one of the most powerful tools for mitigating the negative effects of FDI.

The rest of the paper is organized as follows. Section 2 provides a comprehensive overview of the existing literature. Section 3 presents the data sources and the variables. Section 4 outlines the empirical approach employed, and section 5 reports the estimation results. Finally, we discuss the conclusions and policy implications in Section 6.

2. Literature Review

There is a broad literature on the inequality-FDI nexus (Sylwester, 2005; Jensen and Rosas, 2007; Mahutga and Bandelj, 2008; Halmos, 2011; Chintrakarn, Herzer, and Nunnenkamp, 2012; Asteriou, Dimelis, and Moudatsou, 2014; Herzer, Hühne and Nunnenkamp, 2014; Chen, 2016; Ucal, Haug, and Bilgin, 2016). However, since we focus on the role of absorptive capacity, we limit our review specifically to the sub-literature on the use of a conditioning factor(s) to explain this nexus.

Before discussing these factors in relation to FDI and inequality, we briefly overview the concept of absorptive capacity, its evolution over time and its reinterpretation in the context of FDI. The roots of absorptive capacity can be traced back to the concept of social capability, first introduced by Ohkawa and Rosovsky (1973) to capture the role of social and political institutions in economic growth. Abramovitz (1986) later considered social capability as the pre-condition for the less technologically developed countries to successfully catch-up with leading economies. In this way, this concept includes the attributes and quality of people and institutions shaping a society's ability to adopt, adapt, and enhance external technologies. This national-scale social capability notion bears resemblance to the firm-oriented concept of absorptive capacity introduced by Cohen and Levinthal (1990). In their seminal work, they defined it as a firm's ability "to recognize the value of new information, assimilate it, and apply it for commercial ends". In the subsequent studies, various scholars (Zahra and George, 2002; Schmidt, 2005; Todorova and Durisin, 2007) refined and expanded this concept, introducing sub-concepts and

5Nowbutsing (2009) constructs a composite index with a simple average in examining the impact of absorptive capacity on the FDI-growth link. In addition, Feeny and De Silva (2012) create an index using cross-sectional data with alternative methods, such as factor analysis and a simple average, while examining the role of absorptive capacity on the foreign aid-growth link. The shortcoming of the first study is related to the employed methodology since the variables are assumed to have equal weights, and that of the second study is that it has to use cross-country data due to the limitations of data availability. Further, in the second study, the selected variables for the absorptive capacity index, such as donor practices, are not relevant to a general concept of absorptive capacity but rather to the literature on foreign aid effectiveness.

6The index we create with these variables can be adapted to other fields as it is a proxy for the general concept of absorptive capacity. As noted in Abramovitz's (1986) article, human capital, economic and political stability, liberalization of markets, and adequate infrastructure are the minimum necessities to absorb foreign investment and its benefits.

extending its dimensions. Despite varying interpretations, these studies consistently depict absorptive capacity as a set of organizational processes that enable a firm to acquire, integrate, transform, and leverage new knowledge, ultimately adapting to rapidly changing environments. While the majority of conceptual discussions revolve around the notion in relation to firms, a number of studies (Narula, 2004; Juknevičienė, 2013)[7] reconsider it from different aspects on a regional or national scale. In the context of FDI, a higher level of absorptive capacity can enhance a country's capacity to benefit from the expertise and technology brought in by foreign investors. This is because a nation with strong absorptive capacity is better equipped to learn and integrate innovations and practices introduced by foreign enterprises, resulting in increased capital, advanced technology and improved managerial skills (Nguyen et al., 2009). Within this framework, the concept of absorptive capacity can be delineated as "the maximum FDI that an economy can effectively assimilate," as posited by Kalotay (2000).

Apart from conceptual discussions, many empirical studies have examined the absorptive capacity-FDI linkage by employing a range of distinct absorptive capacity indicators. Some studies focus on human capital (Borensztein, de Gregorio, and Lee 1998; Van den Berg 2001; Blomström and Kokko 2003), while others consider financial development (Huang and Xu 1999; Hermes and Lensink 2003), institutional quality (Meyer and Sinani 2009; Jude and Levieuge 2014), and infrastructure development (Zhang and Markusen 1999; Kumar 2006) to understand this relationship. All these studies conclude that good quality absorptive capacity in developing countries can improve the investment climate for FDI, thereby attracting more FDI. Furthermore, sufficient absorptive capacity in an environment of trust drives FDI as technology diffusers rather than resource exploiters.

In addition, there is also a strand of studies examining absorptive capacity-inequality linkage. Again, this relationship is discussed with several absorptive capacity measures. In general, the studies considering human capital (Checchi, 2001; de Gregorio and Lee, 2002), institutional and governance quality (Zhuang, de Dios, and Martin, 2010), infrastructure development (Calderón and Servén, 2004; Ajakaiye and Ncube, 2010) find that good quality of these factors has reducing impact on income inequality. However, the effect of financial development on income inequality seems inconclusive, even though the theories mostly argue for a reducing impact (Banerjee and Newman, 1993; Galor and Zeira, 1993). Some studies find that financial development has an equalizing impact on income distribution (Li, Squire, and Zou, 1998; Beck, Demirguc-Kunt, and Levine, 2005), while others find the opposite (Jauch and Watzka, 2016; Haan and Sturm, 2017). In sum, since FDI and income inequality have strong relationships with absorptive capacity variables, and studies considering the FDI-inequality link obtain conflicting results, there has been a growing interest in absorptive capacity's involvement in the linkage between FDI and inequality.

Table 1 summarizes the empirical studies investigating the relationship between FDI and inequality link with the different accompanying variables. As shown in Table 1, FDI inflow leads to widening income inequality in all studies except for the study of Lee, Lee and Lien (2020). When the accompanying variables exceed a certain level, most studies suggest that the distorting effect of FDI diminishes (Wu and Hsu, 2012; Mihaylova, 2015; Majeed, 2017; Tsaurai, 2020; Huynh, 2021; Le et al., 2021) or may become an income equalizer (Yeboua, 2019). However, the remaining studies (Lin, Kim, and Wu, 2013; Khan and Nawaz, 2019; Lee, Lee, and Lien, 2020) argue that accompanying variables do not affect income inequality reduction through FDI. Wang and Lee (2020) also do not find a significant relationship between FDI and inequality based on the fixed-effects regression

7For instance, Narula (2004) views national or regional absorptive capacity as more than the sum of individual enterprise capacities; it also considers the capabilities of mediating organizations in the region and the interconnections between them. Juknevičienė (2013) redefines national absorptive capacity within the national innovation system framework and refers to a capacity to absorb knowledge from public administration institutions in addition to other stakeholders such as research institutes and role players of businesses.

model. However, they find the varying effects of FDI when including country risk as a concomitant variable in their FMM analysis.[8]

Table 1. A Summary of Empirical Literature Examining the Relationship Between FDI and Income Inequality Using Accompanying Variables

Authors (year)	Countries, Sample Period	Absorptive Capacity Variables	Methodology	Summary Findings
Wu & Hsu (2012)	54 countries, 1980-2005	Infrastructural development	Endogenous threshold regression model	FDI leads to deteriorating income distribution in the whole sample. The worsening impact of FDI increases in countries with lower infrastructure development.
Lin, Kim & Wu (2013)	73 countries, 1970-2005	Average years of schooling	Instrumental variable threshold regression model	Below the threshold of schooling years, FDI reduces the income gap between low and high-income countries. Beyond this threshold, however, the relationship reverses and widens the gap.
Mihaylova (2015)	10 CEE countries, 1990-2012	- Secondary school enrollment ratio - Economic development (GDPPC)	Fixed effects regression model	FDI leads to deteriorating income distribution in the whole sample. However, as human capital and economic development improve, the worsening impact of FDI on distribution diminishes.
Majeed (2017)	65 developing countries, 1970-2008	- Secondary school enrollment ratio - Financial development -Economic development (GDPPC)	Panel regression model	FDI leads to deteriorating income distribution in the whole sample. However, as the levels of human capital, financial, and economic development increase, the worsening effect of FDI on the distribution becomes less pronounced.
Yeboua (2019)	26 African countries, 1990-2013	- Secondary school enrollment ratio	Panel smooth transition regression model	The impact of FDI is twofold. FDI worsens income distribution in countries with a low level of human capital while improving with a higher level of human capital.
Khan and Nawaz (2019)	11 CIS countries, 1990-2016	- Secondary school enrollment ratio	Panel regression model	FDI stock causes income inequality to increase. Human capital is not effective in reducing income inequality through FDI.
Tsaurai (2020)	12 transitional economies, 2005-2015	ICT	Fixed effects regression model	FDI has a positive, but insignificant, effect on income inequality, while ICT does not play an important role in this relationship.
Lee, Lee & Cheng (2022)	37 countries, 2001-2015	Financial development	Panel smooth transition regression model	FDI leads to improving income distribution in the whole sample. However, this improving impact weakens when financial development indicators reach a threshold.
Le, Do, Pham &Nguyen (2021)	Vietnam (63 cities), 2012-2018	- Ratio of trained employers - Institutional quality	Panel regression model	FDI leads to deteriorating income distribution in Vietnam. However, at higher levels of human capital, and institutional quality, the worsening impact of FDI on distribution diminishes.
Huynh (2021)	36 Asian countries, 2000-2018	- Worldwide Governance Indicators (WGI)	Panel regression model	FDI leads to deteriorating income distribution in Asia. As institutional quality improves, the worsening effect of FDI on distribution diminishes.
Wang & Lee (2020)	60 countries, 1998-2014	- Country Risk	Fixed effects regression model & FMM	FDI has a positive but insignificant effect on income inequality. FDI worsens inequality under high country risk while it reduces inequality in countries with low risk.

3. Empirical Strategy

In this section, we specify a canonical model for income inequality and discuss the technical details of our estimation techniques. Firstly, we describe the augmented mean group estimation technique that is robust for cross-section dependency and slope heterogeneity. Then, we discuss Finite Mixture Modeling which addresses possible distributional heterogeneity in the FDI-inequality link. Finally, we provide a brief technical note on a random-effects regression approach that we employ to understand the role of absorptive capacity on varying impacts of FDI on inequality.

8Since they use a country risk measure that reflects the institutional quality and they cite a country's absorption as a partial reason to explain the varying effects in each cluster, we would like to mention this study in the context of this literature.

3.1 Empirical Model for Income Inequality

While many factors other than FDI may affect inequality, we attempt to specify a canonical model for inequality by including a set of control variables based on the relevant literature, such as inflation (Blank and Blinder, 1986; Blejer and Guerrero, 1990), GDP per capita (Kuznets, 1955), trade openness (Reuveny and Li, 2003), population growth (Deaton and Paxon, 1997; Firebaugh, 1999), urbanization (Kanbur and Zhuang, 2014), and the unemployment rate (Mocan, 1999). Accordingly, inequality measured by GINI coefficient is defined as

$$\mathrm{Gini}_{i,t} = \beta_0 + \beta_1 \mathrm{FDI}_{i,t} + \beta_2 \ln \mathrm{GDPpc}_{i,t} + \beta_3 \mathrm{Pop}_{i,t} + \beta_4 \mathrm{Urban}_{i,t} + \beta_5 \mathrm{Trade}_{i,t} + \beta_6 \mathrm{Unemp}_{i,t} + \beta_7 \mathrm{Inf}_{i,t} + u_{i,t},\; u_{i,t} = \delta_i f_t + \varepsilon_{i,t} \tag{1}$$

where i and t are country and time indices, β_1 is our main parameter of interest, and $u_{i,t}$ contains the unobserved common factor (f_t) with heterogeneous factor loadings (δ_i), and the error term($\varepsilon_{i,t}$).

3.2. Augmented Mean Group Estimation

Since FMM is a model-based clustering technique, it is essential to determine an appropriate estimation technique for the underlying panel regression model. To this end, we check for the existence of cross-sectional dependency, considering the possible effects of unobserved common shocks on income inequality. We also check the presence of slope heterogeneity since the homogeneity assumption of traditional regression models, such as fixed effects, may be unable to hold due to varying country-specific characteristics (Breitung, 2005). Further, ignoring cross-sectional dependency and slope heterogeneity issues may cause the estimates to be biased and inconsistent (Pesaran, 2006). To do so, first, we apply several cross-sectional dependency tests such as Friedman (1937), Frees (1995), Pesaran (2004) and Pesaran (2015). Then, we apply the slope heterogeneity test of Pesaran and Yamagata (2008), which is appropriate for our panel data where the cross-section dimension is more than the time series dimension (N>T) and robust for non-normally distributed errors.

If these tests demonstrate the presence of (weak) cross-sectional dependency and slope heterogeneity, the results for first-generation panel models may be questionable.[9] We will, therefore, use the Augmented Mean Group (AMG) estimator, which accounts for cross-sectional dependence and slope heterogeneity by including common dynamic effects in the cross-country regressions (Eberhardt and Bond, 2009). AMG approach consists of two stages: In the first stage, AMG estimates a pooled regression model with year dummy variables (D) using the first difference OLS and collects the coefficients (∂) related to dummies. These coefficients reflect the estimates of the cross-country average of the evolution of unobservable common factors, called the "common dynamic process." In the second stage, the estimated variable ($\hat{\partial}$) is included in the model to account for cross-sectional dependency.

Technically, AMG approach is shown as follows:

Stage 1:

$$\Delta Y_{it} = \beta \Delta X_{it} + \sum_{t=2}^{T} \partial_t \, \Delta D_t + \varepsilon_{i,t} \tag{2}$$

Stage 2:

$$Y_{it} = \alpha_i + \beta_i X_{it} + \partial_i \, t + d_i \, \hat{\partial}_t + \varepsilon_{i,t} \tag{3}$$

$$\hat{\beta}_{AMG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}_i \tag{4}$$

9The results from these tests are presented and discussed in results section 5.

where Δ represents the difference operator, Y and X are dependent and independent variables and ε the error term. The second stage regression includes the common dynamic effect derived from the first stage estimation. As a baseline estimation, we apply to mean group estimation to the second-stage AMG regression. At this juncture, as we are interested in distributional heterogeneity in the slopes of the second-stage regression based on the mixture of inequality distributions, we further apply FMM to the second-stage regression. Then, we will present technical details of FMM incorporating the common dynamic process obtained from the first stage of the AMG technique.

3.3. Finite Mixture Modeling

FMM is an unsupervised model-based clustering technique and addresses possible distributional heterogeneity in FDI-inequality linkage. We present a brief technical note on FMM approach. (for more details see e.g. McLachlan and Peel, 2000; Conway and Deb, 2005) Equation (1), including the cross-sectional dependency, can be respecified within the FMM framework as follows:

$$f(\mathrm{Gini}|\mathrm{x},\Theta) = \sum_{g=1}^{G} \pi_g \, f_g(\mathrm{Gini}|\mathrm{x}; \beta_g, \mu_g) \tag{5}$$

where the value G represents the unknown numbers of classes, $\Theta=(\pi_{1,\ldots\ldots,}\pi_{g},\beta_{1,\ldots\ldots,}\beta_g; \mu_1 \ldots., \mu_g)$ specifies the set of parameters, π_g denotes the posterior probability of belonging to class g, $f_g(\mathrm{Gini}|\mathrm{x}; \beta_g, \mu_g)$ represents the distribution of income inequality (Gini) conditional on belonging to class g, explanatory variables x (with the coefficients β_g), and the parameters μ_g (the standard deviations of the error term).

Following a multinomial logit model (Owen, Videras, and Davis, 2009; Liu, Lee, and Liu, 2020), the posterior probability of component membership in a latent class m (i.e.,g=m) as:

$$\pi_m = \frac{\exp(\gamma_m)}{\sum_{g=1}^{G} \exp(\gamma_g)} \text{ with } 0<\pi_m<1 \quad \text{and} \quad \sum_{m=1}^{G} \pi_m = 1 \tag{6}$$

The model is estimated by maximum likelihood with the estimation maximization (EM) algorithm of Dempster, Laird, and Rubin (1977). If the error term is normally distributed, the log-likelihood function is:

$$Log\ L = \sum_{i=1}^{N}(\log(\sum_{g=1}^{G} \pi_g \prod_{t=1}^{T} f_g(\mathrm{Gini}|\mathrm{x}; \beta_g, \mu_g)) \tag{7}$$

where T represents the number of repeated observations per country.

The country-specific posterior probabilities for a given country i belonging to cluster m are as follows:

$$\hat{\pi}(\mathrm{m}|\mathrm{Gini_i}) = \frac{\pi_m f_m(\mathrm{Gini_i}|\mathrm{x_i}; \hat{\beta}_m, \hat{\mu}_m)}{\sum_{g=1}^{G} \pi_g f_g(\mathrm{Gini_i}|\mathrm{x_i}; \hat{\beta}_g, \hat{\mu}_g)} \tag{8}$$

We will estimate this model with several cluster alternatives (1,2,3 cluster or more) and choose the most appropriate model with the smallest AIC, BIC, and CAIC values to minimize information loss.

3.4. Panel Probit Estimation Technique

If FMM results indicate the existence of more than one cluster, the next question will be to see if absorptive capacity or its sub-components have any role in the differing impacts of FDI on inequality. Based on the results from FMM, we will employ the probit estimation technique in the following panel regression models.

$$\mathrm{Equalizing_{i,t}} = \beta_i + \mathrm{Index_{i,t}} + \alpha_i + u_{i,t} \quad \text{for cluster 2,} \tag{9}$$

$$\text{Distorting}_{\mathrm{i,t}} = \beta_{\mathrm{i}} + \text{Index}_{\mathrm{i,t}} + \alpha_{\mathrm{i}} + u_{\mathrm{i,t}} \quad \text{for cluster 3.} \tag{10}$$

where $\text{Equalizing}_{\mathrm{i,t}}$ ($\text{Distorting}_{\mathrm{i,t}}$)is a dichotomic variable which takes the value of 1 for those countries in which FDI has an income-equalizing (distorting) effect and of zero otherwise. $\text{Index}_{\mathrm{i,t}}$ represents absorptive capacity index, and sub-indexes such as human capital, financial development, infrastructural development, and institutional quality. α_{i} refers the individual unobserved effect, and $u_{\mathrm{i,t}}$ denotes the random error term. We will treat α_{i} as random effects (Heckman, 1981) since this technique considers all available data including country-specific and time-invariant characteristics that may affect the probability of a country belonging to each class, while fixed effects model omits the time-invariant values for each country.[10] Random effects model assumes that the unobservable effect α_{i} is not correlated with independent variables [$\text{cov}(\text{Index}_{\mathrm{i,t}}, \alpha_{\mathrm{i}}) = 0$, t=1,2,...............T]. This model is estimated using GLS (Wooldridge, 2002).

4. Data Sources and Construction of Absorptive Capacity Index

Our sample covers panel data from 26 developing countries over the period between 2004-2019[11]. We select countries based on the data availability. Regionally, seven countries are from the Asian continent, six are from the European continent, and thirteen are from the Americas.

Income inequality is measured by Gini index, and the independent variable of interest is FDI inflow. The inflation rate, GDP per capita, trade openness (measured by the rate of the sum of exports and imports over GDP), population, urbanization, and unemployment rate are the control variables. Data on all variables in our empirical model are obtained from the WDI database. Table A2 shows the definition and descriptive statistics of all of the variables.

To construct an absorptive capacity index, we use twelve variables[12]derived from the relevant literature (Abramovitz, 1986; de Mello, 1999; Durham, 2004; Nguyen et al., 2009) under four components: human capital, financial development, governance/institutional quality, and infrastructure development. We obtain the data on human capital from the UNESCO Institute for Statistics, on financial and infrastructural development from the WDI, and institutional quality from the WGI database. Table A2 shows the summary statistics on these variables. We apply principal component analysis (PCA) that reduces the number of variables to a few components using linear weighted combinations of the original variables (Sharma, 1996). Mathematically, from a set of variables $(X_1, X_2, \ldots, X_n)$

$$PC_m = \beta_{m1}X_1 + \beta_{m2}X_2 + \beta_{m3}X_3 + \cdots + \beta_{mn}X_n \tag{11}$$

where β_{mn} represents the weight for the *m*th principal component and the *n*th variable. Then, we use the first component (PC_1)[13] as the index, which has the highest explanatory power of variation. With this methodology, more than 60% of the variation is explained by the absorptive capacity index in most countries (Table A3).

5. Empirical Results

This section first presents the impact of FDI on income inequality based on the AMG estimation which accounts for cross-sectional dependency and slope heterogeneity. Since

10Since some countries are in the same cluster all over the period in our data, we do not prefer these countries to be ignored as is the case in fixed effects modeling. In addition, the fixed effects model has an incidental parameters problem, which generates biased coefficients by mismeasuring the estimated t-statistics as well as standard errors (Greene, 2004).

11The list of countries is presented in Table A1 of the Appendix.

12The list of subcomponents under four main components is presented in Table A2 of the Appendix. To mitigate the potential variance-biased result while identifying principal components through PCA, we standardized all these variables prior to the application of PCA, aligning with the approach outlined by Hastie et al. (2009).

13Specifically, we define coefficients $(\beta_{11}, \beta_{12}, \ldots\ldots\ldots, \beta_{1n})$ for the first component in such a way that its variance is maximized, subject to the constraint that the sum of the squared coefficients is equal to one.

we are interested in distributional heterogeneity in the FDI-inequality linkage, this section continues with the results of FMM, which includes the common dynamic process from the first stage of AMG. Finally, the role of absorptive capacity and its subcomponents in varying effects of FDI is explained.

We start to test the presence of slope homogeneity and cross-sectional independence to determine the appropriate panel modeling. As shown in Table 2, since two out of three tests (Friedman, 1937; Frees, 1995; Pesaran, 2004) show that the model is cross-sectional dependent, we also apply the test of Pesaran (2015) to observe whether this dependence is weak. When the cross-section dimension is sufficiently large, as is the case with our panel data, the hypothesis of weak dependence is more relevant than the null hypothesis of independence. The results reveal that this model has (weak) cross-sectional dependence. As for slope homogeneity, we apply delta and adjusted delta tests of Pesaran and Yamagata (2008) and find the presence of slope heterogeneity.

Therefore, we first use the Augmented Mean Group (AMG) estimator as baseline estimation results, which is robust to slope heterogeneity and cross-sectional dependence and produces unbiased and efficient results. As shown in the second column of Table 4, FDI has an insignificant effect on income inequality in developing countries, which is not in line with most existing studies. One explanation for this finding could be that countries are clustered together based on their unobserved specific characteristics in such a way that FDI has opposing effects, rendering its effect obsolete. Therefore, we secondly apply FMM analysis to see if distributional heterogeneity exists in the impacts of FDI in different clusters of countries.

To do so, we must first optimally select the number of clusters by using three kinds of information criteria (i.e., Akaike information criterion (AIC), Bayesian information criterion (BIC), corrected Akaike information criteria (CAIC)) that are commonly used in the literature on FMM applications (Zuo, 2016; Ouédraogo, Sawadogo R., and Sawadogo H., 2020; Wang and Lee, 2021). Table 3 demonstrates the results from these criteria for each number of clustered models. To minimize information loss, it is better to select the model with the lowest values. The values of the 1-cluster model are the highest among alternative models. This means that AMG may cause misleading results by mean group averaging the slope parameters for all countries. Accordingly, we choose the 3-cluster model since two out of three criteria have the lowest values.

Table 2. CD, normality, and slope heterogeneity test results

	CD test	**Null hypotheses**
Friedman	16.308	Ho: cross-sectional independence
Frees	3.599***	
Pesaran (2004)	4.060***	
	Weak CD test	
Pesaran (2015)	0.662	Ho: weakly cross-sectional dependence
	Normality test	
Jarque-Bera	21.37***	Ho: error term is normally distributed
	Slope Heterogeneity	
Pesaran and Yamagata (Delta)	5.841***	Ho: slope coefficients are homogenous
Pesaran and Yamagata (Adjusted Delta)	9.052***	

[1] ***p<0.01 significant at 1%.

Table 3. Selection of the number of clusters

	1- cluster (C=1)	**2-cluster (C=2)**	**3-cluster (C=3)**	**4-cluster (C=4)**
AIC	2652.3	2567.4	2512.7	**2480.4**
BIC	2692.2	2651.3	**2640.5**	2652.1
CAIC	2692.2	2651.3	**2640.6**	2652.2

Table 4 (columns 3-5) shows the estimation results from the 3-cluster FMM analyses. In the first cluster, we find that FDI has a reducing effect on income inequality. Some scholars point to this relationship, citing that increased productivity and real wages through FDI inflows cause the host country's capital owners and laborers to equalize their incomes (Mundell, 1957). Considering the posterior probability, which means the group size, the first cluster is the largest size (62%) among the clusters. In other words, most countries are members of the first cluster, where FDI has an income-equalizing effect.

In the second cluster, we find that FDI has no significant impact on income inequality. This finding can be explained by the fact that income inequality is *relatively dependent* on FDI inflows. Alderson and Nielsen (1999) interpreted this finding by emphasizing the importance of foreign investment outflows as much as inflows in the context of investment dependency. [14] This cluster is in the smallest size (16%).

Table 4. Estimation Results

Variables	AMG	Finite Mixture Model		
		Cluster 1	Cluster 2	Cluster 3
FDI	-0.104 (0.065)	-0.302*** (0.097)	-0.017 (0.059)	0.333*** (0.111)
ln(GDPpc)	1.077 (4.494)	-0.544 (0.948)	-13.708*** (0.551)	-9.317*** (0.814)
Population growth	0.090 (1.723)	3.632*** (0.470)	-0.359 (0.321)	7.785*** (0.304)
Urban	0.048 (0.622)	0.175*** (0.042)	0.563*** (0.030)	0.551*** (0.047)
Trade openness	0.055*** (0.204)	-0.071*** (0.014)	0.096*** (0.011)	0.088*** (0.011)
Unemployment	0.274* (0.159)	-0.524*** (0.093)	-0.375*** (0.070)	-0.124 (0.12)
Inflation	-0.014 (0.023)	-0.242*** (0.046)	0.142*** (0.032)	-0.318*** (0.023)
Constant	-7.286 (41.74)	46.336*** (6.730)	119.076*** (3.647)	75.100*** (3.379)
Common Dynamic Effect	0.608* (0.347)	-0.224*** (0.078)	-0.086 (0.066)	0.317** (0.143)
Observations	401	250	65	86
R^2	0.62			
Posterior probability of clusters		62.4%	16.1%	21.5%
Marg. mean of Gini		39	43	48
FDI (mean value)		4.6	4.0	3.7

[2] Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

In the third cluster, we find that FDI has a widening effect on income inequality. Some scholars emphasize the increasing demand for skilled laborers due to outsourcing activities (Feenstra and Hanson, 1997) or transmitting skill-driven technological changes (Findlay, 1978; Wang, 1990; Wang and Blomström, 1992), which increases the income gap between skilled and unskilled labor. In addition, increased unemployment among unskilled laborers due to skill-driven businesses causes to fuel further income inequality.

14According to Nielsen and Alderson's (1999) study, a country's net foreign investment position (outflows minus inflows) is effective in its income distribution as it determines investment dependency. As a country progresses from underdeveloped to mid-developed levels, investment dependency increases due to increased investment inflows, even though outflows remain low. In this case, income inequality increases as MNCs use modern capital-intensive technologies and pay more to employed workers. While the country's economy is developing further, investment dependency decreases as investment outflows exceed inflows. In this case, increasing manufacturing employment leads to reduce income inequality. In sum, the role of investment outflow is just as crucial as investment inflow in determining income inequality within the framework of investment dependency.

Although empirical studies in the existing literature mostly point to the income-widening effect of FDI in developing countries, the size of this cluster is almost 22%.

After we define the clusters, we evaluate the effects of control variables, where FDI is significantly correlated with income inequality. Despite some differences in their magnitudes, all control variables in clusters 1 and 3 move in the same direction except for trade openness and unobserved common shocks. Further, in the first cluster, where FDI improves income distribution, trade openness and unobserved common shocks improve as well. On the contrary, in the third cluster, where FDI deteriorates income distribution, trade openness and unobserved common shocks also deteriorate. In other words, economic globalization, a fundamental factor underlying FDI, trade openness, and common shocks, is the principal determinant in grouping clusters 1 and 3. As seen in the last row of Table 4, the major difference in FDI mean values between these two clusters also supports this interpretation. On the other hand, in cluster 2, we see the worsening impact of inflation on inequality, which can be viewed as a symptom of economic instability and may be a barrier to attracting FDI (Botrić and Škuflić, 2006) or reducing the benefits of FDI (Sajilan et al., 2019) in the host country.

Let us examine the composition of these clusters. To do this, we assign each country to a given cluster only when its probability of being in that class exceeds its probability of belonging to all other classes. When we look at the distribution of clusters per country, we determine some spatial proximities between countries in each cluster (Table 5). For instance, countries in the first cluster in all years during the period are Armenia, Bulgaria, Moldova, Turkey, and Ukraine located around the Black Sea. On the contrary, the countries mostly in the third cluster are Latin American countries such as Brazil, Costa Rica, and Panama. This finding can be explained by the results of Tsai (1995). In this study, he argues that the significant linkage between FDI-inequality is mainly due to the regional differences in income inequality.

For further evaluation of the characteristics of clusters, let us return to Table 4 to consider the marginal mean values of Gini. The first cluster has the lowest mean value of Gini, whereas the third cluster has the highest. In other words, FDI inflows increase (decrease) inequality in developing countries where income inequality is already higher (lower). When we interpret this finding by combining it with regional characteristics, we can conclude that Latin American countries in the third cluster are more unequally distributed than other developing countries, and FDI further exacerbates this unequal income situation. This inference is also consistent with the study of Te Velde (2003). In his paper, he argues that FDI perpetuates inequalities in Latin America, where it has been high- and persistent- income inequality since the reforms in the 1980s because FDI triggers skill-driven technological changes and the corresponding skill-specific wage bargaining. In addition, we find that all transition countries[15] in our sample are more likely to be members of the first cluster. In other words, FDI is more likely to have an improving impact on income inequality in transition countries. Even though this finding does not exactly overlap with the existing literature, previous studies (Bhandari, 2007; Barlow, Grimalda, and Meschi, 2009; Franco and Gerussi, 2013) do not find an inequality-widening impact of FDI in transition countries.

At this point, we turn to the question of whether absorptive capacity has any role as a conditioning factor in explaining the opposing impacts of FDI in each cluster. To do so, we estimate equations *(6,7)* by the random effects probit technique.

15Armenia, Bulgaria, Belarus, Georgia, Hungary, Moldova, Romania, Russia, Ukraine

Table 5. Cluster membership

	The distribution of clusters in the period 2004-2019 per country		
	Cluster 1	Cluster 2	Cluster 3
Argentina	53%	20%	27%
Armenia	**100%**	0%	0%
Belarus	88%	0%	13%
Bolivia	40%	27%	33%
Brazil	20%	0%	**80%**
Bulgaria	**100%**	0%	0%
Colombia	43%	0%	57%
Costa Rica	13%	0%	**88%**
Dominican Republic	63%	31%	6%
Ecuador	88%	0%	13%
El Salvador	44%	25%	31%
Georgia	75%	25%	0%
Honduras	6%	63%	31%
Indonesia	44%	56%	0%
Kazakhstan	47%	53%	0%
Kyrgyz Republic	94%	0%	6%
Moldova	**100%**	0%	0%
Panama	6%	0%	**94%**
Paraguay	50%	0%	50%
Peru	31%	38%	31%
Romania	62%	0%	38%
Russian Federation	53%	40%	7%
Thailand	33%	47%	20%
Turkey	**100%**	0%	0%
Ukraine	**100%**	0%	0%
Uruguay	44%	56%	0%

Table 6 reports the results of the random effects probit model. We find that the countries with high absorptive capacity index are less likely to be part of cluster 3. Further, the results show that the marginal effects of human capital, financial and infrastructural development are negatively associated with the probability of being in cluster 3. That is, countries with a high capacity in terms of human capital, financial systems, and infrastructure are less likely to be in the group of countries where FDI has a worsening impact on income inequality. However, the fact that countries have high absorptive capacities does not significantly affect the probability of being in cluster 1. The marginal impacts of absorptive capacity and its sub-indexes are not significant in the group of countries where FDI has an improving impact on income inequality. In fact, absorptive capacity protects from the harmful effects of FDI, whereas it is not a factor in revealing the beneficial effects of FDI on income distribution. Our findings are also in line with the study of Wu and Hsu (2012), although they use only infrastructural development as a representative variable of absorptive capacity. They reported that FDI is likely to be harmful to countries with low absorptive capacities while it has an insignificant effect on income distribution in the countries with better absorptive capacity.

Table 6. Panel Probit Model Estimation after FMM analysis

	Dependent Variables:	
Independent Variables:	The probability of being in 1st cluster: improving impact of FDI on distribution	The probability of being in 3rd cluster: deteriorating impact of FDI on distribution
Absorptive Capacity Index	0.060 (0.037)	**-0.082*** **(0.046)**
Human Capital Index	0.063 (0.065)	**-0.212**** **(0.917)**
Financial Development Index	0.051 (0.051)	**-0.100*** **(0.059)**
Infrastructural Development Index	-0.099 (0.062)	**-0.146*** **(0.077)**
Institutional Quality Index	0.017 (0.049)	0.036 (0.058)
Mean value of absorptive capacity index	0.303	-1.376

[3] Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

6. Conclusion

In this study, we investigated the effect of FDI inflows on income inequality in developing countries with the possibility of countries separating into different classes. We used FMM analysis to classify countries considering possible distributional heterogeneity in the linkage between inequality and FDI. We also included common dynamic effects, a representative variable of unobserved common shocks, in the model to control cross-sectional dependency.

Using panel data from 26 developing countries between 2004–2019, we found that the impact of FDI on income inequality varies across country clusters. More specifically, FDI improves income inequality in the first cluster, while it does not significantly affect income inequality in the second and deteriorates income inequality in the third cluster. Then we examined the question of whether the absorptive capacity of countries is the main reason for varying impacts of FDI. We found that countries with a high absorptive capacity are less likely to be impacted by FDI's negative effects on income distribution. Further, considering the components of absorptive capacity, the human capital index is more important in avoiding the negative distributional impact of FDI.

Our findings have important policy implications for developing countries. The main suggestion of this study is that developing economies should improve their domestic conditions to prevent the worsening effects of FDI. In particular, investments in human capital, financial systems, and quality infrastructure not only reduce the potential negative impact of FDI on income inequality (Yeboua, 2019) but also attract more FDI (Le et al., 2021). In addition, this study shows that FDI inflows further exacerbate inequality in developing countries that are more unequally distributed than other developing countries. Therefore, regardless of FDI's role in the host country, host countries' governments should implement redistributive policies that adjust inequality through social transfers, social benefits, and other public investments, especially in educational activities. Moreover, an important finding from this study highlights that in transition countries, there is a higher probability that FDI will positively affect the reduction of income inequality. In these nations, the types (such as horizontal, vertical, and conglomerate) and industries associated with FDIs, as well as how they affect the labor market, offer potential research for the future. Such studies can potentially serve as a guiding model for other developing economies.

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Çıkar Çatışması: Yoktur.
Finansal Destek: Yoktur.
Etik Onay: Yoktur.
Yazar Katkısı: Bengi SARSILMAZ (%100)

Conflict of Interest: None.
Funding: None.
Ethical Approval: None.
Author Contributions: Bengi SARSILMAZ (100%)

APPENDIX

Appendix 1.

Table A1. Developing Countries Used in This Study

Country Name	Region
Argentina	South America
Armenia	Western Asia
Belarus	Eastern Europe
Bolivia	South America
Brazil	South America
Bulgaria	Eastern Europe
Colombia	South America
Costa Rica	Central America
Dominican Republic	North America
Ecuador	South America
El Salvador	Central America
Georgia	Western Asia
Honduras	Central America
Indonesia	South-eastern Asia
Kazakhstan	South-central Asia
Kyrgyz Republic	South-central Asia
Moldova	Eastern Europe
Panama	Central America
Paraguay	South America
Peru	South America
Romania	Eastern Europe
Russian Federation	Eastern Europe
Thailand	South-eastern Asia
Turkey	Western Asia
Ukraine	Eastern Europe
Uruguay	South America

Appendix 2.

Table A2. Descriptive Statistics, Definition & Data Sources

Variables (Abbreviation)	Obs.	Mean	Std. Dev	Definition:	Data Source:
Dependent variable:					
GINI	401	41.15	8.78	GINI index	WDI
Explanatory variable of interest:					
FDI	416	4.26	3.57	Ratio of foreign direct investment net inflows over GDP	WDI
Control variables:					
Inflation (Inf)	416	8.14	8.50	The growth rate of the GDP deflator	WDI
Trade openness (Trade)	416	77.43	33.03	Ratio of sum of exports and imports over GDP	WDI
ln(GDP per capita)(lnGDPpc)	416	8.55	0.65	Log of GDP per capita (constant 2015 US$)	WDI
Population growth (Pop)	416	0.72	0.88	Annual population growth rate	WDI
Urbanization (Urban)	416	65.91	14.27	Urban population rate	WDI
Unemployment rate (Unemp)	416	7.04	3.79	Ratio of unemployment over total labor force	WDI
Absorptive capacity variables:					
Human capital variables:					
Average years of schooling	344	8.91	1.95	Average number of years completed in 25 aged and older population	UIS
Tertiary enrollment	313	51.69	19.28	Gross enrollment ratio for tertiary school	UIS
Vocational education enrollment	371	15.67	13.27	Share of students in secondary education enrolled in vocational programs	UIS
Financial development variables:					
Domestic Credit	361	42.89	24.60	Ratio of domestic credit to private sector over GDP	WDI
Broad Money (M3 to GDP)	403	47.74	21.10	Ratio of broad money over GDP	WDI
Bank Deposits	409	37.78	8.22	Ratio of bank deposits over GDP	WDI
Institutional quality variables: [16]					
Regulatory Quality	416	49.04	17.84	The role of government in implementing regulations	WGI
Government Effectiveness	416	45.37	15.29	The quality of public services, policy formulation, and implementation	WGI
Control of Corruption	416	39.02	18.92	The power of government for private gain	WGI
Voice & Accountability	416	46.05	18.29	Freedom of citizens in matters relating to association, expression, etc.	WGI
Infrastructural development variables:					
Fixed broadband subscriptions	407	2960830	5731784	Fixed broadband subscriptions	WDI
Air freight	405	503.63	1122.98	Air transport, freight (million ton-km)	WDI

16 We use four over six aggregate indicators which are existed in the Worldwide Governance Indicators database. We exclude Political Stability and Absence of Violence/Terrorism indicator since it is more relevant to the country's governance rather than institutions. In addition, we do not either include Rule of Law indicator since it is highly correlated with the other indicators such as regulatory quality, government effectiveness, and control of corruption in our sample.

Appendix 3.

Table A3. Variance Explained by the First Component (%):

Country Name	Absorptive Capacity Index	Human Capital Index	Financial Development Index	Institutional Quality Index	Infrastructural Development Index
Argentina	46	53	93	72	88
Armenia	61	78	97	59	98
Belarus	73	59	67	89	87
Bolivia	N.A.	N.A.	94	42	57
Brazil	65	68	81	78	62
Bulgaria	63	76	73	42	94
Colombia	70	77	96	65	58
Costa Rica	54	86	81	72	52
Dominican Republic	77	92	60	63	N.A.
Ecuador	62	91	88	51	68
El Salvador	43	89	69	59	89
Georgia	73	78	99	80	92
Honduras	57	67	93	49	87
Indonesia	79	94	93	83	92
Kazakhstan	81	73	98	74	92
Kyrgyz Republic	69	100	92	45	89
Moldova	59	75	86	59	51
Panama	N.A.	93	N.A.	40	75
Paraguay	80	95	99	71	93
Peru	78	74	99	72	83
Romania	48	73	70	45	76
Russian Federation	65	81	98	61	98
Thailand	59	62	98	51	67
Turkey	72	88	82	75	96
Ukraine	N.A.	N.A.	92	45	62
Uruguay	54	88	91	65	84

[4] N.A.: Not applicable due to an insufficient number of observations