Hacettepe University Graduate School Of Social Sciences

Department of Economics

THE ROLE OF ABSORPTIVE CAPACITY ON THE EFFECTS OF FOREIGN DIRECT INVESTMENT ON INCOME INEQUALITY AND PRODUCTIVITY

Bengi Sarsılmaz Özekinci

Ph.D. Dissertation

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ACCEPTANCE AND APPROVAL

The jury finds that Bengi Sarsılmaz Özekinci has on the date of 25/10/2024 successfully passed the defense examination and approves her Ph.D. Dissertation titled “The Role of Absorptive Capacity on the Effects of Foreign Direct Investment on Income Inequality and Productivity”.

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ETİK BEYAN

Bu çalışmadaki bütün bilgi ve belgeleri akademik kurallar çerçevesinde elde ettiğimi, görsel, işitsel ve yazılı tüm bilgi ve sonuçları bilimsel ahlak kurallarına uygun olarak sunduğumu, kullandığım verilerde herhangi bir tahrifat yapmadığımı, yararlandığım kaynaklara bilimsel normlara uygun olarak atıfta bulunduğumu, tezimin kaynak gösterilen durumlar dışında özgün olduğunu, **Prof. Dr. Lütfi Erden** danışmanlığında tarafımdan üretildiğini ve Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Yazım Yönergesine göre yazıldığını beyan ederim.

Bengi Sarsılmaz Özekinci

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor, Prof. Dr. Lütfi Erden, for his invaluable help, guidance, and encouragement throughout every phase of this study. This dissertation would not have been possible without his support.

I would also like to thank my thesis committee, Prof. Dr. Pelin Öge Güney, Prof. Dr. Filiz Elmas Saraç, Assoc. Prof. Dr. Onur Yeni, and Assoc. Prof. Dr. Halis Kıral for sharing their knowledge and insightful suggestions to improve this dissertation.

I want to express my deepest gratitude to my mother, father, brother, and sister-in-law for their unwavering support and motivation.

I am grateful to my husband, Volkan, for his understanding and support, which made this journey more meaningful. And finally, a special thank you to our baby, Vera, who joined our family along the way.

ABSTRACT

SARSILMAZ ÖZEKİNCİ, Bengi. *The Role of Absorptive Capacity on the Effects of Foreign Direct Investment on Income Inequality and Productivity*, Ph.D. Dissertation, Ankara, 2024.

This dissertation investigates the impacts of foreign direct investment (FDI) inflows on income inequality and productivity growth, emphasizing the role of absorptive capacity. While traditional theories posit that FDI yields favorable outcomes in developing economies by mitigating inequality and enhancing productivity, empirical evidence regarding these relationships is inconclusive. Such disparities may stem from varying responses of income inequality or productivity growth to FDI inflows, attributable to unique characteristics such as absorptive capacity of recipient nations. In order to scrutinize the distributional heterogeneity in FDI-inequality and FDI-productivity associations, this study employs a distinctive empirical approach by utilizing a finite mixture model (FMM) as an unsupervised model-based clustering technique. Then, the study investigates the role of absorptive capacity as a conditioning factor on the heterogeneous effects of FDI on inequality and productivity growth. For this purpose, a country-wise absorptive capacity index is constructed using panel data from 26 developing countries. The first chapter, focusing on FDI-inequality, reveals divergent effects of FDI across three clusters. Meanwhile, the second chapter, centered on FDI-productivity, identifies disparate effects across two clusters. Specifically, our findings indicate that FDI contributes to income inequality improvement in one cluster, exhibits no significant impact in another, and exacerbates it in the third cluster. Moreover, nations with high absorptive capacity, particularly in terms of quality human capital, are better positioned to alleviate the adverse effects of FDI on income distribution. Regarding the productivity impact of FDI, our results indicate a negative effect on productivity growth in one cluster, but a positive effect in the other. Furthermore, countries with high absorptive capacity, characterized by quality human capital, robust institutions, and advanced financial and infrastructural development, are more likely to experience positive FDI effects on productivity growth.

Keywords

Finite Mixture Model, Foreign Direct Investment, Income Inequality, Productivity, Absorptive Capacity, Panel Data

ÖZET

SARSILMAZ ÖZEKİNCİ, Bengi. *Özümseme Kapasitesinin Doğrudan Yabancı Yatırımın Gelir Eşitsizliği ve Verimlilik Üzerine Etkilerindeki Rolü*, Doktora Tezi, Ankara, 2024.

Bu tez, doğrudan yabancı yatırım (DYY) girişlerinin gelir dağılımı eşitsizliği ve verimlilik artışı üzerindeki etkilerini, özümseme kapasitesinin rolü ile birlikte incelemektedir. Geleneksel teoriler, DYY'ın eşitsizliği azaltma ve verimliliği artırma yoluyla gelişmekte olan ekonomilerde olumlu sonuçlar doğurduğunu öne sürerken, bu ilişkilere dair ampirik kanıtlar kesin değildir. Bu farklılıklar, gelir eşitsizliği veya verimlilik artışının DYY girişlerine verdiği farklı tepkilerden kaynaklanabilir ve alıcı ülkelerin özümseme kapasitesi gibi kendilerine özgü ayırt edici özellikleri ile açıklanabilir. Bu çalışma, DYY-eşitsizlik ve DYY-verimlilik ilişkilerinde dağılımsal heterojenliği detaylı bir şekilde incelemek için, denetimsiz model tabanlı kümeleme tekniği olan sonlu karışım modelini (SKM) kullanarak farklı bir ampirik yaklaşım sunmaktadır. Ardından, çalışma DYY'ın eşitsizlik ve verimlilik artışındaki heterojen etkileri üzerinde koşullu bir faktör olarak özümseme kapasitesinin rolünü araştırmaktadır. Bu amaçla, 26 gelişmekte olan ülkenin panel verileri kullanılarak ülke bazlı bir özümseme kapasitesi endeksi oluşturulmuştur. DYY-eşitsizlik ilişkisine odaklanan ilk bölüm, DYY'ın üç kümede farklı etkilerini ortaya koymaktadır. DYY-verimlilik ilişkisine odaklanan ikinci bölüm ise, iki küme üzerinden farklı etkileri tanımlamaktadır. Spesifik olarak, bulgularımız DYY'ın bir kümede gelir eşitsizliğini iyileştirdiğini, başka bir kümede anlamlı bir etki göstermediğini ve üçüncü kümede ise kötüleştirdiğini ortaya koymaktadır. Ek olarak, özellikle nitelikli beşeri sermaye açısından özümseme kapasitesi yüksek olan ülkelerin DYY'ın gelir dağılımı üzerindeki olumsuz etkilerini azaltma konusunda daha avantajlı konumda olduğu tespit edilmiştir. DYY'ın verimlilik üzerindeki etkisi ile ilgili olarak ise, sonuçlarımız DYY'ın bir kümede verimlilik artışı üzerinde olumsuz, diğer kümede olumlu bir etkisine işaret etmektedir. Ek olarak, nitelikli beşeri sermaye, güçlü kurumlar, gelişmiş finansal ve altyapı gelişimine sahip olan yüksek özümseme kapasiteli ülkelerin, verimlilik artışı üzerinde olumlu DYY etkileri deneyimleme olasılıkları daha yüksektir.

Anahtar Sözcükler

Sonlu Karışım Modeli, Doğrudan Yabancı Yatırım, Gelir Eşitsizliği, Verimlilik, Özümseme Kapasitesi, Panel Veri

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ABBREVIATIONS

AMG: Augmented Mean Group Estimator

CD: Cross-Section Dependence

CES: Constant Elasticity of Substitution

FDI: Foreign Direct Investment

FMM: Finite Mixture Model

GDP: Gross Domestic Product

MNE: Multinational Enterprise

OECD: The Organization for Economic Cooperation and Development

OLS: Ordinary Least Square

PCA: Principal Component Analysis

PWT: Penn World Table

R&D: Research and Development

STEM: Science, Technology, Engineering, and Mathematics

TFP: Total Factor Productivity

UIS: The UNESCO Institute for Statistics

WDI: World Development Indicators

WGI: Worldwide Governance Indicators

INTRODUCTION

Foreign direct investment (FDI) stands as a pivotal component within an open and efficient global economic framework, which might act as one of principal drivers for development. Developing countries have recognized FDI as a crucial instrument for economic progress, modernization, heightened productivity and income. Consequently, these countries have implemented policies aimed at liberalizing their FDI frameworks and employing various strategies to attract foreign investment. Nonetheless, the benefits of FDI do not materialize automatically and are not uniformly distributed among countries (OECD, 2002). Furthermore, the impact of FDI on income distribution within the host developing country remains contentious. The primary challenges lie in host countries' endeavors to establish transparent, comprehensive, and efficient policy frameworks conducive to investment, while also enhancing their absorptive capacities to effectively implement these policies.

This dissertation investigates FDI's impact on key macroeconomic indicators, such as income distribution and productivity, in developing countries, considering the role of their absorptive capacities. Conceptually, absorptive capacity denotes a host country's ability to assimilate and apply new external technology from more developed foreign counterparts (Dahlman & Nelson, 1995). While most existing empirical studies use human capital level as a Proxy to represent absorptive capacity, it is imperative to recognize that human capital level, albeit necessary, does not singularly ensure the absorption of foreign investment and subsequent benefits for the host country. Abramovitz (1986; 1995) advances a theoretical framework positing that a country's developmental potential hinges on its social capabilities, a notion evolving within the domain of absorptive capacity. According to this perspective, a host country derives benefits from FDI through various elements, including technical proficiency, political and commercial institutions, industrial infrastructure, financial systems, and the organization and management of extensive enterprises, alongside markets capable of facilitating large-scale capital mobilization for businesses. Following the lead of Abramovitz (1986;

1995) framework, this study constructs a cross-country absorptive capacity index using four primary factors: human capital, institutional quality, and financial and infrastructural development.

At this point, it is worth elaborating these factors. Firstly, the human capital level of the host country plays a pivotal role in determining its capacity to attract FDI and the ability of local firms to assimilate new knowledge. Consequently, nations endowed with higher human capital tend to draw technology-intensive multinational enterprises (MNEs), thereby augmenting local labor skills. Conversely, countries with comparatively weaker initial conditions may attract less FDI, leading to the adoption of simpler technologies by foreign firms, which in turn contributes less to the development of local skills (Blomström & Kokko, 2002). Secondly, the development of the local financial system significantly impacts MNEs' ability to access funds for expanding their innovative endeavors within the host nation. This, in turn, widens the potential for technological knowledge transfer to domestic enterprises (Hermes & Lensink, 2003). Moreover, a robust financial system empowers MNEs to embark on riskier ventures, such as research and development (R&D) projects employing cutting-edge technologies (Huang & Xu, 1999). Thirdly, institutions represent another critical facet of absorptive capacity, encompassing various aspects such as property rights protection, regulatory frameworks, business laws, corruption prevention, and economic freedom. Well-established institutions facilitate knowledge spillovers by fostering competitive dynamics and demonstration effects among MNEs. For instance, institutional frameworks establish incentives and business protocols that shape the competitive landscape, encouraging both foreign and domestic firms to engage in market competition within regulatory boundaries (Meyer & Sinani, 2009). Conversely, elevated transaction costs and increased risks associated with long-term trade commitments weaken linkages between foreign and domestic enterprises. Moreover, uncertainties arising from inadequate investor protection, the threat of expropriation, or ineffective law enforcement discourage high-end technological investments while attracting low-tech, resource-oriented FDI with limited growth potential (Jude & Levieuge, 2014). Finally, physical infrastructure emerges as another pivotal factor in attracting MNEs to developing countries. The presence of adequate infrastructure aligns with investors' market preferences, ensuring reduced production costs and maximized returns. Conversely, inefficient infrastructure leads to time wastage and escalated investment costs, ultimately reducing investors' profitability (Nguyen et al., 2013). In summary, absorptive capacity constitutes a multifaceted construct evaluated not through singular factors but through the interplay of various elements.

This dissertation consists of two chapters. The first chapter investigates the linkage between FDI and income inequality in developing countries, taking into account the absorptive capacities of these nations. The impact of FDI on income distribution in developing countries has been a focal point of interest in both political and academic spheres for an extended period. This interest stems from the recognition that widening income inequality entails adverse impacts for economic growth and macroeconomic stability. It can concentrate political and decision-making power among a select few, result in suboptimal utilization of human resources, instigate political and economic instability that deters investment, and elevate the risk of crises. Particularly in developing countries, income inequality engenders significant disparities in access to education, healthcare, and financial services compared to advanced nations (Dabla-Norris et al., 2015). Theoretical research in this realm presents diverse perspectives, with some positing that FDI exacerbates income inequality (Findlay, 1978; Wang & Blomström, 1992; Feenstra & Hanson, 1997) in developing countries, while others (Mundell, 1957) suggest its potential to improve income distribution. Empirical studies similarly yield mixed outcomes. The varying effects of FDI imply potential distributional heterogeneity in responses across country clusters. Unlike exisiting empirical studies, we employ finite mixture modeling (FMM) as an unsupervised model-based clustering technique to explore potential distributional heterogeneity. Subsequently, we investigate the role of absorptive capacity and its components as conditioning factors on altering effects of FDI on inequality. Based on panel data from 26 developing countries spanning from 2004 to 2019, our empirical findings unveil heterogeneity in FDI impacts on income inequality across three clusters of countries. FDI enhances income inequality in one cluster, exhibits no significant effect in another, and exacerbates it in a third. The clustering of these effects is notably influenced by the absorptive capacities of the countries. Nations with high absorptive capacity, particularly in terms of quality human capital, are more likely to mitigate the adverse impact of FDI on their income distributions.

The second chapter explores the association between FDI and Total Factor Productivity (TFP) growth in developing countries, also considering the absorptive capacities of these nations. Productivity has been a central focus for economists examining developing countries in their pursuit of sustainable growth. This emphasis arises from the understanding that economic growth is primarily driven by enhancements in productivity (Hall & Jones, 1999; Easterly & Levine, 2001), rather than mere capital accumulation. Additionally, FDI serves as a conduit for technology transfer, influencing long-term growth through its effect on productivity (Borensztein et al., 1998). Although theoretical studies (Das, 1987; Findlay, 1978; Wang, 1990) suggest that FDI could positively influence productivity growth in developing countries, empirical evidence does not consistently support this notion. Both micro and macro-level studies demonstrate that the impact of FDI in these countries is either insignificant or negative. To explore potential distributional heterogeneity in this association, we employ the same empirical approach as in the first chapter. Employing panel data from 28 developing countries over the period from 2004 to 2019, our results demonstrate the existence of distributional heterogeneity in this linkage across two clusters of countries. Specifically, FDI adversely affects productivity growth in one cluster but positively impacts it in another. Countries endowed with robust absorptive capacity, characterized by high-level human capital, effective institutions, and advanced financial and infrastructural development, are more likely to experience the beneficial effects of FDI on productivity growth.

CHAPTER 1

FDI – INEQUALITY NEXUS AND THE ROLE OF ABSORPTIVE CAPACITY: A FINITE MIXTURE MODELING APPROACH*

1.1. 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 & Itskhoki, 2017; Lee et al., 2020). Therefore, many studies have been conducted to examine the factors contributing to income inequality, such as economic growth (Kuznets, 1955), population growth (Deaton & Paxson, 1997; Firebaugh, 1999), unemployment (Mocan, 1999), inflation (Blank & Blinder, 1986; Blejer & Guerrero, 1990), trade openness (Reuveny & Li, 2003), and urbanization (Kanbur & Zhuang, 2013).

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 & Hanson, 1997) or skill-driven

* During my dissertation study, an article entitled “FDI-Inequality Nexus and the Role of Absorptive Capacity: A Finite Mixture Modeling Approach” has been published based on the first chapter in the Journal of Politik Ekonomik Kuram with doi number of 10.30586/pek.1322531.

technological changes (Findlay, 1978a; Wang, 1990; Wang & 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 & 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 & Chen, 2003; Basu & Guariglia, 2007; Mahutga & Bandelj, 2008; Herzer et al., 2014; Suanes, 2016), some studies find that FDI reduces income inequality (Jensen & Rosas, 2007; Jalilian & Weiss, 2002) while others find no significant link (Alderson & Nielsen, 1999; Milanovic, 2005; Sylwester, 2005; Franco & Gerussi, 2013). Further, another line of research finds evidence of an inverted U-shaped pattern (Figini & Görg, 2011; Herzer & Nunnenkamp, 2014; Ucal et al., 2016).

As a consequence, 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 & 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

[1] Kuznets 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.

decisions on the choice of threshold for the conditioning factor (Wang & 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 & Robinson, 2002; Bumann & Lensink, 2016; Sayed & Peng, 2021). FMM is a data-driven methodology that endogenously identifies clusters based on the similarity of the conditional

[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 & 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).

[3] As an exception, a study by Wang and Lee (2021) 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.

distributions of income inequality and thus avoids the arbitrary choice of threshold problem encountered in previous studies (Ouédraogo et al., 2020; Wang & 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 & 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 & 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 & Nawaz, 2019; Yeboua, 2019), information and communication technologies (Tsaurai, 2020), air transport, electricity consumption (Wu & Hsu, 2012), financial indicators (private credit, bank deposits) (Majeed, 2017; Lee et al., 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 developed using a formal method in the context of the FDI-income inequality nexus[5]. We construct an absorptive

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

[5] Nowbutsing (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

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 et al., 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.

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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.

[6] The 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.

1.2. LITERATURE REVIEW

There is a broad literature on the inequality-FDI nexus (Sylwester, 2005; Jensen & Rosas, 2007; Mahutga & Bandelj, 2008; Halmos, 2011; Chintrakarn et al., 2012; Asteriou et al., 2014; Herzer et al., 2014; Chen, 2016; Ucal et al., 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 & George, 2002; Schmidt, 2005; Todorova & Durisin, 2007) refined and expanded this concept, introducing sub-concepts and 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

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[7] For 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

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 & Lee, 1998; Van den Berg, 2001; Blomström & Kokko, 2003), while others consider financial development (Huang & Xu, 1999; Hermes & Lensink, 2003), institutional quality (Meyer & Sinani, 2009; Jude & Levieuge, 2017), and infrastructure development (Zhang & 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; Gregorio & Lee, 2002), institutional and governance quality (Furceri & Ostry, 2019), infrastructure development (Calderón & Servén, 2004; Ajakaiye &

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.

Ncube, 2010) find that good quality of these factors has reducing impact on income inequality. For example, higher levels of education can enhance the earning potential of lower income groups which reduces income inequality (Checchi, 2001). Similarly, institutions guaranteeing civil liberties can help prevent the exploitation of economically disadvantaged individuals by privileged classes during economic negotiations (Furceri & Ostry, 2019). Infrastructure also plays a role by connecting poorer populations to core economic activities and lowering production and transaction costs (Calderón & Servén, 2004). However, the effect of financial development on income inequality seems inconclusive. While some studies suggest that a developed financial market can decrease income inequality by facilitating access to borrowing for investment, education, and consumption (Galor & Maov, 2004), others find that it may initially benefit the wealthy, particularly during the early stages of financial development (Greenwood & Jovanovic, 1990). Empirical studies on financial development's impact on income distribution also yield conflicting results, with some indicating an equalizing effect (Li, Squire & Zou, 1998; Beck, Demirguc-Kunt & Levine, 2005) while others suggest the opposite (Jauch & Watzka, 2016; Haan & 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 Cheng (2022). When the accompanying variables exceed a certain level, most studies suggest that the distorting effect of FDI diminishes (Wu & 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 et al., 2013; Khan & Nawaz, 2019; Lee et al., 2022) 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 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)	**Country & Period**	**Absorptive Capacity Variables**	**Method**	**Summary Findings**
Wu & Hsu (2012)	54 countries, 1980-2005	Infrastructure 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.

[8] Since 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.

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.

1.3. 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.

1.3.1. 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 & Blinder, 1986; Blejer & Guerrero, 1990), GDP per capita (Kuznets, 1955), trade openness (Reuveny & Li, 2003), population growth (Deaton & Paxson, 1997; Firebaugh, 1999), urbanization (Kanbur & Zhuang, 2013), and unemployment rate (Mocan, 1999).

We include these control variables since these variables have been extensively discussed in the literature as robust determinants across countries and time, and empirically studied as key factors of income inequality. For instance, **inflation** is viewed as a monetary factor affecting income inequality, with theoretical considerations suggesting that delayed wage adjustments due to inflation can shift income from wage earners to profits, potentially increasing inequality (Parkin & Laidler, 1975; Fischer & Modigliani, 1978). Furthermore, inflation imposes a heavier burden on the poor, who possess a larger proportion of their wealth in liquid assets, compared to the affluent who have holdings in both capital and liquid assets. On the other hand, inflation may diminish income inequality by boosting nominal income, subsequently raising income tax obligations for those who earn profits (Heer & Süssmuth, 2003). The empirical results (Blank & Blinder, 1986; Blejer & Guerrero, 1990) on this linkage are inconclusive.

The examination of economic development, particularly economic performance (as measured by ***GDP per capita***) in the context of urbanization, has long been a focal point concerning income inequality. Kuznets' (1955) theory of an inverted U-shaped curve posited that economic development initially exacerbates inequality but eventually stabilizes and diminishes beyond a certain threshold, attributing this phenomenon to the transition from agrarian to urban societies[9]. Thus, in addition to economic growth, another measure serving as a proxy for development is the proportion of the population residing in urban areas (Furceri & Ostry, 2019). While earlier studies (Ahluwalia, 1976; Papanek & Kyn, 1986; Eusufzai, 1997) provided empirical support for this theory, subsequent research has contested its universal applicability, both in less-developed (Li et al., 1998) and advanced economies (Piketty, 2014; Costantini & Paradiso, 2018). The debates surrounding the relationship between development and inequality persist within the empirical literature.

The link between ***trade openness*** and distributive outcomes has been another notable subject in the literature, predominantly examined within the classical theoretical framework, particularly the Heckscher-Ohlin (HO) model (Ohlin, 1933). According to this model, countries specialize in goods aligned with their relatively abundant factor and export these products when engaging in trade. Stolper and Samuelson's theorem (1941) extends this model, suggesting that trade openness is expected to reduce income inequality in developing countries since unskilled labor, which is abundant and intensively utilized in local production, would benefit from trade openness through increased wages. However, although some studies empirically support this theorem (Reuveny & Li,

[9] In the initial phases of economic growth, urbanization may heighten income inequality due to higher wages in urban jobs compared to rural ones. Yet, over the long term, as economic growth advances and urbanization intensifies through industrialization, the proportion of urban jobs rises. Consequently, the disparity in income distribution between the two regions may diminish, leading to a reduction in overall income inequality.

2003; Hamori & Hashiguchi, 2012), numerous studies have attempted to provide explanations for why observed inequality patterns deviate from the predictions of this theorem. For example, offshoring and outsourcing of less-skilled production activities may be relatively skill-intensive in developing countries (Feenstra & Hanson, 1996; 1999). Furthermore, the import of capital goods (Acemoglu, 2003) and trade-induced technological transfers, catch-up processes (Bloom et al., 2016; Burstein et al., 2013) along with exporting activities (Helpman, 2016) may incease the need for skilled, potentially resulting in disparities between the wages of high-skilled and low-skilled workers.

As another factor, ***population growth*** strongly affects income inequality through various mechanims. First, population growth tends to be higher in lower-income groups where fertility rates are high, resulting in less investment in the education of young people (De la Croix & Doepke, 2003). Second, population growth affects inequality via the dependency ratio, with rapid increases associated with higher youth dependency ratios. It often leads to economic lag compared to countries with lower population growth (Rougoor & Charles, 2014). Likewise, countries with very low population growth rates are linked to a higher old age-dependency ratio. According to Deaton and Paxson (1997), a decrease in population growth redistributes the population towards older, more unequal cohorts, potentially increasing national inequality. Last, population growth may augment inequality by altering the distribution of income among labor earnings, profits, rent, and interest (Boulier, 1975). Given that income from profit and rent is less evenly distributed than labor income, a faster population growth rate leads to a less equitable income distribution over time.

The relationship between ***unemployment*** and income inequality has also long attracted the attention of scholars. It is widely agreed that rising unemployment exacerbates the economic standing of low-income groups (Mocan, 1999), as workers with lower skills, situated at the lower end of the income distribution, face increased job vulnerability during economic downturns. Furthermore, measures such as unemployment insurance, welfare benefits, and other forms of income support are insufficient to fully compensate for the income loss resulting from unemployment.

Accordingly, inequality measured by GINI coefficient is defined as

$$Gini_{i,t}=\beta_0+\beta_1 FDI_{i,t}+\ \beta_2 lnGDPpc_{i,t}+\beta_3 Pop_{i,t}+$$
$$\beta_4 Urban_{i,t}+\beta_5 Trade_{i,t}+\beta_6 Unemp_{i,t}+\beta_7 Inf_{i,t}+u_{i,t},\ u_{i,t}=\delta_i f_t+\varepsilon_{i,t} \tag{1}$$

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($\varepsilon_{i,t}$).

1.3.2. 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[10]. 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 & 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:

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

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

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

[10] The results from these tests are presented and discussed in results section 5.

present technical details of FMM incorporating the common dynamic process obtained from the first stage of the AMG technique.

1.3.3. 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 & Peel, 2000; Conway & Deb, 2005). Equation (1), including the cross-sectional dependency, can be respecified within the FMM framework[11] as follows:

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

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, $f_g\left(\text{Gini}\middle|x;\beta_g,\mu_g\right)$ 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).

[11] This model refers to a standard FMM without concomitant variable(s). An alternative approach known as FMM with concomitant variable(s) is also employed in the literature (Ouédraogo et al., 2021; Wang & Lee, 2021; Ndoya et al.,2023). Both represent unsupervised model-based clustering techniques that detect latent subgroups by accommodating various distributions and capturing intricate patterns. The primary difference lies in the inclusion of additional explanatory variables, termed concomitant variables, in the FMM with concomitant variables. By assuming that these variables effect both the clustering process and the outcome of interest (in this case, the FDI-inequality linkage), it is possible to examine their impact on the relationship between the observed variables.

Following a multinomial logit model (Owen et al., 2009; Liu et al., 2020), the marginal 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). Assuming that the error term is normally distributed, the log-likelihood function is:

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

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:

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

We will estimate the 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.

We will also calculate the mean square error of mixing proportions ($MSE(\hat{\pi}_m)$) and misclassification error (Err) to asses the performance of both finite mixture models (with and without concomitant variable) (Vaňkátová & Fišerová,2017). The mean square error of mixing proportions refers the proximity of estimated proportions ($\hat{\pi}_m^i$) belonging to class m to actual proportions (π_m^i). Accordingly, $MSE(\hat{\pi}_m)$ is calculated as follows:

$$\mathrm{MSE}(\hat{\pi}_m)=\frac{1}{N}\sum_{i=1}^{N}(\pi_m^i-\hat{\pi}_m^i)^2 \tag{9}$$

A lower MSE indicates a closer estimate to the actual proportions, which reflects the better predictive accuracy of the model. The misclassification error which represents a mean ratio of incorrectly assigned observations, is defined as:

$$\mathrm{Err}=1-\frac{1}{N}\sum_{i=1}^{N}(\hat{z}_i=z_i) \tag{10}$$

where z_i is the true component membership of each observation and $\hat{z}_i$ is the estimate. A lower classification error value indicates a higher performance of the classification model.

1.3.4. 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.

$$\mathrm{Equalizing}_{i,t} = \beta_i + \mathrm{Index}_{i,t} + \alpha_i + u_{i,t} \quad \text{for cluster 1,} \tag{9}$$

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

where $\mathrm{Equalizing}_{i,t}$ ($\mathrm{Distorting}_{i,t}$)is a dichotomic variable which takes the value of 1 for those countries in which FDI has an income-equalizing (distorting) effects and of zero otherwise. $\mathrm{Index}_{i,t}$ 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 $u_{i,t}$ 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.[12] Random effects model assumes that the unobservable effect α_i is not correlated with independent variables [$cov(Index_{i,t},\alpha_i)=0$, $t=1,2,...............T$]. This model is estimated using GLS (Wooldridge, 2012).

1.3.5. The Construction of Absorptive Capacity Index with Principal Component Analysis

To construct an absorptive capacity index, we use twelve variables[13] derived from the relevant literature (Abramovitz, 1986; de Mello, 1999; Durham, 2004; Nguyen et al., 2009), categorizing them into four components: human capital, financial development, governance/institutional quality, and infrastructure development. We employ principal component analysis (PCA), a method that utilizes linear weighted combinations of the original variables to reduce the dimensionality of the data to a few components (Sharma, 1996).

To mitigate the potential variance-biased result while identifying principal components through PCA, we standardized all these variables before applying PCA, in line with the methodology outlined by Hastie et al. (2009). Mathematically, from a set of variables (X_1,X_2,…, X_n)

[12] Since 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).

[13] Absorptive capacity variables: Average years of schooling, tertiary enrollment, vocational education enrollment, domestic credit, broad money (M3toGDP), bank deposits, regulatory quality, government effectiveness, control of corruption, voice and accountability, fixed broadband subscriptions, air freight

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

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) as the index, which has the highest explanatory power of variation. Specifically, we define coefficients (β_{11},β_{12},………, β_{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 equals one.

1.4. DATA SOURCES AND DESCRIPTIVE STATISTICS

Our sample covers panel data from 26 developing countries over the period between 2004-2019.[14] 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.

In order to construct an absorptive capacity index and its four subcomponents (human capital, financial development, governance/institutional quality, and infrastructure development) for each country in the sample we use twelve variables: average years of schooling, tertiary enrollment, vocational education enrollment, domestic credit, broad money (M3toGDP), bank deposits, regulatory quality, government effectiveness, control of corruption, voice and accountability,

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[14] The list of countries is presented in Table A1 of the Appendix A.

fixed broadband subscriptions, air freight. Variables related to human capital (average years of schooling, tertiary enrollment, vocational education enrollment) are sourced from the Unesco Institute for Statistics Database. Financial development variables (domestic credit, broad money (M3toGDP), bank deposits) and infrastructure development variables (fixed broadband subscriptions and air freight) are obtained from the World Development Indicators. Governance/institutional quality variables (regulatory quality, government effectiveness, control of corruption, voice and accountability) are sourced from the Worldwide Governance Indicators. Applying principal component analysis (PCA) to all twelve variables, the first principal component is used as absorptive capacity index, which constitutes more than 60% of the variation for almost all countries. In addition, on average, the first principal components employed for the sub-indexes -human capital, financial development, infrastructure development, and governance/institutional quality- explain 80%, 88%, 80%, and 62% of the variance, respectively. The detailed results from PCA are presented in appendix Table A1.

1.5. 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 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 et al., 2020; Wang & 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 hypothesis
Friedman	16.308	
Frees	3.599***	Ho: cross-sectional independence
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***	

Notes: ***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.[15] 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

[15] I employ FMM analysis without concomitant variable(s) as a baseline application. An alternative is to use FMM with concomitant variable(s) (Ouédraogo et al., 2021; Wang & Lee, 2021; Ndoya et al.,2023) such as absorptive capacity index in our study. To see if FMM with or without concomitant is preferable, I compute mean square of error (MSE) and classification error statistics. For 3 cluster, MSE turns out 0.11 and 0.17 while classification errors 16% and 12% respectively for without and with concomitant FMMs. As smaller MSE suggests a better fit to data and classification errors are close, we prefer FMM without concomitant variable. Therefore, I proceed with the rest of the analysis using the results from baseline application of FMM without concomitant variable. However, I report the results from FMM with the absorptive capacity index as a concomitant variable in Table A3 of Appendix A for an interested reader.

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.[16] This cluster is in the smallest size (16%).

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 & Hanson, 1997) or transmitting skill-driven technological changes (Findlay, 1978a; Wang, 1990; Wang & 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. 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%.

[16] According to Alderson and Nielsen'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.

Table 4. Estimation Results

Variables		Finite Mixture Model		
	AMG	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

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

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 & 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[17] 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 et al., 2009; Franco & Gerussi, 2013) do not find an inequality-widening impact of FDI in transition countries.

Table 5. Cluster membership

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

[17] Armenia, Bulgaria, Belarus, Georgia, Kyrgyz Republic, Moldova, Romania, Russia, Ukraine

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.

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

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

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.

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.

CHAPTER 2

FDI – PRODUCTIVITY NEXUS AND THE ROLE OF ABSORPTIVE CAPACITY

2.1. INTRODUCTION

There appears to be a consensus regarding the pivotal role of FDI inflows for economic development. To attract FDI and harness its growth potential, virtually all countries try to actively adopt favorable investment policies. The impact of FDI on economic growth might operate through two primary mechanisms: capital accumulation and total factor productivity (TFP). Neo-classical growth theory primarily considers the role of FDI in capital accumulation. According to this theory, when countries ease restrictions on capital inflows, they initially experience an increase in their capital stock, leading to short-term economic growth. However, over the long term, the diminishing returns on capital investment ultimately result in a convergence toward a steady state, rendering FDI ineffective in promoting economic growth. In contrast, endogenous growth theory places a stronger emphasis on the TFP channel, viewing FDI as a source of advanced technology and knowledge spillover. Essentially, this theory endogenizes the sources of technological progress, providing a framework in which FDI serves as a mechanism for technology transfer that affects long-term growth primarily through its impact on TFP, rather than solely through its impact on capital accumulation (Borensztein et al.,1998). A substantial amount of evidence (Hall & Jones, 1999; Easterly & Levine, 2002; Hsieh & Klenow, 2010) also indicates that the variation in economic growth rates among countries is predominantly explained by disparities in technological improvements rather than the capital accumulation. Furthermore, the technological knowledge stock not only enhances productivity in the long term but also induces structural transformations in the host country by introducing innovative management practices and organizational structures (De Mello, 1997).

Nevertheless, the results from empirical studies at both micro and macro levels raise doubts about the benefits of FDI host countries. Early micro-level studies relying on firm-level data have generated inconclusive or conflicting results when examining FDI's knowledge spillover effects (Görg & Greenaway, 2004). Despite attempts to analyze FDI spillovers by considering factors such as a local firm's ability to adjust to new competitors and technologies since the 2000s, the results have continued to be inconclusive (Demena & van Bergeijk, 2017). At the macro level, previous studies primarily focused on investigating the presence of knowledge spillovers within host countries resulting from FDI. These studies relied on indirect evidence of spillovers, investigating associations between an increased presence of MNEs and TFP improvements in a country (Alfaro et al., 2009). However, recent studies seek to understand the underlying mechanisms of this relationship by scrutinizing country-specific factors in order to come up with effective policy suggestions that can enhance the spillover effects of FDI. That is, the focus has shifted towards understanding how a country's characteristics may influence its capacity to reap benefits from FDI, often referred to as absorptive capacities. Among these studies, some incorporate variables related to human capital (Cecchini & Lai-Tong, 2008), while others consider financial development (Alfaro et al.,2009), or both (Woo, 2009; Wang & Wong, 2009; Herzer & Donaubauer, 2018) as accompanying factors to examine the relationship between FDI and TFP. While these studies provide valuable insights, they also yield mixed results. Although sufficient level of skilled labor and advanced financial markets are found to increase the positive impact of FDI on TFP in some studies (Cecchini & Lai-Tong, 2008; Alfaro et al.,2009) and mitigate the negative impact of FDI in others (Wang & Wong, 2009; Herzer & Donaubauer, 2018; Li & Tanna, 2019), they may not offer a comprehensive understanding of the host country’s ability to absorb and integrate new knowledge across all dimensions. In addition, another set of studies opts to use technology gap[1] (Baltabaev,2014;

[1] Theoretical studies (Findlay, 1978b; Wang & Blomstrom, 1992) strongly suggest that larger technological gap from industry leader is advantageous for host countries. When domestic firms lag behind multinational corporations, they can derive greater benefits from the "catching up" effect.

Ali et al., 2016; Abdullah & Chowdhury, 2020) to explore this linkage. However, while the use of the technology gap serves as an indicator for aspects like human capital, physical infrastructure, and distribution networks for multinational companies (Görg & Greenaway, 2004), substituting them interchangeably may introduce potential flaws (Demena & van Bergeijk, 2017)[2].As emphasized in an influential study by Abramovitz (1986), human capital, economic and political stability, market liberalization, and sufficient infrastructure are the essential prerequisites for absorbing foreign investment and reaping benefits for the host country. Therefore, exclusively examining FDI contributions from the perspectives of human capital or financial development might be insufficient to comprehend its overall impact.

Furthermore, a notable issue in recent macro-level literature is the variability in the impacts of FDI on TFP growth depending on the chosen samples. Consequently, the variations in impacts across country groups underscore the necessity of considering distributional heterogeneity when scrutinizing the relationship between FDI and productivity. From this point of view, recent macro-level empirical studies may often lack robust methodological rigor. These studies commonly assume that the marginal effect of FDI on productivity is the same for all countries in their samples, disregarding the potential heterogeneity stemming from distinct country-specific characteristics. Although a few studies (De Mello, 1999; Cecchini & Lai-Tong, 2008) have attempted to address this issue using estimation techniques like fixed-effects, FM-OLS, and Pooled Mean Group estimators to control for heterogeneity, these methods only enable them to examine unobserved country-level characteristics. In short, all these methods typically overlook possible distributional heterogeneity within the FDI-productivity linkage, which can result in a failure to capture the diverse impacts of FDI on productivity across different groups of countries.

[2] In their meta-analysis, they discover that the technological gap is statistically significant, while the absorptive capacity is not, emphasizing the need to separate the absorptive capacity hypothesis from the technological gap hypothesis.

This study addresses the aforementioned issues in the following manner. First, this study adopts a distinct empirical approach by employing Finite Mixture Modeling (FMM) as an unsupervised model-based clustering technique to examine possible distributional heterogeneity in the linkage between FDI and productivity growth. FMM is a data-driven methodology that endogenously identifies clusters based on the similarity of the conditional distributions of TFP growth, enabling us to capture varying effects of FDI on TFP growth across these clusters. Second, this study explores whether the absorptive capacity plays a significant role in determining whether FDI has a favorable or adverse impact on productivity. To this end, we construct an absorptive capacity index for each country in our 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 et al., 2013). Comprised of twelve variables selected from the relevant literature[3], we grouped absorptive capacity index into four subcomponents: human capital, financial development, governance/institutional quality, and infrastructure development.

Our findings reveal the existence of two clusters among the countries in our sample, each of which exhibiting significantly diverse effects of FDI on TFP growth. FDI has a negative impact on TFP growth in the first cluster wheras it has a positive impact in the second cluster. The absorptive capacity index and its sub-components significantly account for the varying impacts of FDI on TFP growth. Countries characterized by high absorptive capacity, which includes factors such as quality human capital, well-established institutions, and advanced financial and infrastructural development, are more likely to belong to the second cluster where FDI contributes to TFP growth. Conversely, those with lower absorptive capacity are more inclined to be in the first cluster where the impact of FDI on TFP growth is negative.

[3] Average years of schooling, tertiary enrollment, vocational education enrollment, domestic credit, broad money (M3toGDP), bank deposits, regulatory quality, government effectiveness, control of corruption, voice and accountability, fixed broadband subscriptions, air freight.

2.2. LITERATURE REVIEW

Extensive research within the literature has scrutinized how FDI contributes to enhancing TFP through the facilitation of technological knowledge spillovers. These investigations have sought to understand the various pathways through which technological knowledge disseminates from MNEs to their host countries. Essentially, increased productivity resulting from these spillovers can be attributed to multiple channels: Local companies can either imitate the technological production processes of MNEs (Das, 1987; Wang & Blomstrom, 1992), enhance their skills and adopt advanced managerial practices by attracting labor from MNEs (Haacker, 1999; Fosfuri et al., 2001), or accelerate the adoption of new technology, or alternatively, use existing technology more efficiently to compete with MNEs (Glass & Saggi, 2002). In addition to them, domestic firms can learn how to penetrate export markets through the collaboration with MNEs (Aitken et al., 1997).

Despite theoretical propositions suggesting a positive impact of FDI on host country TFP through these channels, empirical evidence does not consistently support it. For instance, Görg and Greenaway (2004) examined 40 plant or industry level studies and they found only six of them has positive horizontal (intra-industry) productivity spillovers and none of them is developing countries. In the same vein, Demena and van Bergeijk (2017) reviewed 69 plant or industry level studies covering 31 developing countries, found that almost one-third of the empirical findings validate a significantly positive effect. There are some explanations for a failure to find any evidence for aggregate spillovers. First, domestic firms experience relatively higher marginal costs compared to foreign counterparts, who enjoy reduced marginal costs due to their firm-specific advantages and specialized knowledge. Because of these cost disadvantages, local firms lose market share to MNEs, resulting in decreased output and a shift along the average cost curve (Aitken & Harrison, 1999). As a result, with the presence of foreign firms, local companies may lose market share, operate less efficiently on a smaller scale, making it challenging for them to invest in new technologies. Second, MNEs can effectively protect their unique advantages to prevent any knowledge or benefits from leaking to domestic firms. Third, positive spillovers may only affect a sub-set of firms and aggregate studies, therefore, underestimate the true significance of such effects. Fourth, spillovers do not occur horizontally (intra-industry) but it is possible that MNEs voluntarily or involuntarily help to increase productivity of domestic customers and suppliers through upward and backward vertical linkages (Javorcik, 2004; Blalock & Gertler, 2008). Although all these factors contribute to the negative effects of MNEs, these are insufficient to explain the country differences in a macro perspective since not all countries may enjoy the preconditions to take advantage of potential benefits from FDI. The domestic success is, to some extent, determined by local country characteristics such as human capital, institutional quality, financial or infrastructural development of the country. Consequently, while the literature initially focused on the underlying reasons for the positive and/or negative FDI effects in micro-level studies, in subsequent literature, it has attempted to understand the macro-level impact of FDI on TFP growth by considering the differences in such country characteristics.

Table 1 summarizes macro-level empirical studies investigating the relationship between FDI and TFP growth. These studies consider diverse country characteristics across various samples. When examining the range of samples, some investigations include both developed and developing countries in their analyses. Among these studies, notable findings from Woo (2009) and Baltabaev (2014) reveal a positive impact of FDI on TFP growth, while De Mello (1999) and Alfaro et al. (2009) indicate a lack of significant impact. Conversely, specific studies concentrate on particular regions; for instance, Cecchini and Lai-Tong (2008) focus on Mediterranean countries and find no significant relationship between FDI and TFP growth. In contrast, Ali et al. (2016), examining European countries, identify a positive relationship. Furthermore, four studies have restricted their samples to developing countries, reporting either negative effects (Wang & Wong, 2009; Herzer & Donaubauer, 2018) or no significant impacts (Li & Tanna, 2019; Abdullah & Chowdhury, 2020) of FDI. In addition to these studies, Woo (2009) focuses on developing countries as a subset and observes a positive impact of FDI on TFP growth. Similarly, Baltabaev (2014) finds a significant positive relationship in countries where the GDP per worker, in comparison to the technology frontier, falls below a specific threshold. When considering country characteristics as accompanying variables, a common trend in most studies suggests that the negative impact of FDI on TFP growth diminishes when these accompanying variables exceed a certain threshold (Wang & Wong, 2009; Herzer & Donaubauer, 2018) or may even turn positive (Cecchini & Lai-Tong, 2008; Alfaro et al., 2009; Wang & Wong, 2009; Herzer & Donaubauer, 2018; Li & Tanna, 2019). However, only the investigation conducted by Woo (2009) contends that accompanying variables do not play a role in the augmentation of TFP growth through FDI.

Table 1. A Summary of Macro-Level Empirical Literature Examining the Relationship Between FDI and TFP Growth

Authors (year)	**Country & Period**	**Accompanying Variables**	**Dependent Variable (TFP growth)**	**Methodology**	**Summary Findings**
De Mello (1999)	33 countries, 1970-1990	-	TFP is measured as the difference between per capita output growth and per capita capital accumulation	Pooled, Fixed-effect, Pooled Mean-Group	FDI has no significant effect on TFP growth in total sample. The effect becomes significantly positive for the developed countries.
Cecchini & Lai-Tong (2008)	7 Mediterranean countries,1980-2000	Human capital	Cobb-Douglas production function without human capital	FM-OLS	FDI has no significant effect on TFP growth. However, this effect becomes positive and significant when the human capital reaches the threshold.
Woo (2009)	92 countries, 1970-2000	Human capital, Financial development, Institutional quality	Cobb-Douglas production function including human capital augmented labor.	OLS, Pooled, Fixed Effects	FDI has a positive direct effect on TFP growth. The levels of absorptive capacity variables do not strength. There is no substantial difference in the results between the total sample and a sample restricted to developing economies.
Alfaro, Kalemli-Ozcan, Sayek (2009)	62 countries, 1975-1995	Financial market	The data obtained from Bernanke and Gurkaynak (2001), available for 1975–95.	OLS	FDI has no significant effect on TFP growth. However, FDI enhances TFP growth only in countries with well-developed financial markets.
Wang & Wong (2009)	69 developing countries, 1970-1989	Human capital, Financial depth	Cobb-Douglas production function without human capital.	SUR	FDI has a negative effect on TFP growth in developing countries with low levels of human capital, but the negative effect first mitigates and then turns to positive as the level of human capital increases.

Baltabaev (2014)	49 countries, 1974-2008	Distance from world's technological frontier (labor productivity)	Cobb-Douglas production function without human capital.	One-step system GMM	FDI has a positive effect on TFP growth, but this impact is statistically significant only for countries where GDP per worker relative to the USA falls below a certain threshold.
Ali, Cantner, Roy (2016)	20 European countries, 1995-2010	Distance from world's technological frontier (techno gap) and R&D	Törnqvist index methodology, data is obtained from PWT.	Dynamic OLS	FDI stock has a positive effect on TFP growth.
Herzer and Donaubauer (2018)	49 developing countries, 1981-2011	Human capital, Financial development Trade openness	Cobb-Douglas production function including human capital augmented labor, data is obtained from PWT.	Dynamic OLS	FDI has a negative long-run effect on TFP growth. However, the negative impact mitigates in the countries with high levels of human capital & trade openness. In addition, the sign turns positive in the countries with well-developed financial markets.
Li & Tanna (2019)	51 developing countries, 1984-2010	Human capital, Institutional quality	The difference between per capita GDP growth and per capita physical capital stocks growth.	SYS-GMM	FDI has no significant effect on TFP growth. However, FDI enhances TFP growth only in countries with high-levels of human capital and institutional quality.
Abdullah & Chowdhury (2020)	77 low & middle income countries	Distance to the technology frontier	Cobb-Douglas with/out human capital	GMM	FDI has no significant effect on TFP growth. This finding is explained by the lack of absorptive capacity.

2.3. EMPIRICAL STRATEGY

In this section, we present a canonical model for TFP growth. As we utilize the same estimation methods discussed in Chapter 1, we refrain from reiterating these technical details in this section. To summarize, we initiate to apply with the augmented mean group estimation technique, known for its robustness against cross-section dependency and slope heterogeneity, as detailed in section 1.3.2. Subsequently, we employ Finite Mixture Modeling approach to explore potential distributional heterogeneity in the impacts of FDI across different country clusters, as technically outlined in section 1.3.3[4]. As the FMM results suggest the existence of more than one cluster, we proceed to investigate the role of absorptive capacity or its sub-components in the varying effects of FDI on productivity growth. For this purpose, we employ the probit estimation technique in the panel regression (see section 1.3.4). To conduct this analysis, we construct absorptive capacity index and its sub-indexes by principal component analysis[5], as technically formulated in section 1.3.5.

2.3.1. Empirical Model for Total Factor Productivity

Although many factors beyond FDI could affect TFP growth, our objective is to define a canonical model for productivity growth by including a set of control variables derived from relevant literature, such as inflation (Clark, 1982; Gilson, 1984), initial development level (Veblen, 1915), trade openness (Barro & Sala-i-Martin, 1995), population growth (Kremer, 1993), and public expenditure (Arrow & Kurz,1970; Barro, 1990).

We incorporate these control variables because they have been widely debated in the literature as reliable factors influencing productivity growth across various

[4] In this chapter, the dependent variable is TFP growth instead of Gini.

[5] Using this methodology, the absorptive capacity index explains over 60% of the variation in most countries (see Table B1).

countries and time, and have been empirically analyzed as significant determinants. For instance, ***inflation*** is known to have adverse effects on productivity growth through several different mechanisms. First, it leads to a misperception of relative price levels, resulting in inefficient investment plans. Second, inflation diminishes tax reductions for depreciation and increases the rental price of capital, leading to a reduction in capital accumulation, and consequently, lower productivity (Clark, 1982). Third, it increases corporate income tax rates, further dampening productivity (Gilson, 1984). Last, it can hinder labor productivity by promoting an inefficient mix of factor inputs, increasing buffer stocks, and reducing R&D expenditures (Narayan & Smyth, 2009). Empirical studies align with the theoretical understanding, indicating a negative relationship between inflation and productivity growth (Cameron et al., 1996; Christopoulos & Tsionas, 2005).

The level of ***economic development***, commonly represented by GDP per capita, is also expected to influence productivity growth. The relationship between a country's developmental stage and its productivity has been a subject of extensive scholarly inquiry. This potential arises from their ability to adopt existing technologies, invest in new capital, and reallocate surplus labor—particularly from agriculture—into more productive sectors. Additionally, productivity gains in such economies can be expanded by overall output and market size generating further efficiencies through economies of scale (Abramovitz, 1990).

The link between ***trade openness*** and productivity growth has been another notable subject in the literature. The removal of trade barriers prompts significant restructuring within sectors and industries, leading to the exit of less efficient import-competing firms and the redistribution of market shares to more advanced and productive firms. On a national level, when a developing country opens up to trade, it gains access to a variety of capital goods and foreign technology through imports from industrialized countries, thereby accelerating productivity growth (Barro & Sala-i-Martin, 1995). Increasing exports also helps alleviate foreign exchange constraints and facilitates greater imports of key inputs in the production process (Miller & Upadhyay, 2000). The expansion of both imports and exports also fosters competition in global markets, which ultimately leads to enhanced productivity. Although most empirical research supports the notion that trade openness positively affects productivity growth and thereby economic growth, some scholars (Rodriguez and Rodrik, 2000)[6] maintain a skeptical stance on this relationship. The mechanism they suggest that under endogenous growth conditions, trade restrictions might lead to higher output growth rates by increasing productivity if they encourage the development of technologically dynamic sectors over others.

As another factor, ***population growth*** strongly impacts productivity growth. The underlying concept suggests that an increase in population is likely to stimulate the generation of more ideas and innovations (Jones, 1995). This population expansion can enhance productivity by encouraging technological advancements and fostering economies of scale, specialization, and agglomeration effects (Boserup, 1981; Kremer, 1993). Nevertheless, recent theories (Strulik, 2005) indicate that the impact of population growth may vary depending on the presence of skilled labor and can be either positive or negative.

Another contributing factor to a country's productivity growth is ***public expenditure.*** Theoretical perspectives (Arrow & Kurz,1970; Barro, 1990) suggest that such expenditures enhance the marginal product of private capital by providing infrastructure inputs for private production, thereby increasing private sector productivity. Moreover, public spending generates positive societal externalities by offering essential social services like healthcare, education, and scientific research, which in turn stimulate productivity and economic growth. However, while theoretical underpinnings suggest a positive relationship between public expenditure and productivity, empirical investigations yield divergent

[6] In their seminal work, Rodriguez and Rodrik (2000) argue that the positive impact of openness found in most empirical studies may lack robustness due to measurement issues and methodological approaches.

outcomes. Chakraborty and Dabla-Norris (2011) suggest that the heterogeneous effects of public expenditure depend on a country's income level and the quality of institutions. They suggest that in economically disadvantaged countries with weaker public institutions, deficiencies in expenditure management, and the resulting negative impacts on productivity and growth are often tied to ineffective or corrupt bureaucracies. In addition, empirical variations may stem from factors such as data aggregation, methodologies, and specific types of public spending employed (Nguyen-Van et al., 2019).

Incorporating these variables scrutinized extensively in scholarly discourse, productivity growth is defined as

$$TFP_{i,t}=\beta_0+\beta_1 FDI_{i,t}+\ \beta_2 lnGDPpc_{i,t}+\beta_3 Pop_{i,t}+\beta_4 Trade_{i,t}+\beta_5 Inf_{i,t}+\beta_6 Public_{i,t}+u_{i,t},$$
$$u_{i,t}=\delta_i f_t+\varepsilon_{i,t} \quad (1)$$

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($\varepsilon_{i,t}$).

2.4. DATA SOURCES AND DESCRIPTIVE STATISTICS

Our dataset covers panel data from 28 developing countries over the period between 2004-2019[7]. The selection of countries is based on data availability. Geographically, thirteen countries are located in Asia, eleven in the Americas, two in Europe and two in Africa.

Measuremet of TFP: While many studies compute TFP using the Cobb-Douglas production function with the assumption of constant returns to scale, others have challenged this specification. For example, Duffy and Papageorgiou (2000) have

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[7] The list of countries is presented in Table B1 of the Appendix B.

identified various regression model specifications that provide empirical support for a broader Constant Elasticity of Substitution (CES) model. Similarly, Kneller and Stevens (2003) have opted for a more comprehensive translog model[8] rather than the Cobb-Douglas specification for aggregate production. Another common issue arises from the assumption that the labor/capital share's value remains constant across all countries and time periods. Some studies, such as those conducted by Herzer and Donaubauer (2018) and Karabarbounis and Neiman (2014), have presented data-driven evidence indicating a notable decline in the labor share in many countries since the 1980s. For TFP measurement, we rely on data from the Penn World Table, generated using the more adaptable Törnqvist index methodology. This approach aligns well with the translog production function, allowing for variations in the elasticities of substitution among inputs, unlike other production functions, such as Cobb-Douglas and CES (Christensen et al., 1973). Therefore, this method eliminates the need for assuming a uniform labor share across countries or periods. By employing data generated through this method, our study stands out in providing more reliable TFP estimates by reflecting cross-country differences in technology and production processes over time.

Accordingly, we obtain TFP data, from Penn World Table version 10.0 (PWT) with constant national prices (2017=1) as it facilitates the comparison of productivity growth across different countries over time. Technically, $Q^{T}_{t,t-1}$ represents Törnqvist quantity index of factor inputs in a country at a given year and the previous year. $Q^{T}_{t,t-1}$ is calculated as follows:

$$\ln Q^{T}_{t,t-1} = \frac{1}{2}\,(\alpha_t + \alpha_{t-1}) \ln\left(\frac{K_t}{K_{t-1}}\right) + \left[1 - \frac{1}{2}\,(\alpha_t + \alpha_{t-1})\right] \ln\left(\frac{L_t}{L_{t-1}}\right) \tag{6}$$

[8] The translog (transcendental logarithmic) production function places no restrictions on returns to scale or the elasticity of substitution. One significant benefit of this function is its variable elasticity of substitution for each input component. Additionally, this function allows for a more detailed specification of input relationships compared to other production functions (Han & Yan, 2014).

where K denotes a capital stock at constant 2017 national prices, L denotes labor force engaged, and α is output elasticity of capital (share of gross fixed capital formation in real GDP).

Growth of productivity is subsequently given by:

$$TFP_t = \frac{GDP_t / GDP_{t-1}}{Q_{t,t-1}^{T}} \tag{7}$$

where GDP represents the real GDP at constant 2017 national prices. For the further calculation details, please see Feenstra, Inklaar and Timmer (2015).

As outlined in equation 1, the independent variable of interest is the FDI inflow, while the control variables encompass GDP per capita, population growth, trade openness (measured by the rate of the sum of exports and imports over GDP), the inflation rate, and public expenditure. All these variables are sourced from the WDI database. As previously mentioned in Chapter 1, for the absorptive capacity variables, 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 2 provides the detailed definition and descriptive statistics for each variable.

Table 2. Descriptive Statistics, Definition & Data Sources

Variables	Obs.	Mean	Std. Dev	Definition:	Data Source:
Dependent variable:					
TFP	448	0.98	0.10	TFP at constant national prices (2017=1)	Penn World Table, ver. 10.0
Explanatory variable of interest:					
FDI	448	4.13	4.75	Ratio of foreign direct investment net inflows over GDP	WDI
Control variables:					

lnGDPpc	448	8.57	0.65	Log of GDP per capita (constant 2015 US$)	WDI
Population growth	448	1.19	0.96	Annual population growth rate	WDI
Trade openness	447	75.10	32.93	Ratio of sum of exports and imports over GDP	WDI
Inflation	448	6.91	6.07	The growth rate of the GDP deflator	WDI
Public Expenditure	395	22.56	7.10	Government's expense for operating activities in providing goods and services (% of GDP)	WDI
Absorptive capacity variables: Human capital variables:					
Average years of schooling	348	8.43	1.75	Average number of years completed in 25 aged and older population	UIS
Tertiary enrollment	375	44.67	19.63	Gross enrollment ratio for tertiary school	UIS
Vocational education enrollment	360	13.38	9.10	Share of students in secondary education enrolled in vocational programs	UIS
Financial development variables:					
Domestic Credit	411	50.58	27.72	Ratio of domestic credit to private sector over GDP	WDI
Broad Money (M3 to GDP)	446	59.25	27.47	Ratio of broad money over GDP	WDI
Bank Deposits	446	46.79	25.56	Ratio of bank deposits over GDP	WDI
Institutional quality variables:					
Regulatory Quality	448	53.45	14.03	The role of government in implementing regulations	WGI
Government Effectiveness	448	50.79	15.76	The quality of public services, policy formulation, and implementation	WGI

Control of Corruption	448	43.34	19.91	The power of government for private gain	WGI
Voice & Accountability	448	44.16	20.09	Freedom of citizens in matters relating to association, expression, etc.	WGI
Infrastructural development variables:					
Fixed broadband subscriptions	432	3.638,469	6.142,434	Fixed subscriptions to the internet	WDI
Air freight	426	781.54	1135.609	Air transport, freight (million ton-km)	WDI

2.5. EMPIRICAL RESULTS

This section initially discusses the impact of FDI on TFP growth using the AMG estimation, which considers cross-sectional dependency and slope heterogeneity. Given our focus on the FDI-TFP linkage, the section proceeds with the application of FMM, incorporating the common dynamic process observed in the initial stage of AMG. Ultimately, the explanation delves into the role of absorptive capacity and its components in influencing the varying effects of FDI.

We start to test the existence of slope homogeneity and cross-sectional independence to ascertain the appropriate panel modeling approach. As shown in Table 3, Pesaran (2004) and Pesaran (2015) tests show that error term of the model is cross-sectionally dependent and this dependence is strong. Furthermore, as for slope homogeneity, we apply delta and adjusted delta tests of Pesaran and Yamagata (2008) and find the presence of slope heterogeneity.

Hence, initially, we employ the Augmented Mean Group (AMG) estimator. This approach is resilient against slope heterogeneity and cross-sectional interdependence, ensuring unbiased and efficient results. As indicated in the second column of Table 5, the impact of FDI on productivity growth in developing countries is not statistically significant, which is a finding that aligns with the results of various studies (Demena & van Bergeijk, 2017; De Mello, 1999; Li & Tanna, 2019; Abdullah & Chowdhury, 2020) consistently revealing an insignificant effect of FDI on the host country's productivity. This finding may imply the existence of opposing impacts of FDI in sampled countries rendering the effect of FDI obsolete. Accordingly, to check if there is the potential distributional heterogeneity in the impacts of FDI at different country clusters, we subsequently apply FMM analysis.

Table 3. CD, normality, and slope heterogeneity test results[9]

	CD test	**Null hypothesis**
Pesaran (2004)	35.72***	Ho: cross-sectional independence
Pesaran (2015)	37.91***	H0: weakly cross-sectional dependence, H1: strong cross-section dependence
	Normality test	
Jarque-Bera	38.22***	Ho: error term is normally distributed
	Slope Heterogeneity	
Pesaran and Yamagata (Delta)	7.412***	Ho: slope coefficients are homogenous
Pesaran and Yamagata (Adjusted Delta)	11.265***	

Notes: ***p<0.01 significant at 1%.

To do so, the initial step involves the optimal selection of the number of clusters. This is determined through the utilization of three types of information criteria namely, the Akaike information criterion (AIC), Bayesian information criterion (BIC), and corrected Akaike information criteria (CAIC). These criteria are widely employed in the literature on FMM applications (Zuo, 2016; Ouédraogo et al.,

[9] In addition to these tests, I examine the possibility of reverse causality, wherein the increased productivity growth of countries might impact FDI inflows, as suggested by relevant literature (Karpaty & Lundberg, 2004; Li & Tanna, 2019). Therefore, I investigate the endogeneity bias arising from potential reverse causality. To achieve this, I employ a two-stage least squares (2SLS) estimator and use one and/or two lagged levels of explanatory variables as instruments. Subsequently, I conduct endogeneity tests following Durbin (1954), Wu (1973), and Hausman (1978) methodologies, and find no evidence of endogeneity bias. The results of the endogeneity tests are presented in Table B2 of Appendix B.

2020; Wang & Lee, 2021). Table 4 presents the results based on these criteria for various numbers of clustered models. Optimal model selection aims to minimize information loss, favoring models with lower values. The 1-cluster model yields the highest values compared to alternative models, indicating that mean group averaging of slope parameters for all countries in AMG may lead to misleading results. Consequently, we opt for the 2-cluster model, as two out of three criteria demonstrate the lowest values.

Table 4. Selection of the number of clusters

	1- cluster (C=1)	**2-cluster (C=2)**	**3-cluster (C=3)**	**4-cluster (C=4)**
AIC	-1002.24	-1152.11	**-1172.05**	Not concave
BIC	-966.43	**-1076.51**	-1056.67	
CAIC	-996.41	**-1076.46**	-1056.59	

Table 5 (columns 3-4) shows the estimation results from the 2-cluster FMM analysis[10]. In the first cluster, we find that FDI has a negative effect on productivity growth. This finding aligns with the findings of many scholars (Wang & Wong, 2009; Herzer & Donaubauer, 2018; Abdullah & Chowdhury, 2020) who argue that the inflow of FDI alone does not foster the productivity growth of the host country. According to their views, to mitigate the negative impact or to shift it towards a positive direction, a country should achieve a certain threshold level of human capital, financial development or institutional quality. On the other side, we find that FDI has a positive effect on productivity growth in the second cluster, which

[10] I employ FMM analysis without concomitant variable(s) as a baseline application. An alternative is to use FMM with concomitant variable(s) (Ouédraogo et al., 2021; Wang & Lee, 2021; Ndoya et al.,2023) such as absorptive capacity index in our study. To see if FMM with or without concomitant is preferable, I compute mean square of error (MSE) and classification error statistics. For 2 cluster, MSE turns out 0.14 and 0.15 while classification errors 15% and 14% respectively for without and with concomitant FMMs. As smaller MSE suggests a better fit to data and classification errors are close, we prefer FMM without concomitant variable. Therefore, I proceed with the rest of the analysis using the results from baseline application of FMM without concomitant variable. However, I report the results from FMM with the absorptive capacity index as a concomitant variable in Table B3 of Appendix B for an interested reader.

is in line with the studies of Woo (2009) and Baltabaev (2014). As a result, the two diverse effects of FDI derived from the FMM analysis align with the contradictory findings documented in the existing macro-level literature. Moreover, the posterior probabilities signifying the group size show that the first cluster has a larger size (57%) compared to the second one (43%).

As for the impacts of control variables on productivity growth within these clusters, each control variable has a significant impact on productivity growth in the first cluster whereas only the common dynamic process and inflation have significant effects in the second cluster. The adverse impact of inflation remains consistent across both clusters, aligning with theoretical and empirical studies from existing literature (Clark, 1982; Gilson, 1984; Cameron et al., 1996). Moreover, the common dynamic process, which reflects common shocks, may demonstrate varying effects; for instance, unexpected adverse political and financial shocks may result in a negative impact on productivity growth (Bloom, 2009; Estevão & Severo, 2010; Kose et al., 2020)[11], while advanced technological shocks may contribute positively (Triplett, 1999)[12].

In addition, considering the mean values presented in Table 6, FDI, on average, is higher in the first cluster compared to the second one, pointing to an increased likelihood of a negative impact on productivity growth in countries with larger FDI.

[11] To elaborate, Bloom (2009) examines how uncertainty resulting from major political and financial shocks, such as the Cuban Missile Crisis, the assassination of JFK, the OPEC I oil price shock, and the 9/11 terrorist attack, can negatively impact productivity growth. Estevão & Severo (2010) also find that financial shocks, caused by distortions introduced by financial frictions, reduce productivity by disrupting resource allocation among firms. Additionally, Kose et al. (2020) highlight that financial crises associated with episodes of national debt accumulation often result from external shocks, such as sudden increases in global interest rates. These shocks disproportionately affect countries with high government debt, hindering long-term growth by constraining private investment aimed at increasing productivity.

[12] Technological advancements may significantly impact productivity growth. Technology may diffuse from other firms or be enhanced by industry-wide shocks, such as general innovations (Triplett, 1999).

Notably, these countries also tend to exhibit higher inflation rates and lower levels of economic development (see Table 6). Additionally, examining the mean values of TFP growth in the two clusters reveals another important finding: FDI inflows strengthen (weaken) productivity growth in developing countries where productivity growth is already higher (lower)[13].

Table 5. Estimation Results

Variables		**Finite Mixture Model**	
	AMG	**Cluster 1**	**Cluster 2**
FDI	-0.000	-0.002**	0.005***
	(0.001)	(0.001)	(0.001)
ln(GDPpc)	0.449***	0.063***	-0.003
	(0.051)	(0.008)	(0.004)
Population growth	0.013	0.043***	-0.002
	(0.051)	(0.004)	(0.004)
Trade openness	0.000	-0.000***	-7.98e-06
	(0.000)	(0.000)	(0.000)
Inflation	-0.001**	-0.002**	-0.001***
	(0.000)	(0.001)	(0.000)
Public Expenditure	-0.001	0.005***	-0.000
	(0.001)	(0.001)	(0.000)
Constant	-2.769***	0.329***	1.014***
	(0.483)	(0.065)	(0.033)
Common Dynamic Effect	0.472***	-0.005***	0.001**
	(0.162)	(0.001)	(0.001)
Observations	395	225	170
R^2	0.007		
Posterior probability of cluster		57%	43%

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

[13] We may explain this result that countries with lower levels of productivity may face challenges in efficiently utilizing the new technologies introduced through FDI or may struggle to integrate capital and technology-intensive advancements (De Mello, 1999).

Table 6. Mean values by clusters and t-test results

Mean values	Cluster 1 *(Detoriating Impact of FDI on TFP growth)*	Cluster 2 *(Improving Impact of FDI on TFP growth)*
Dependent Variable:		
TFP growth	0.94	**1.00*** **
Explanatory Variables:		
FDI	**4.91*** **	3.42
Ln (GDPpc)	8.51	**8.62***
Population growth	1.21	1.09
Trade openness	**83.93*** **	68.17
Inflation	**7.14***	6.08
Public Expenditure	22.00	23.10

Notes: *p<0.1 significantly higher at 10%, **p<0.05 significantly higher at 5%, ***p<0.01 significantly higher at 1% compared to other group based on two sample t-test.

For a more comprehensive examination of cluster characteristics, we shall delve into the composition of these clusters. To achieve this, we allocate each country to a specific cluster only if its likelihood of belonging to that class surpasses its likelihood of belonging to the alternative class. Table 7 presents country memberships. Interestingly, the first cluster includes ten out of eleven Asian nations in our sample: Armenia, India, Indonesia, Jordan, Kazakhstan, Malaysia, Mongolia, Philippines, Saudi Arabia, and Thailand. As mentioned earlier, our results show a negative impact of FDI on productivity growth in the first cluster[14]. This finding cannot be directly compared with studies in the empirical literature due to the scarcity of cross-country research focusing on this particular region. However, the empirical literature focused on Asia mostly seeks to elucidate the spillover effects on productivity from FDI inflows and yield mixed outcomes[15]. For

[14] While Eastern European and North African countries are likely to be in the second cluster, the limited number of countries in each region impedes making a conclusive assessment, as there are only two countries in each region. In Latin American countries, however, no regional proximity pattern is observed.

[15] In this context, while some studies attempt to explain FDI spillover effects within the absorptive capacity concept in the literature (Ahmed, 2012; Tu & Tan, 2016; Ahmed & Kialashaki, 2019), this concept is restricted to human capital only.

instance, in their comprehensive meta-analysis, Wooster and Diebel (2006) observed a prevalent positive spillover effect in studies focused on FDI in Asia; however, they underscored the high sensitivity of these findings to model specification and time period. In contrast, a recent study by Ahmed and Kialashaki (2019) emphasizes a lack of positive impact of FDI on productivity spillover effects in Asian countries, extending Ahmed (2012)'s study only for Malaysia.

Table 7. Cluster membership

Countries	Region	The distribution of clusters in the period 2004-2019 per country	
		Cluster 1	Cluster 2
Armenia	Western Asia	**94%**	6%
Brazil	South America	**60%**	40%
Bulgaria	Eastern Europe	47%	**53%**
Chile	South America	50%	50%
Colombia	South America	8%	**92%**
Costa Rica	Central America	**56%**	44%
Dominican Rep.	North America	50%	50%
Egypt	North Africa	17%	**83%**
Guatemala	Central America	6%	**94%**
Honduras	Central America	25%	**75%**
India	South Asia	**80%**	20%
Indonesia	Southeast Asia	**62%**	38%
Jordan	Southwestern Asia	**81%**	19%
Kazakhstan	Central Asia	**64%**	36%
Malaysia	Southeast Asia	**69%**	31%
Mexico	North America	8%	**92%**
Mongolia	East Asia	**85%**	15%
Paraguay	South America	**60%**	40%
Peru	South America	13%	**88%**
Philippines	Southeast Asia	**69%**	31%
Russian Federation	Eastern Europe & North Asia	44%	**56%**
Saudi Arabia	Western Asia	**70%**	30%
Sri Lanka	South Asia	13%	**88%**
Thailand	Southeast Asia	**81%**	19%
Tunisia	North Africa	11%	**89%**
Turkey	Eastern Europe & Western Asia	17%	**83%**
Ukraine	Eastern Europe	31%	**69%**
Uruguay	South America	**69%**	31%

After a comprehensive analysis of the clusters' characteristics, we now investigate whether absorptive capacity and its sub-components play a role as conditioning factors in explaining the opposite effects of FDI. To do so, we create a dummy variable assingning a value of one if the country belongs to the second cluster (positive impact of FDI) and of a zero otherwise. We then run a regression of dummy variable on our counditioning variables by using random effects probit technique. Table 8 presents the estimation results. We find that countries with a high absorptive capacity index are more likely to be part of the second cluster where FDI has a beneficial impact on productivity growth. Moreover, the results show that the marginal effects of all sub-components such as human capital, financial and infrastructural development, and institutional quality are positively associated with the probability of being in second cluster. Conversely, given the existence of two clusters, it can be asserted that countries with a lower absorptive capacity are more likely to be in a cluster characterized by a detrimental impact of FDI on productivity growth. Consequently, absorptive capacity plays an important role in shielding FDI from being merely a resource exploiter in the host country and transforming it into a technology diffuser depending on their absorptive capacities. Consistent with this result, macro-level studies concentrating on developing nations (Wang & Wong, 2009; Herzer and Donaubauer, 2018; Li & Tanna, 2019) similarly underscore the significance of absorptive capacity in obtaining productivity benefits from FDI[16].

[16] However, these studies typically focus on one or two sub-components of absorptive capacity.

Table 8. Panel Probit Model Estimation after FMM analysis

Independent Variables:	The probability of being in 2nd cluster: improving impact of FDI on TFP growth
Absorptive Capacity Index	**0.031*** (0.064)**
Human Capital Index	**0.288*** (0.061)**
Financial Development Index	**0.290*** (0.053)**
Infrastructural Development Index	**0.344*** (0.063)**
Institutional Quality Index	**0.208*** (0.049)**

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

2.6. CONCLUSION

In this study, we investigated the impact of FDI inflows on TFP growth in developing countries, considering the possible categorization of countries into distinct classes. Utilizing FMM analysis allowed us for the classification of countries, considering potential distributional heterogeneity in the relationship between FDI and productivity growth. Furthermore, our model incorporated common dynamic effects, serving as a representative variable for unobserved common shocks, with the aim of addressing cross-sectional dependency.

Using panel data for 28 developing countries spanning from 2004 to 2019, we found that the impact of FDI on productivity growth varies across country clusters. Specifically, FDI exerts a negative impact on productivity growth in the first cluster, contrasting with a positive impact in the second cluster. Subsequently, we examined whether the absorptive capacity of countries explain the differing impacts of FDI. We found that countries with a higher absorptive capacity were more likely to experience the positive effects of FDI on productivity growth, while those with lower absorptive capacity were more prone to the detrimental effects. In addition, all four components of absorptive capacity, including human capital, institutional quality, financial development, and infrastructure, reveal a significant relationship with this linkage. In essence, the ability of a developing host country to effectively integrate new technology and, consequently, derive benefits from FDI inflows depends significantly on its proficiency in human capital, financial and infrastructural development, and institutional quality.

Our research findings have important policy implications for developing countries. The study primarily suggests that developing economies should enhance their domestic conditions comprehensively to optimize the growing productivity impacts of FDI. Instead of singularly focusing on human capital, as often emphasized in existing literature (Borensztein et al., 1998; Xu, 2000; Cecchini & Lai-Tong, 2008; Huynh et al., 2021), it is imperative to assess institutional quality, financial development, and infrastructural development alongside human capital. Improvements in these conditions not only attract FDI but also empower host economies to maximize the benefits derived from foreign investments (Alfaro et al., 2009). Without such improvements, FDI inflows may serve as resource exploiters rather than technology diffusers.

Furthermore, this study highlights that FDI inflows have a more pronounced positive impact on the productivity of countries initially characterized by higher productivity, while adversely affecting countries with lower initial productivity levels. Therefore, regardless of FDI's role in the host country, local governments should enact policies to foster productivity growth. Prioritizing investments in the education system to enhance workforce capacity in assimilating new knowledge and technology becomes crucial. Additionally, strategic infrastructure investments, covering transportation, telecommunications, energy, and sanitation, are indispensable for supporting economic activities among households, businesses, and markets.

This study also suggests potential avenues for future research in Asian countries, as there is a higher probability that FDI negatively affects productivity growth in this region. A more in-depth examination focusing on absorptive capacity with all dimensions through sub-region, country, or sector-level analyses could provide valuable insights for enhancing productivity from FDI inflows in the Asian context.

CONCLUDING REMARKS

This dissertation investigates the impact of FDI inflows on income inequality and productivity growth in developing countries, with a specific emphasis on the potential distributional heterogeneity of FDI across different country clusters. To address this objective, this thesis proposes a novel methodological approach employing FMM analysis, which differs from conventional methods that assume uniformity in explaining the impact of FDI on these macroeconomic variables in the prevailing empirical literature. Our empirical findings yield significant results for both linkages: FDI-inequality and FDI-productivity growth. There is heterogeneity in the impact of FDI across country clusters, with FDI-inequality linkage observed within three clusters and FDI-productivity linkage within two clusters. Specifically, concerning the FDI-inequality linkage, analysis of panel data from 26 developing countries spanning from 2004 to 2019 reveals that FDI improves income inequality in one cluster, has no significant effect in another, and exacerbates it in a third. Regarding the FDI-productivity growth linkage, utilizing panel data from 28 developing countries over the same period, FDI negatively affects productivity growth in one cluster but has a positive impact in another. These findings underscore the variability in the impact of FDI on both macroeconomic variables across country clusters and shed light on the differing effects of FDI in the existing empirical literature.

Differing from the existing literature, this thesis undertakes an assessment of whether FDI will yield beneficial or detrimental outcomes for developing nations, incorporating multiple rationales. The primary finding regarding the diverse impacts of FDI across country clusters can be explained by the absorptive capacities of these nations. Countries with high absorptive capacities are less likely to experience the detrimental effects of FDI on income inequality. Within the realm of absorptive capacity components, human capital, financial systems, and infrastructure play significant roles, with human capital being particularly noteworthy among these components. In addition, countries with high absorptive capacities are more likely to enhance its positive effect on productivity growth, and components such as human capital, institutions, financial systems, and infrastructure significantly contribute on this relationship. Therefore, our findings emphasize the importance of assessing the impact of FDI on developing countries by considering all dimensions of absorptive capacity, rather than focusing solely on a limited number of conditions.

The second finding underlying the heterogeneity among country clusters may be attributed to regional proximity. For example, due to their regional closeness and status as transition economies, countries like Armenia, Bulgaria, Belarus, Georgia, Kyrgyz Republic, Moldova, Romania, Russia, and Ukraine are more likely to belong to the cluster where FDI mitigates income inequality. Conversely, Latin American nations such as Brazil, Costa Rica, and Panama tend to be situated in the cluster where FDI exacerbates inequality. This regional proximity is also evident in the FDI-productivity growth link. Specifically, Asian countries like Armenia, India, Indonesia, Jordan, Kazakhstan, Malaysia, Mongolia, Philippines, Saudi Arabia, and Thailand are more likely to fall into the cluster characterized by a negative impact of FDI on productivity growth.

Another noteworthy finding that sheds light on heterogeneity may be related to the initial domestic conditions of the developing countries. For instance, in countries already characterized by high income inequality, FDI is more likely to exacerbate this inequality, and vice versa. Similarly, FDI is likely to hinder productivity growth in nations where initial productivity levels are lower, and conversely. The countries characterized by lower productivity levels may encounter difficulties in effectively assimilating the new technologies facilitated by FDI, or may find it challenging to incorporate capital and technology-intensive innovations. Hence, while FDI might present higher risks to developing nations under unfavorable local circumstances, it can offer advantages in environments with favorable conditions.

Taken as a whole, contrary to the mixed results found in empirical literature, our study makes a substantial contribution to the field by covering the diverse impacts of FDI, employing FMM analysis. Moreover, we contend that the diverse impacts of FDI cannot be attributed to a singular factor but must be evaluated from multiple angles. Essentially, these impacts are dependent on the host country's absorptive capacity, which includes factors such as human capital, institutional strength, financial, and infrastructure development, in addition to regional context and initial domestic macroeconomic conditions.

Based on these findings, this study recommends several policy measures. To maximize FDI's advantages and/or mitigate potential disadvantages, developing countries should adopt targeted policies that enhance absorptive capacity. Improving human capital through a well-structured educational system, with a strong focus on technical and vocational training, can better equip local workforces to adopt foreign technologies (Borensztein et al. ,1998). Investments in STEM fields (Science, Technology, Engineering, and Mathematics) facilitate the adoption of advanced technologies introduced by foreign firms. Additionally, policies that encourage foreign companies to participate in local training programs can directly boost the skills of local workers, making them more competitive and adaptable. Strengthening financial systems is also critical to maximize FDI's benefit (Alfaro et al., 2009). Expanding access to credit for local businesses, promoting transparency, and broadening financial inclusion can help domestic enterprises collaborate effectively with foreign investors, fostering productivity growth. Moreover, institutional reforms that enhance governance, regulatory quality, and anti-corruption measures are vital for creating a transparent and stable environment that attracts sustainable, high-quality FDI (Busse & Hefeker, 2007). Upgrading infrastructure including transportation, energy, sanitation, and digital networks, is another essential strategy to support FDI by improving connectivity and access to resources, particularly in underserved regions, helping to reduce regional disparities (Calderón & Servén, 2004).

Beyond absorptive capacity dimensions, regional cooperation among neighboring countries through aligning policies on labor standards, environmental protections, and tax incentives can enhance collective bargaining power and better manage FDI spillovers (Dunning, 2000). Furthermore, countries with high inequality or low productivity should selectively promote FDI in sectors offering broad benefits. Policies directing FDI to labor-intensive industries and requiring skill-building and local content initiatives can help reduce inequality and bridge productivity gaps (Görg & Greenaway, 2004).

While this dissertation offers novel methodological contributions and strengthens empirical findings in existing literature, we should also address some of its limitations. Specifically, data related limitations prevent our ability to expand the sample to include more recent years and a broader range of developing countries. Additionally, due to limitations in available data, we are unable to include more specific absorptive capacity variables, such as the number of patents granted, personnel engaged in R&D activities, and graduates from STEM programs. Furthermore, different types of FDI, such as horizontal, vertical, and conglomerate, may potentially influence the productivity growth and income inequality of developing countries in varying manners. Nevertheless, conducting a detailed analysis for each type of FDI falls outside the scope of this dissertation.

This dissertation adopts a comprehensive approach by examining developing countries as a whole, without delving into specific countries or sectors. However, sectoral strategies prioritizing FDI especially in technology-intensive industries could give a light to future. Therefore, future research could yield additional insights by concentrating on some sectors, particularly in technology-intensive industries, enabling the use of higher frequency data concerning absorptive capacity and the integration of sector-level analysis with different types of FDI.

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APPENDIX A

Table A1. Variance Explained by the First Component (%)

Country Name	Absorptive Capacity Index	Human Capital Index	Financial Dev. Index	Institutional Qual. Index	Infrastructure 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

Notes: N.A.: Not applicable due to an insufficient number of observations

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:[*]					
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 subscriptions to the internet	WDI
Air freight	405	503.63	1122.98	Air transport, freight (million ton-km)	WDI

[*] We employ four out of six aggregate indicators available in the Worldwide Governance Indicators database. We omit the Political Stability and Absence of Violence/Terrorism and Rule of Law indicators due to their high correlation with other indicators like regulatory quality, government effectiveness, and control of corruption in our sample.

Table A3. Results of FMM with absorptive capacity index as the concomitant variable

Variables	Cluster 1	Cluster 2	Cluster 3
FDI	-0.171 (0.165)	-0.209 (0.301)	0.354*** (0.117)
ln(GDPpc)	15.154*** (1.888)	-19.537*** (3.069)	-5.322*** (0.509)
Population growth	1.819*** (0.508)	-1.553 (2.589)	1.225*** (0.398)
Urban	0.962*** (0.092)	0.221 (0.248)	0.331*** (0.023)
Trade openness	-0.225*** (0.027)	0.079*** (0.028)	0.081*** (0.012)
Unemployment	-0.271** (0.121)	-1.378*** (0.052)	0.257*** (0.077)
Inflation	0.026 (0.048)	0.082 (0.277)	-0.009 (0.037)
Constant	74.247*** (8.633)	170.792*** (8.948)	74.926*** (5.248)
Common Dynamic Effect	2.867*** (0.260)	1.603*** (0.180)	-0.728*** (0.057)
Concomitant variable: Absorptive capacity index	*(base outcome)*	*-0.315** (0.140)*	*0.006 (0.065)*
Posterior probability of clusters	52.2%	10.4%	37.4%

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

APPENDIX B

Table B1. Variance Explained by the First Component (%)

Country Name	Absorptive Capacity Index	Human Capital Index	Financial Dev. Index	Institutional Qual. Index	Infrastructure Development Index
Armenia	64	78	97	59	98
Brazil	58	68	81	62	62
Bulgaria	56	76	73	35	94
Chile	63	90	72	65	74
Colombia	67	77	96	63	58
Costa Rica	51	86	81	58	52
Dominican Republic	63	86	60	62	N.A.
Egypt	80	93	87	60	89
Guatemala	74	62	88	40	86
Honduras	54	67	93	37	88
India	N.A.	N.A.	95	57	96
Indonesia	79	93	93	85	92
Jordan	55	82	76	43	86
Kazakhstan	75	73	98	63	92
Malaysia	54	90	74	46	85
Mexico	73	92	99	55	95
Mongolia	N.A.	N.A.	87	50	77
Paraguay	68	94	99	67	93
Peru	75	77	99	61	83
Philippines	N.A.	N.A.	96	50	94
Russian Federation	65	81	98	53	98
Saudi Arabia	81	99	95	49	55
Sri Lanka	76	98	97	36	89
Thailand	63	63	98	47	67
Tunisia	69	61	97	74	84
Turkey	74	90	82	69	96
Ukraine	N.A.	N.A.	92	37	62
Uruguay	60	95	91	71	77

Notes: N.A.: Not applicable due to an insufficient number of observations

Table B2. Endogeneity test results

(H0: Variables are exogeneous)	Durbin (score)	Wu-Hausman Test
1-lagged levels of explanatory variables as instruments	0.593 (p = 0.441)	0.581 (p = 0.446)
2-lagged levels of explanatory variables as instruments	0.360 (p = 0.549)	0.352 (p = 0.553)
1-lagged and 2-lagged levels of explanatory variables as instruments	0.811 (p = 0.368)	0.795 (p = 0.373)

Table B3. Results of FMM with absorptive capacity index as the concomitant variable

Variables	Cluster 1	Cluster 2
FDI	-0.011*** (0.002)	0.002** (0.001)
ln(GDPpc)	0.114*** (0.007)	0.009* (0.005)
Population growth	0.032*** (0.009)	0.020*** (0.004)
Trade openness	-0.001*** (0.000)	0.000** (0.000)
Inflation	-0.001 (0.000)	-0.000 (0.001)
Public Expenditure	-0.000 (0.001)	0.000 (0.000)
Constant	0.094 (0.063)	0.868*** (0.051)
Common Dynamic Effect	-0.014*** (0.001)	0.001 (0.001)
Concomitant variable: Absorptive capacity index	*(base outcome)*	*0.521*** (0.138)*
Posterior probability of clusters	44%	56%

Notes: Standard errors in parenthesis. *p<0.1 significant at 10%, **p<0.05 significant at 5%, ***p<0.01 significant at 1%.

APPENDIX C. ETHICS COMMISSION FORM

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 30/09/2024

ThesisTitle (In English): THE IMPACT OF ABSORPTIVE CAPACITY ON THE LINKAGE BETWEEN FOREIGN DIRECT INVESTMENT AND INCOME INEQUALITY

My thesis work with the title given above:

1. Does not perform experimentation on people or animals.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not a research conducted with qualitative or quantitative approaches that require data collection from the participants by using techniques such as survey, scale (test), interview, focus group work, observation, experiment, interview.
5. Requires the use of data (books, documents, etc.) obtained from other people and institutions. However, this use will be carried out in accordance with the Personal Information Protection Law to the extent permitted by other persons and institutions.

I hereby declare that I reviewed the Directives of Ethics Boards of Hacettepe University and in regard to these directives it is not necessary to obtain permission from any Ethics Board in order to carry out my thesis study; I accept all legal responsibilities that may arise in any infrigement of the directives and that the information I have given above is correct.

I respectfully submit this for approval.

Student Information			
Name-Surname	Bengi Sarsılmaz Özekinci		
Student Number	N18140165		
Department	Economics		
Programme	Ph.D. in Economics		
Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

SUPERVISOR'S APPROVAL

APPROVED
(Title, Name Surname, Signature)
Prof. Dr. Lütfi Erden

APPENDIX D. ORIGINALITY REPORT

TO HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 26/09/2024

Thesis Title (In English): THE IMPACT OF ABSORPTIVE CAPACITY ON THE LINKAGE BETWEEN FOREIGN DIRECT INVESTMENT AND INCOME INEQUALITY

According to the originality report obtained by myself/my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options checked below on 26/09/2024 for the total of 85 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled above, the similarity index of my thesis is 24%.

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Student Information				
	Name-Surname	Bengi Sarsılmaz Özekinci		
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	Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

SUPERVISOR'S APPROVAL

APPROVED
(Title, Name and Surname, Signature)
Prof. Dr. Lütfi Erden