IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

DOCTORAL THESIS

THE INTERGENERATIONAL TRANSMISSION OF EARNINGS AND MOBILITY IN TÜRKİYE

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ISTANBUL, 2025

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by
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A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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ÖZ

TÜRKİYE'DE KUŞAKLARARASI KAZANÇ AKTARIMI VE HAREKETLİLİK

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Bu tez, önemli coğrafi farklılıklar ve ekonomik değişimlerle karakterize edilen Türkiye'de nesiller arası hareketlilik (IGM), çok boyutlu yoksulluk ve sosyoekonomik eşitsizlik arasındaki bağlantıyı geniş bir şekilde araştırmaktadır. Bu çalışma, Türkiye'deki hareketlilik dinamiklerini daha kapsamlı bir şekilde açıklamak için çok boyutlu yoksulluk ve teknolojik gelişmeyi birleştiren daha kapsamlı bir çerçeve kullanmaktadır.

Tezin ikinci bölümünde, Bayesci yaklaşım kullanılarak Türkiye'de ebeveyn geliri ile çocukların işgücü piyasasındaki başarısı arasındaki ilişkinin ampirik yönü analiz edilmektedir. Çocukların ebeveynleri ile gelir ilişkisinin, çocuklar orta kariyer seviyesindeyken daha yüksek olduğu bulunmuştur. Ayrıca, kızların gelirleri ile ebeveynlerinin gelirleri arasındaki ilişki, erkek çocuklar için karşılık gelen ilişkiden daha güçlüdür.

Tezin üçüncü bölümünde, teknolojinin bireylerin gelir perspektifini nasıl etkilediğini incelemektedir. Bulgulara göre teknolojinin imkanlarından daha fazla insan sermayesine sahip olanlar (genellikle daha az dezavantajlı hanelerden gelenler) daha fazla yararlandıkları için ekonomik eşitsizlik olumsuz yönde etkilenmektedir. Sosyoekonomik açıdan avantajlı ailelerden gelen çocuklar teknolojik ilerlemelerden orantısız bir şekilde yararlanmaktadırlar. Bu bölümdeki sonuçlar, teknik avantajların eşitsiz dağılımının yanı sıra çok yönlü yoksullukla mücadele etmek için hükümet

önlemlerinin gerekliliğini vurgulamaktadır. Yoksulluk ve teknolojik ilerlemenin etkileşime girerek gelecekteki sosyo-ekonomik yörüngeleri oluşturduğu Türkiye gibi geçiş ekonomilerinde, hükümetler yapısal eşitsizlikleri ele alarak daha adil bir kalkınmayı teşvik edebilir ve ekonomik hareketliliği artırabilir.

Tezin dürdüncü bölümü Alkire-Foster yöntemini kullanarak konut, sağlık, eğitim ve temel yaşam standartları gibi önemli boyutlardaki yoksunluğu yansıtan bir Çok Boyutlu Yoksulluk Endeksi (MPI) oluşturmaktadır. Hanehalkı yoksunluğu ile çocukların geliri arasında güçlü bir negatif korelasyon olduğunu da gösteren ampirik bulgulara göre, çok boyutlu yoksulluğun daha yüksek dereceleri yukarı doğru hareketliliği sınırlamaktadır. Çok yoksul evlerden gelen çocuklar, daha az acil finansal fırsatlara sahip olmanın yanı sıra, sosyoekonomik ilerlemenin önünde uzun vadeli engellerle de karşılaşmaktadır.

Anahtar Kelimeler: Alkire-Foster Yöntemi, Beceri Getirisi, Beşeri Sermaye, Çok Boyutlu Yoksulluk, Kuşaklararası Hareketlilik.

ABSTRACT

THE INTERGENERATIONAL TRANSMISSION OF EARNINGS AND MOBILITY IN TÜRKİYE

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This thesis broadly investigates the connection between intergenerational mobility (IGM), multidimensional poverty, and socioeconomic inequality in Türkiye, a nation characterized by notable geographical differences and economic shifts. This study uses a comprehensive framework, combining multidimensional poverty and technological development to give a thorough explanation of mobility dynamics in Türkiye.

The second chapter of the thesis analyzes the empirical aspect of the relationship between parental income trajectory and children's success in the labor market in Türkiye using a Bayesian approach. It is found that children's income is more closely associated with their parents' income when the children are at the mid-career level. Furthermore, the association between daughters' income and that of their parents is stronger than the corresponding association for sons.

The third chapter of the thesis examines how technology affects individuals' income prospects. By giving preference to those with greater human capital, typically from less disadvantaged households, technology exacerbates economic inequality, according to the findings. Children from socioeconomically advantaged backgrounds gain disproportionately from this technological transition, which perpetuates existing disparities and restricts mobility for those from low-income families. The results highlight the necessity of governmental measures to address the uneven allocation of

technical advantages, as well as the multifaceted nature of poverty. In transitional economies like Türkiye, where poverty and technological progress intersect to shape future socio-economic trajectories, governments can promote more equitable development and enhance economic mobility by addressing structural disparities.

The fourth chapter employs the Alkire-Foster technique to construct a Multidimensional Poverty Index (MPI) utilizing nationally representative Survey of Income and Living Conditions data, reflecting deprivation across important dimensions including housing, health, education, and basic living standards. Higher degrees of multidimensional poverty limit upward mobility, according to the empirical findings, which also show a strong negative correlation between household deprivation and children's income. In addition to having fewer immediate financial opportunities, children from very impoverished homes also suffer long-term obstacles to socioeconomic advancement.

Keywords: Alkire-Foster Methodology, Human Capital, Intergenerational Mobility, Multi-Dimensional Poverty, Return to Skills.

DEDICATION

I dedicate this dissertation to my world's most amazing father, my supportive and loving siblings, and to the cherished memory of my beloved mother, whose whole life and values remain a profound source of inspiration for me.

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I would like to express my deepest gratitude to my dissertation advisor, Prof. Dr. Hasan Vergil, for his continuous support in making this dissertation successful. His motivation, encouragement, and mentorship have been invaluable, and I will always remain grateful for his kindness and guidance. I wholeheartedly want to thank my professor and jury member, Dr Asad Ul Islam Khan, for his constant support and advice throughout my PhD time at Ibn Haldun University.

I extend my deepest love and respect to my family and friends, who supported me unfailingly throughout every stage of my thesis. I am endlessly grateful to my sister Noshaba for always believing in me, for pushing me to be my best, and for inspiring me in countless ways. Having you by my side is one of my greatest blessings. I feel truly fortunate to have found wonderful friends during my PhD who made these years both memorable and rewarding. I am especially grateful to Nilab and Amaama for their unwavering support and cherished friendship throughout the ups and downs of my PhD journey.

Sundas Iftikhar

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LIST OF SYMBOLS AND ABBREVIATIONS

AF	Alkire-Foster Methodology
CPI	Consumer Price Index
GDP	Gross Domestic Product
GGC	Great Gatsby Curve
IGE	Intergenerational Elasticity
IGE	Intergenerational Elasticity
IGM	Intergenerational Mobility
MPI	Multi-Dimensional Poverty Index
OLS	Ordinary Least Square
SBTC	Skilled Biased Technological Change
SILC	Survey of Income & Living Conditions
TUIK	Turkish Statistical Institute

CHAPTER I

INTRODUCTION

Fair opportunities for all, irrespective of one's socio-economic background, are foundational to a just and equitable society. However, achieving such fairness in society requires a deeper understanding of the mechanisms that perpetuate inequality. Analyzing the intergenerational transfer of economic status is critical for evaluating the long-term consequences of persistent income inequality and poverty in an economy. The study of economic and social status persistence has deep roots in sociology (Erikson & Goldthorpe, 2002), and more recently, this focus has gained more prominence within economics as well (Solon, 1999; Jäntti & Jenkins, 2015). This thesis contributes to this growing body of literature by examining the various facets of income mobility and economic transitions across generations in Türkiye. The research is structured into three interconnected chapters, each addressing different dimensions of economic mobility, and together, they provide a comprehensive view of the forces shaping economic opportunities and outcomes in Türkiye.

A society's ability to effectively utilize its human capital is intricately reflected in the dynamics of income mobility within its economy. Income mobility, the capacity for individuals to move across income levels throughout their lifetime, is deeply intertwined with income inequality and the inequality of opportunity (Roemer, 2003). As economic inequality grows, the ability of parents to invest in the human capital of their children also becomes increasingly stratified, directly linked to their socioeconomic status. This trend is particularly pronounced in times when higher education and skill investment are essential to adapt to the changing labor market demands. Without interventions aimed at reducing inequality, children born into wealthier families will likely maintain their privileged status, while those from disadvantaged backgrounds will face significant barriers to overcoming poverty (Smeeding, 2013).

The relationship between income inequality and intergenerational mobility has been widely studied, with numerous studies establishing a negative correlation between the two, known as the Great Gatsby Curve (Corak, 2013). This curve illustrates how higher levels of income inequality are associated with lower levels of intergenerational income mobility, signaling that children in unequal societies are less likely to experience upward mobility. For instance, Chetty et al. (2014) found that in the U.S., children from the bottom income quintile have quite a low chance of reaching the top quintile, reflecting the "stickiness" of economic status in highly unequal societies. According to Björklund & Jäntti (2009), Nordic nations have much greater rates of mobility because of their strong social safety nets and reduced levels of inequality. The main conclusion from prior studies is that inequality perpetuates immobility, but the mechanisms vary across contexts. In advanced economies, inequality often operates through educational disparities and labor market polarization (Autor et al., 2003). My dissertation contributes to this body of research by providing a detailed analysis of intergenerational mobility in Türkiye, how returns to task due to technology reward individuals' earning abilities without family influence, and how the households' multi-dimensional poverty impacts the income mobility of children across generations. Through this analysis, this thesis aims to highlight how income disparities impact the opportunities available to future generations and the potential for policy interventions to alter these dynamics.

The transfer of socio-economic status across generations is referred to as intergenerational mobility (IGM). This transfer can occur through two main channels: the transmission of human capital (such as education, skills, and health) or the direct transfer of financial resources. Research on IGM primarily focuses on comparing the socio-economic status of individuals as adults to that of their parents, examining how parental income and occupation influence the income and career trajectories of their children. A key finding from this body of work is that parental income is a strong predictor of children's earnings, with studies like Chetty et al. (2014) showing that children from the top 1% of earners in the U.S. are 10 times more likely to attend elite colleges than those from the bottom 20%.

Chapter Two of this thesis investigates the dynamics of intergenerational income and career mobility in Türkiye. Using data from the Survey of Income & Living Conditions (SILC), this chapter aims to quantify the extent to which parental income and occupational status affect the career and income outcomes of their offspring. This analysis is particularly relevant for developing countries, where studies on intergenerational mobility have often been limited due to the lack of longitudinal data on earnings, income, and taxes. Previous research, notably by Chetty et al. (2014) and Corak (2013), has demonstrated that parental income and occupational status play a significant role in shaping offspring's economic outcomes in developed countries. However, such studies often rely on extensive longitudinal data on earnings, income, and taxes—resources that are typically scarce in developing economies. This scarcity has limited our understanding of intergenerational mobility in these contexts, creating a critical gap in the literature. This chapter makes a twofold contribution to the existing body of research. First, by leveraging the SILC dataset, it extends the investigation of intergenerational mobility to Türkiye, a developing country context that has received comparatively little attention in prior studies. Second, the analysis applies advanced econometric techniques such as Bayesian methodology and logistic model to quantify the impact of parental income and occupational status on children's career and income trajectories. In doing so, it not only corroborates the findings from developed countries but also provides new insights into how these dynamics manifest in Türkiye.

Using Bayesian methodology, this research demonstrates that household-level survey data can be leveraged to effectively estimate intergenerational mobility in the context of Türkiye. By incorporating data on income and occupational status, this chapter offers insights into the mechanisms through which parental socio-economic status influences the career and income trajectories of children in a developing economy such as Türkiye. This approach provides a valuable contribution to the literature on IGM, especially in the context of countries with limited access to more traditional longitudinal datasets.

The findings from Chapter Two highlight a significant gender-based discrepancy in intergenerational mobility (IGM) coefficients. Specifically, the study shows that daughters' economic outcomes are more closely tied to their parents' economic outcomes than those of sons. The intergenerational income mobility coefficient for

parent-daughter pairs is notably higher than for parent-son pairs. This aligns with findings from Demirtaş & Torul (2023), who found intergeneration earning elasticity between fathers and daughters to be 1 in Türkiye. Moreover, the finding of this chapter reveals that the association between parental income and children's income is strongest when the children are in the middle of their career stage. This suggests that the influence of parental income on children's economic outcomes may diminish as they progress further in their careers.

Chapter Three of the dissertation delves into the influence of technological advancements on individuals' earnings in Türkiye. Recent empirical work has documented that technological change, particularly automation and the rise of advanced information technologies, has contributed to labor market polarization by boosting high-skill occupations while eroding middle-skill jobs. Recent contributions (e.g., Hennig, 2021; Guo, 2022) indicate that although technological advancements can theoretically promote meritocracy by emphasizing skill over inheritance, they may simultaneously exacerbate inequality when access to high-skill opportunities is unevenly distributed. With the recent surge in technological change, there has been a structural shift in the labor market, favoring high-skill and low-skill occupations at the expense of middle-wage jobs. This transformation, often associated with Skilled-Biased Technological Change (SBTC), has led to greater income polarization and heightened disparities in income mobility.

In this chapter, a novel approach is introduced to explore how technological advancements affect individual earnings in Türkiye by isolating the impact of paternal income on the income of sons across 26 regions of Türkiye. The rise of technology, which disproportionately benefits high-skilled workers and leaves low-skilled workers with fewer opportunities, has redefined the labor market structure. The middle-skilled jobs, traditionally a path for upward mobility, have diminished, resulting in reduced mobility opportunities for children from lower-income families who lack access to the high-skilled job market.

The analysis suggests that technology rewards skills disproportionally. The high-skilled occupations, as compared to manual jobs, have a positive impact on individuals' earnings, especially in technologically advanced regions such as Istanbul

and Ankara. While the routine occupations or repetitive tasks have a negative impact on an individual's earnings as compared to manual tasks. The findings underscore the importance of region-specific policies that not only foster technological innovation but also address the educational and skill development needs of the population. This would ensure that children, especially those from disadvantaged backgrounds, are equipped to take advantage of the new opportunities presented by technological advancements, ultimately promoting greater intergenerational mobility in Türkiye.

The chapter analyzes how skilled biased technological hypothesis (SBTC) impacts the economic trajectories of individuals based on their abilities when the impact of parental background has been controlled. By incorporating human capital theory with the SBTC hypothesis, the analysis posits that regions experiencing technological advancement might show different mobility outcomes. The findings from this section suggest a nuanced impact of technological advancement on individuals' mobility in Türkiye. Specifically, in regions with higher technological exposure, children from families where fathers hold abstract or high-skill jobs experience lower intergenerational mobility. This can be attributed to the increasing polarization in the labor market, where high-skill jobs are becoming even more concentrated in certain sectors, while the demand for middle-skill jobs decreases (Autor, 2014). As technological advancements continue to favor high-skilled workers, children from such families may face more rigid economic trajectories.

However, the analysis also reveals a contrasting dynamic in regions with high technological exposure, where children from families with fathers in manual or low-skill jobs exhibit more upward mobility. In these areas, the rise of technology has created new opportunities for high-skill jobs, enabling children from disadvantaged backgrounds to break out of their families' economic constraints (Goldin & Katz, 2008).

These results highlight the dual nature of technological change: while it can entrench economic disparities, it can also provide pathways for mobility for certain groups, particularly those from disadvantaged backgrounds. This underscores the need for targeted policies in regions with high technological exposure to ensure that

opportunities for upward mobility are accessible to all, regardless of their parental background or initial skill level.

The Fourth Chapter uses the approach beyond a unidimensional focus on income or earnings to include various aspects of well-being, such as education, health, and living conditions. This chapter of the thesis looks at the dynamics of intergenerational mobility from a different perspective. Instead of looking at the impact of fathers' income on children's income, I analyze the impact of household poverty on children's income and educational outcomes.

The household poverty has been estimated using the multi-dimensional poverty index, developed by Alkire & Foster (2011). Looking at the dynamics of intergenerational mobility from the perspective of the multi-dimensional poverty index gives a fresh perspective on understanding which deprivation of a household might affect the upward mobility of children. The benefit of using household deprivations instead of just using parents' income matrices is that it would help policymakers in understanding which deprivations limit the children's chances of upward mobility. I have used OLS methodology, logit model, and transition matrix analysis to estimate the impact of multi-dimensional poverty on children's income and educational mobility.

The finding of the chapter shows that there is a negative association between children's income and educational outcomes and the multi-dimensional poverty of a household. The households that are facing more deprivation across various dimensions face more constraints in achieving higher education and income. The children from impoverished households face diminished prospects for upward economic mobility, largely due to inadequate access to quality education and skill acquisition, essential prerequisites for securing high-paying employment opportunities.

This chapter transitions from traditional measures of intergenerational mobility to a multidimensional framework, where the focus extends beyond the classical reliance on fathers' or families' socio-economic status as the sole determinant of children's socio-economic mobility. By integrating a comprehensive evaluation of household deprivations across key dimensions—such as education, health, housing quality, and basic living standards—this study offers a more holistic perspective on the

mechanisms through which poverty hinders upward mobility and reinforces socio-economic disparities.

This nuanced approach underscores that poverty is not merely a deficiency of income but an amalgamation of deficits across critical domains that shape life opportunities. By addressing these multidimensional aspects, the analysis enriches the discourse on intergenerational mobility and emphasizes the necessity of policies that target the broader spectrum of deprivations. The chapter's contribution lies in highlighting the centrality of multidimensional poverty in constraining children's economic prospects, especially in settings where traditional income-centric metrics fail to capture the full extent of barriers impeding long-term mobility.

A substantial body of research has consistently demonstrated that intergenerational mobility is significantly shaped by parental income and occupational status. For example, Chetty et al. (2014) provide compelling evidence that parental earnings have a lasting influence on children's long-term economic prospects, while Corak (2013) emphasizes that higher income inequality is linked to lower mobility across generations. In parallel, studies by Autor, Dorn, and Hanson (2013) reveal that technological changes have accelerated wage polarization by favoring high-skilled, abstract occupations at the expense of routine jobs, thereby intensifying income disparities. More recent contributions (e.g., Hennig, 2021; Guo, 2022) further refine this narrative by examining how skill-biased technological change (SBTC) not only affects earnings but also intergenerational mobility. In addition, multidimensional poverty frameworks (such as those advanced by Alkire and Foster, 2011) have underscored the compounded effects of deprivations in education, health, and living conditions on social mobility.

Building on these established findings, this thesis makes three key contributions to the literature to illuminate the intricate dynamics of intergenerational mobility within the context of Türkiye. Chapter 2 establishes a foundational understanding of income and career mobility, demonstrating the persistent influence of parental income and occupational status on children's long-term earnings and professional outcomes. Chapter 3 advances this discourse by exploring the implications of return to skills on individuals' earning abilities, revealing how advancements in technology amplify

disparities in income inequality, disproportionately benefiting those with higher education and skills while exacerbating barriers for individuals from disadvantaged backgrounds. Chapter 3 introduces a multidimensional poverty framework, emphasizing how intersecting deprivations—spanning education, health, and living conditions—further constrain socio-economic mobility and entrench inequality across generations.

Through this work, the thesis emphasizes the importance of not only understanding the persistence of income across generations but also the multifaceted nature of poverty and how it can constrain or enable economic mobility. By considering factors beyond income, such as education, health, and access to basic services, this study builds on existing theories and approaches to provide a more nuanced understanding of how poverty affects long-term mobility (Corak, 2013; Chetty et al., 2014). Ultimately, the findings have implications for policymakers, encouraging a more holistic approach to addressing inequality in Türkiye and beyond.

Together, these chapters underscore that intergenerational mobility is not solely a function of economic resources but is profoundly shaped by structural inequalities and technological transformations. The synthesis of income dynamics, technological shifts, and multidimensional poverty provides a holistic perspective, revealing the multifaceted challenges that perpetuate inequality. Addressing these issues requires comprehensive policies that integrate income redistribution, skill enhancement, and targeted interventions to alleviate multidimensional deprivation. By framing intergenerational mobility through these interconnected lenses, this thesis contributes to the broader discourse on achieving equitable socio-economic outcomes in rapidly evolving societies.

CHAPTER II

UNDERSTANDING INTERGENERATIONAL MOBILITY IN TÜRKİYE

2.1. Introduction

For fair earnings distribution, one's wage should not be determined based on their family background. Literature on intergenerational mobility focuses on the dynamics and extent of it to increase the welfare and equality of opportunity in society, see (Solon, 1999). Intergenerational economic mobility is a crucial element in the fair distribution of opportunities. Many studies are available focused on intergenerational economic mobility and its various aspects for many countries, mostly developed economies (Solon, 2002). However, Türkiye still lacks such studies to understand the share of inequalities caused due to the transfers of socio-economic outcomes from one generation to the next.

The studies on intergenerational mobility (IGM) aim to understand the dynamics and factors affecting economic mobility, eradicate economic inequalities, and promote welfare and equality. Higher intergenerational immobility shows persistence of socio-economic status within generations, which is caused due to unequal opportunities and disproportionate family resources instead of differences in individuals' effort and diligence. Higher intergenerational economic persistence could indicate inefficient use of human capital, and children coming from disadvantaged family backgrounds might feel that the odds of being successful/ jumping up on the ladder of socio-economic class are stacked against them, and that could result in less cooperation in the society (Mogstad & Torsvik, 2023).

Among the measures to estimate the association between children's and fathers' income and other economic opportunities, intergenerational income earning elasticity (IGE) is the most widely utilized. However, the studies using IGE for the analysis of

IGM have mostly been done for developed countries (Solon, 1999; Solon, 2002; Corak, 2013; Chetty, Hendren, Kline, & Saez, 2014; Cervini-Plá, 2015; Corak et al., 2014). Most of this literature targeted the developed economies; developing economies have been ignored so far, mainly because of the unavailability of the data required to examine intergenerational economic mobility and its dynamics.

The literature on the transmission of economic/social outcomes to the next generation that exists in Türkiye is focused on intergenerational education mobility because of the unavailability of reliable longitudinal data on household income. Consequently, Türkiye lacks comprehensive studies on intergenerational mobility. The studies conducted on intergenerational mobility include Mercan (2012), Mercan & Barlin (2016), and Duman (2021), which have biased results due to either the use of the household budget survey or insufficient data used for the analysis. However, a recent study by Demirtaş & Torul (2023) analyzes the intergenerational income mobility in Türkiye using TS2SLS methodology using SILC data, and the intergenerational earning elasticity is 0.51 among fathers-sons and 1 among fathers-daughters pairs according to their study, which is the same as in this chapter. The elasticity is similar to many other developing countries: between 0.44 & 0.5 in Indonesia (Adli & Sahadewo, 2023), 0.63 in China (Gong, Leigh, & Meng 2012), 0.57 in South Africa (Piraino, 2015).

This chapter aims to study this strand of the literature by analyzing intergenerational earnings and occupational mobility in Türkiye; I focus on how these elasticities change at the different career levels of the children. To achieve the objectives and make the best use of the rotational panel data available for Türkiye, I use pseudo panel data and Bayesian methodology to estimate intergenerational mobility. In this chapter, the microdata Survey of Income and Living Conditions from the Turkish Statistical Institute (TUIK) has been used. The data is cross-sectional data covering the period of 2006-2021, consisting of four survey waves: 2006-2009, 2010-2013, 2014-2016, and 2017-2021. It follows a rotational panel design, where 25% of the sample is replaced annually with a new 25% sample within each survey wave. Intergenerational mobility studies require long panel datasets, which help developing countries to have a comprehensive analysis of intergenerational mobility studies. I will use cross-sectional data and make a pseudo-panel to estimate IGE, and make cohorts in pseudo-panel

settings without taking averages for Bayesian analysis. I switched to Bayesian for the analysis because averages from the pseudo-panel do not represent the population well. This study is the first to analyze intergenerational earnings and occupational mobility using Bayesian methodology in Türkiye, as per my knowledge.

The study focuses on the following questions:

- How does the association between parental and children's income vary across different income groups? Is this association stronger when a father is in the higher wage distribution?

- Does educational attainment mediate the relationship between parental economic outcomes and offspring's economic outcomes?

- What's the trend of occupational Persistence in Türkiye among different economic groups? Is occupational persistence higher for children whose fathers are in the higher wage distribution?

By answering these questions, this chapter analyzes the dynamics of intergenerational income and occupational mobility in Türkiye, and also looks at the various determinants of children's earnings in Türkiye.

The next section presents a literature review, followed by a section that describes data and methodology, after that is a section on discussion, followed by the conclusion.

2.2. Literature Review

The literature on the empirics of intergenerational economic mobility has grown considerably in recent decades. Solon (1992) highlights the sources of bias and measurement error in early empirical studies in his seminal paper and proposes a standard methodology for accurately estimating intergenerational income persistence, which led to methodological advances and improved data availability. Comparable estimates have recently become available for several developing countries (Narayan et al. 2018). The study is motivated by the lack of such estimates for Türkiye.

Türkiye lacks research on income intergenerational mobility studies and has mostly focused on education mobility rather than income due to the lack of suitable longitudinal datasets on children's & parents' income. On the literature of intergenerational education mobility, Tansel (2015) utilized TurkStat's Adult Education Survey (AES) and demonstrated that the educational background of mothers plays a more significant role compared to that of fathers, and the association between children and parents' education attainment is stronger when parental education is below the primary school level. The study by Öztunalı and Torul (2022) examined both ordinal and cardinal measures of intergenerational educational mobility using the Intergenerational Transmission of Disadvantages Module of SILC in 2010, and it concluded that Türkiye's educational mobility is lower than that of developed countries. Aydemir and Yazıcı (2019) study focused on cross-regional variation in intergenerational educational mobility in Türkiye and found a positive relationship between educational mobility and regional development.

The literature on intergenerational income mobility for Türkiye is limited. Mercan (2012) estimated intergenerational income mobility and reported the mobility elasticity in Türkiye to be 0.1, which is very low as compared to other developed countries, concluding that Türkiye is a very mobile country. Still, this study didn't use longitudinal data; thus, the results could be biased. Mercan & Barlin (2016) estimated intergenerational income elasticity using the Survey of Income and Living Conditions (SILC) data set and employed OLS and IV estimation techniques and found intergenerational income elasticity to be between 0.3 and 0.6, which is much higher than the previous study done for Türkiye. Another study for Türkiye was done by Duman (2021), using Household Budget Survey data for the period between 2003 and 2011, and found a mobility correlation in the range of (0.10, 0.51) for sons and (0.17, 1.00) for daughters. The most recent study, which is conducted by Demirtaş & Torul (2023) for the period of 2005-2017 using TS2SLS for SILC data, found the intergenerational earning elasticity to be 0.51 among fathers-sons and 1 among fathers-daughters pairs. This chapter provides the first insights into the empirical transmission of income between generations using a Bayesian approach, utilizing the most recent data available, contributing to a better understanding of Türkiye's intergenerational mobility. This study complements previous research on the topic.

The findings suggest that Türkiye's intergenerational income mobility dynamics are like developed countries such as the United Kingdom. (Ng, 2023) analyzes intergenerational income mobility for the UK using various approaches such as rank-based estimation, IV method, and OLS. The study used a longitudinal data set for the UK and found the intergenerational income mobility to be between 0.27 & 0.50. The coefficient around 0.5 shows that there are barriers in the economy affecting children's mobility, where children's outcomes are dependent on their family's economic background.

A key aspect of social mobility[1]- which is required because of the innovation brought about by industrialization—is occupational mobility. New income and occupation opportunities are being created due to recent developments in education, communication, technology, and urbanization (Treiman, 1970). However, structural change can often be slow because younger generations may need to change careers (generational occupations) to find work, and their parents may not be able to provide adequate guidance due to their experience in a different working environment.

Economists and sociologists, both, have been investigating the dynamics of occupation mobility as a form of social mobility, followed by the seminal contribution of Blau & Duncan (1967) and Erikson & Goldthorpe (1992). Andrade et al. (2003) found that borrowing constraints significantly impact intergenerational transfers. If parents are unable to access loans, their ability to invest in their children's human capital is limited, which in turn reduces intergenerational skill transfers. Removing parents' borrowing constraints leads to an increase in investment in their children's human capital, resulting in higher educational levels and abilities. According to Tyree et al. (1979), children often aspire to careers in the same occupational group as their parents and mostly end up working at the same workplace as their parents at the start of their career.

The literature has examined various factors affecting occupational mobility. Ermisch and Francesconi (2002) investigated the impact of the social status of the parents of married couples on their socioeconomic mobility for the British Household Survey. Their findings suggest that men were influenced by their parents with a correlation of

[1] Social mobility is commonly defined as the transition from lower social class or economic group to a higher one, or from one degree of education or occupational status to another, see Iversen et al., (2021)

0.2, and by their spouses' families with a correlation ranging from 0.17 to 0.25. Women, on the other hand, were influenced by their parents with a correlation ranging from 0.17 to 0.23, and by their spouses' parents with a correlation ranging from 0.16 to 0.18. Bean and Swicegood (1979) stated that ineffective family planning leads to lower social mobility; this conclusion is supported by Corak and Piraino (2010). Hellerstein and Morrill (2008) reported that a girl's career choice is more influenced by her father's occupation than her father-in-law's occupation which leads to the conclusion that there is an increase in the transmission of intergenerational occupation-specific human capital.

Carmichael's (2000) study on intergenerational mobility in the UK demonstrates that the success of a generation is dependent on the success of the previous generation. The study by Louw et al. (2007) on intergenerational mobility in South Africa suggests that, despite an increase in educational attainment over time, children's mobility remains inconsistent and is significantly influenced by race and parental education, with enduring obstacles hindering advancement for the most disadvantaged groups. Motiram and Sing (2012) found a significant lack of occupational mobility in India, particularly among those in low-skilled and low-paid jobs.

Children's occupational choices and thus mobility can be explained by parents' socio-economic status, e.g., 40.5% of children of university graduate parents are high-skilled, while only 11% of children, whose fathers completed high school, worked in jobs that required high skills. Generally, the longer children and parents spend in school, the higher the probability of entering occupations with a higher social status (Andrade et al., 2003). Hellerstein & Morrill (2011) found that 30% of men and 20% of women followed their fathers. These findings were supported by Ermish and Francesconi (2002), Carmichael (2000), Di Pietro and Urwin (2003), and Ferrie (2005). The study also focuses on occupational mobility, besides investigating the dynamics of income mobility for Türkiye.

2.3. Data & Methodology

The survey of income and living conditions (SILC) data from 2006-2021 has been utilized in this chapter, it's a rotational panel data which tracks individuals for four

years. The cohorts have been formed for analysis based on career level to better understand the impact of family income at different career stages of children. The cohorts are made by grouping children based on their age: the 26-35 age group is considered to be at the beginning of their career level, the 36-45 age group is considered to be at the mid-career level, and the 46-55 age group is considered to be at the peak of their career level. Before the analysis, it is better to look at the descriptive statistics of the data. Table 2.1 shows descriptive statistics of the data.

Table 2.1. Descriptive Statistics

Variables	**Full Sample**		**Beg. of Career**		**Mid-career-level**		**At peak-career level**	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Children Earnings	9.266	1.052	9.375	1.024	9.167	1.059	9.042	1.142
Father's Earnings	9.915	0.887	10.022	0.868	9.717	0.892	9.642	0.897
Education	3.702	1.521	3.809	1.522	3.630	1.548	3.413	1.566
Marital Status (1=single, 0=otherwise)	0.613	0.486	0.691	0.461	0.465	0.498	0.406	0.491
Gender (1=male, 0=otherwise)	0.680	0.466	0.688	0.463	0.676	0.467	0.626	0.4838
No. of obs	11651	11651	6709	6709	3993	3993	949	949

Notes: Author's calculation by using the SILC data from TUIK.

The dataset spans 26 NUTS-2 regions of Türkiye from 2006 to 2021, capturing socio-economic dynamics across diverse geographic and developmental contexts, from industrialized urban centers like Istanbul to agrarian regions in southeastern Anatolia. Descriptive statistics are reported for the full sample and disaggregated by career stages (beginning, mid-career, and peak-career) for children aged 26–55 with non-zero wages. Children's monthly real wages show a notable decline from early-career (mean = 9.375) to peak-career stages (mean = 9.042), a pattern that may reflect Türkiye's

dual labor market structure: early-career workers in urban formal sectors (e.g., tech, finance) may initially earn higher wages, while peak-career workers in rural or informal roles (e.g., agriculture, small trade) face stagnation. This trend is compounded by rising wage dispersion (SD increases from 1.024 to 1.142), suggesting growing inequality as workers age, likely due to limited upward mobility pathways in low-skilled sectors.

Fathers' household earnings (representing parental income, including mothers in female-headed households) also decline across cohorts (mean = 10.022 early-career vs. 9.642 peak-career). This could signal intergenerational economic regression in certain regions or survivorship bias, where older fathers in lower-income households are overrepresented in later cohorts. Education levels decrease slightly across career stages (mean = 3.809 early-career vs. 3.413 peak-career), likely reflecting generational gains from Türkiye's post-2000 education reforms (e.g., expanded secondary schooling), which younger cohorts benefited from more than older workers.

Gender disparities persist but narrow modestly at peak-career (62.6% male vs. 68.8% early-career), potentially due to attrition of male workers in physically demanding sectors (e.g., construction) or delayed female labor force entry post-childbearing. Marital status trends align with lifecycle norms: 69.1% of early-career workers are single, declining to 40.6% at peak-career, as marriage rates rise with age.

2.3.1. Pseudo Panel Data

Panel data, which entails both time series and cross-sectional dimensions, is widely recognized to be advantageous when used for empirical research. However, the cost it takes to follow the same individual over time, panel data might not be available in many settings, unlike the cross-sectional data, which is more commonly available, where each wave observes a different set of individuals in the panel data. Those individuals could be grouped in cohorts based on some common characteristics that don't change over time, such as birth year, gender, etc. Then, the mean of these cohorts is treated as if they are observations of an actual panel.

Pseudo-panel has various benefits over panel data set with a smaller sample set; at the same time, cross-sectional datasets are a better representative of the population, e.g., household surveys, health and demographic surveys. The averaging process involved in creating pseudo-panels diminishes measurement error at an individual level, which is very common in survey data.

Many developing countries lack panel data to study intergenerational mobility, where specific households are followed over time. This study uses rotational panel surveys to analyze intergenerational dynamics in Türkiye using data from TUIK. The survey has four waves: 2006-2009, 2010-2013, 2014, 2017, and 2018-2021. To find intergenerational earning elasticity, panel data is required, so I will use the available cross-sectional data under some assumptions to treat it as panel data. In a pseudo-panel setting, I will follow cohorts instead of following households. From each cohort, successive random samples will be produced via the surveys. A time series gets generated from these random samples' summary statistics, which can be used to predict behavioral relationships for the cohorts, just as if the panel data were available. In the following paragraph, the construction of such a cohort and its use for the estimation of intergenerational earning elasticity have been discussed in detail. To the best of my knowledge, this would be the first study to use cross-sectional data under pseudo-panel settings for intergenerational mobility analysis.

The primary concern about using a pseudo panel is that the sample means of each cohort might not be the actual representation of the whole cohort population's means. Usually, a cell size (the number of individuals in a cohort) of 100 might be sufficient to reduce sampling error (Verbeek & Nijman, 1992). Also, pseudo-panel methodology assumes cohort homogeneity, which may fail if intra-cohort heterogeneity is high. This leads to the following methodology, which I will be using for the analysis.

2.3.2. Bayesian Methodology

The Bayesian approach has the following form for the general panel data model, which has been used by Carrington and Zaman (1994).

$$\boldsymbol{Y_{it}} = \boldsymbol{X_{it}\beta_{it}} + \boldsymbol{\varepsilon_{it}} \qquad (2.1)$$

Where Y is the dependent variable representing children's income at different career levels, the age of children has been used as a proxy variable to show their experience. The first group, 26-35, represents children at the early career level, 36-45 shows children at the mid-career level, and 46-55 is for children at the peak of their career level. X represents the independent variable, t is the number of periods, and *t=1, 2, ----, T*, i is the number of age groups, i.e., i=1, 2, and 3 in the study: 26-35, 36-45, and 46-55. β is the coefficient of each age group. Equation (1) can be explained as

$$Y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ . \\ . \\ . \\ y_{it} \end{bmatrix}_{t\times 1}, \; X_{it} = \begin{bmatrix} x_{i1} \\ x_{i2} \\ . \\ . \\ . \\ x_{it} \end{bmatrix}_{t\times k}, \; \varepsilon_{it} = \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ . \\ . \\ . \\ \varepsilon_{it} \end{bmatrix}_{t\times 1} \text{ and where } X_{it} = \begin{bmatrix} X_{it}^1 & X_{it}^2 & ..... & X_{it}^k \end{bmatrix}_{k-Regressors}$$

$\varepsilon_{it} \sim N(0, \delta_i^2)$

δ_i^2 is the variance of the error term of each age group.

The data density is

$$\beta^{\wedge}/_{\beta} \sim N(\beta, \Omega_i) \tag{2.2}$$

And the prior density is

$$\beta \sim N(\mu, \Lambda) \tag{2.3}$$

So, then the posterior density will become

$$\beta/_{\beta^{\wedge}_i} \sim N(m_i, \mathrm{V}_i) \tag{2.4}$$

Where the values of Equation (2.4) are as

$$m = V\left(\Omega^{-1}\hat{\beta} + \Lambda^{-1}\mu\right) \text{ and } V = \left(\Omega^{-1}+\Lambda^{-1}\right)^{-1} \tag{2.5}$$

The details of the Analytical solutions of posterior density can be found in (Zaman, 1996). The classical Bayes estimator is the mean of the posterior. So

$$\hat{\beta}_{i(CB)} = V_i\left(\Omega_i^{-1}\hat{\beta}_i + \Lambda^{-1}\mu\right) \text{ and its variance-covariance matrix is } V_i = (\Omega_i^{-1} + \Lambda^{-1})^{-1} \tag{2.6}$$

The two hyperparameters, μ and Λ are unknown. If these two are estimated from the data, then. $\hat{\beta}_{i(CB)}$ will be termed as Empirical Bayes estimator, and equation (2.6) becomes

$$\hat{\beta}_{i(EB)} = \hat{V}_i\left(\hat{\Omega}_i^{-1}\hat{\beta}_i + \hat{\Lambda}^{-1}\hat{\mu}\right) \tag{2.7}$$

Where the values of equation (2.7) are

$$\hat{\Lambda} = \left(\sum_{i=1}^{n}\Omega_i^{-1}\right)^{-1} \text{ and } \hat{\mu} = \hat{\Lambda}\left(\sum_{i=1}^{n}\hat{\Omega}_i^{-1}\hat{\beta}_i\right) \tag{2.8}$$

The advantage of the empirical Bayes technique is that it considers heterogeneity with great care, and the Empirical Bayes has much lower standard errors as compared to other techniques in the literature. Moreover, in this case, as it is a pooled panel, the heterogeneity matters a lot and the simple estimators like OLS with robust standard errors or GLS do not perform well, see (Zaman, 1996) and Carrington and Zaman (1994).

The empirical Bayes estimator[2] is the precision-weighted average of the first-level estimates of each cohort. Intuitively, it makes sense as it takes the first regressions

[2] For detailed discussion on empirical bayes and other estimators, see (Zaman, 1996).

from each cohort and deals with issues related to regression models (heteroskedasticity, autocorrelation, and endogeneity) at first-level regressions. The other advantage is that it takes the variation of each cohort into account at the second level of estimation (prior estimation). After that, when it goes back to each cohort estimation, it considers two types of variation (first level and second level(prior)). The empirical Bayes Estimator is more efficient than GMM and traditional estimators (OLS, 2SLS, GLS, etc.); therefore, it may be preferred. On the intuitive side, empirical Bayes is better than the rest of all above as it takes into account two types of variations, see (Zaman, 1996) and Carrington and Zaman (1994).

This chapter applies two methodologies, namely fixed effects on pseudo-panel data and empirical Bayesian modelling in a pseudo-panel data setting.

2.4. The Measurement of Intergenerational Earning Mobility

First, this section estimates intergenerational elasticity using individuals' earnings data taken from SILC surveys from 2006-2021. I have converted nominal earnings into real earnings using the consumer price index[3]. Following Becker & Tomes (1986), I will estimate IGE to estimate the relationship between children's and fathers' income using the following equation:

$$y_i^c = \alpha + \beta y_i^f + \varepsilon_i^c \tag{2.9}$$

Where y_i^c is the children's income, β is the slope coefficient, which measures the impact of the family's income status on the children's income, ε_i^c is a white noise error term. The value of β $closer$ to 1 shows lesser mobility, while estimates of β closer to zero shows rapid regression to the mean, indicating higher mobility. The coefficient of β would further be decomposed into its causal components to take into account the other factors, such as genetic and cultural endowments that are transmitted from parents to children: education of children (β_2), gender of children β_3, and the marital status of children β_4. Gender is a dummy variable, 1 for male and 0 for female.

[3] By using the formula Real Income= Nominal Income/Consumer Price Index*100

$$y_i^c = \alpha + \beta_1 income^f + \beta_2 education^c + \beta_3 gender^c + \beta_4 marital\ status^c + \varepsilon_i^c \quad (2.10)$$

The second goal of the chapter is to estimate the occupational mobility dynamics in Türkiye. As the dependent variable is a dichotomous variable, where 1 is assigned when parents & children are in the same occupation, and the value of 0 is assigned otherwise. The logit model has been regressed to estimate the trend of occupational persistence in Türkiye among various economic groups. The logistic function is used in the logit model to estimate the likelihood of occupational persistence as a function of explanatory factors, guaranteeing that projected probabilities fall between 0 and 1. Interpretable odds ratios, which measure the impact of changes in explanatory factors on the likelihood of occupational persistence, are a major strength of the logit model. For instance, the model can estimate how income or education affects the odds of children remaining in the same occupation as their parents.

$$occupation^c = \alpha + \beta_1 income^c + \beta_2 education^c + \beta_3 gender^c + \beta_4 marital\ status^c + \varepsilon_i^c \quad (2.11)$$

Where β_1 accounts for the impact of children's income on the decision of whether to follow the father's occupation or not, β_2 represents the impact of children's education on their decision whether to follow their father's occupation, the slope coefficient β_3 estimates the role of gender and the coefficient β_4 measures the impact of marital status on the dynamics of children following their fathers' occupation.

2.5. Results

Table 2.2. presents estimates of intergenerational elasticity between children and fathers, first row results have been estimated using Bayesian methodology, while the second-row results have been calculated using the pseudo panel fixed effect model.

The first and second columns report results for males and females separately to see how the elasticity differs for both genders, and the last column reports results for the whole sample. The association between fathers' and daughters' earnings is slightly higher than the association between sons' and fathers' income. This shows that mobility is lower for daughters in Türkiye, and this could be due to cultural and

institutional factors such as sons can find a job more easily and daughters' education and economic outcomes are more dependent on their family income The IGE coefficient is 0.526 for the overall sample which is close to the recent study done by Demirtaş & Torul (2023) for Türkiye.

Table 2.2. Intergenerational Earning Elasticity (IGE)

	IGE-Male	IGE-Female	IGE-Full Sample
Bayesian	0.523 (0.008)	0.528 (0.007)	0.526 (0.010)
Pseudo Panel	-	-	0.948 (0.085)
No. of obs	7916	3735	11651

Notes: The data has been taken from TUIK.

Table 2.3 shows the result of the IGE coefficient for the three cohorts, which have been made based on a pseudo panel but without taking the average of observations in each cohort. The first columns report the result of IGE between fathers' income and children' income when children are between the ages of 26 and 35, the second columns report the IGE between fathers and children' income when children are between the age of 36 and 45, and the last columns represents the association between fathers' income and children' income when children are between the age of 46-55.

Table 2.3. IGE at Different Career Levels

	Child Income	**Child Income**	**Child Income**
Variables	26-35	36-45	46-55
Father Income	0.505* (0.011)	0.543* (0.015)	0.480* (0.035)
Constant	4.370* (0.112)	3.981* (0.147)	4.519* (0.342)
Observations	6709	3993	949
R-squared	0.188	0.210	0.137

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

These three age groups have been formed to represent the different career levels of children: 26-35 age shows when children are at the beginning of their career level, 36-45 when they are in the middle of their career journey, and 46-55 age group represents children being at the peak-age of their career. All the coefficients are positive and highly significant; however, the IGE coefficient is highest when children are between the ages of 36-45, representing that children's income is highly explained by their father's income when they are at the middle of their career level.

Table 2.4 shows the result of the association between fathers' and children's income when fathers are divided into different income quantiles. The first column shows the result of the IGE coefficient for children when their fathers are in the first quantile, which shows the poor class of the sample, similarly 2nd, 3rd and 4th quantiles are representing middle, upper middle class and rich fathers in the sample- all the IGE coefficients are significant at 1% level, the coefficient of association among fathers' income and children' income is the highest when fathers are in 2nd quantile and 4th quantile. The results from table 4 show the association between fathers' income and sons' income in the low-income families. On the other hand, sons' income dependence on fathers' income gets stronger for high-income families; the association is strongest for the middle income, followed by families on the fourth quantile (the richest income group).

Table 2.4. IGE for Different Quantiles

Variables	1st quantile	2nd quantile	3rd quantile	4th quantile
Father Income	0.483*	0.525*	0.516*	0.521*
	(0.008)	(0.008)	(0.009)	(0.008)
Constant	4.474*	4.041*	4.127*	4.111*
	(0.081)	(0.088)	(0.094)	(0.083)
No. of obs	1150	2486	3040	4975

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 2.5 has results from Bayesian regression when fathers' income, education, marital status, and the gender of children at different career levels are regressed on children's income. The first column entails results of the initial career stage regression,

the second column is for when children are at mid-career level and the third column is for when children are at the peak of their career level: children income is explained 51.3% by the father's income when he is at the initial and 51.2% when he is at the mid-stage of his career and 51% when he is at the peak of his career level representing children' income is less affected by the fathers' income when children are at the peak of their career level as compared to when they are at the beginning or mid-career level. Income is affected by the education level at all career levels; it's the highest for children at their peak career level, which is 2.09%, followed by the children at their initial career level, 2.04%. The coefficients on the gender variable are significant and positive, showing that being male has a positive effect on personal income- the highest coefficient is for sons at the peak of their career level, followed by sons at the peak of their career level. Being single has the highest positive impact when you are at the middle of your career level, followed by when you are at the peak of your career level.

Table 2.5. Determinants of Sons' Income

Variables	Beginning of Career	Mid-Career	At the Peak of Career
Father's Income	0.513* (0.007)	0.512* (0.008)	0.510* (0.009)
Education	0.020* (0.004)	0.019* (0.004)	0.020* (0.005)
Gender	0.068* (0.014)	0.077* (0.016)	0.075* (0.018)
Marital Status	0.154* (0.014)	0.171* (0.015)	0.161* (0.017)
Constant	3.987* (0.078)	3.987* (0.084)	4.001* (0.084)
No of obs	6709	3993	949

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 2.6 shows the results for occupational mobility trends in Türkiye. The dependent variable, occupational persistence, which is a binary variable, 1 when sons are in same occupation as of their fathers and 0 when otherwise. Income is the most crucial factor affecting the occupational mobility of the children: higher income is negatively related to occupational mobility- this relationship is higher for children whose fathers have low-income, showing given the higher income, the tendency to follow a different occupation than of their father is more elevated in low-income families as compared to wealthy families- which confirms the hypothesis that occupational mobility is lower in rich families. Being highly educated is negatively related to occupational mobility as well; however, this relationship, just like income, is stronger for children belonging to low-income families: being highly educated would lead to occupation mobility of 6.4 % of children with lower income families and 3.5 % for children of rich families. The gender coefficient shows the impact of being male on occupational mobility: being male in rich families has a higher probability of following the father's occupation than being female, and the relationship is more robust in rich families. The coefficient of marriage shows the impact of being single on the probability of a child following their father's occupation- being single reduces the likelihood of children following their father's occupation by 1.64% in low-income families; at the same time, this relationship is positive for rich families. Being single in a rich family would have a 0.02% chance of children following their father's occupation.

Table 2.6. Occupational Mobility

	1st and 2nd quantile	3rd and 4th quantile
Variables	Poor-Lower Middle	Upper Middle-Rich
Income	-.221* (.033)	-.052* (.064)
Education	-.064* (.016)	-.035* (.020)
Gender	.039* (.054)	.207* (.068)
Marriage	-.015* (.039)	.002* (.044)
Constant	1.131* (.3105)	.676* (.65554)
No. of obs	3636	8016

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

2.6. Conclusion

Intergenerational mobility leads to a rise in individuals' well-being and higher economic equality. This chapter sheds light on intergenerational income and occupational mobility in Türkiye using microdata from Turk-Stat on the Survey of Income and Living Conditions (SILC) from 2006-2021, using pseudo-panel (fixed effect) and Bayesian methodology.

This chapter also contributes to the literature by estimating the intergenerational earning elasticity and occupational mobility for children at different career levels, using their age as a proxy variable: 26-35 (beginning career level), 26-45 (mid-career level), and 46-55 (peak of the career level). I have considered the association among education, gender, marital status, and intergenerational mobility throughout the analysis. The results offer detailed insights that are significant and robust.

The intergenerational income mobility for males in Türkiye is slightly higher for the parents-son pair than for the parents-daughter pair. The intergenerational elasticity for the whole sample is 0.52, which is very close to the IGE found by Demirtaş & Torul (2023). The results show intergenerational mobility is lower when parents are in the 2nd and 4th quantiles of the income distribution. On estimating the impact of family income on children's income at different stages of career levels, I found a higher association with parents' income when children are at the middle of their career level.

This chapter also analyses how the different variables affect the intergenerational occupational mobility dynamics from different socio-economic backgrounds in Türkiye. The findings show that income is a strong incentive for children to break the cycle of intergenerational occupational persistence. This relationship is strong when children are in poor families- the coefficient for children coming from richer families is much smaller, which shows that, given the higher income incentive, intergenerational occupational mobility is higher in poor families as compared to the children coming from rich families: intergenerational occupational persistence is higher in wealthier families.

Overall, the finding of the study suggests that high persistence in rich families indicates a barrier to children from low-income families in overcoming generational poverty. Education is a key factor in breaking this cycle, and policies aimed at providing quality education to all children, regardless of the social class they belong to, are essential to increase mobility in the country. The study's conclusions emphasize Turkey's distinct socioeconomic dynamics while still being consistent with global evidence on intergenerational persistence. In line with Chetty et al. (2014), who pinpoint "stickiness" at the top of the American income distribution, this study shows that children from wealthy Turkish families have high income and occupational persistence, which is indicative of ingrained advantages like access to professional networks and prestigious education.

CHAPTER III

EARNINGS & RETURNS TO SKILLS

3.1. Introduction

The recent rise in the use of technology has given rise to a polarized labor market in the sense of employment restructuring and wage polarization. In the debate of whether the technology is making us better off or worse off, one thing has been made clear by the extensive research on the impact of technology on the labor market is that technology favors high skilled workers while substitutes routine and middle skilled jobs (Autor et al., 2003; Goos et al., 2014; Frey & Osborne, 2017). This phenomenon could encourage wage polarization where the demand for high-skilled workers rises, leading to increased wages at the top, while middle-skilled workers face stagnation. This bias of technology towards labor skills causes inequality in the labor market.

Parallel to this, another phenomenon that raises the inequality in the labor market is intergenerational economic immobility. The rich stay rich while the economically challenged don't even get the chance to move up on the ladder of income distribution. Persistent economic disadvantages passed down to generations result in limited access to education and skill development required to compete in a technologically driven labor market. So, intergenerational immobility, just like technology, causes labor market polarization in terms of opportunities. As Corak (2013) documented through the Great Gatsby Curve (GGC) that economies facing higher income inequality tend to exhibit lower intergenerational mobility, which encourages economic stratification.

The literature on the impact of technology on labor markets has examined how technology altered labor market dynamics by disproportionally making high-skilled workers better off at the expense of middle-skilled workers, see (Murphy et al., 1998; Autor & Dorn, 2013). The wage gap between skilled workers and unskilled workers has been widening in recent decades. High-skilled workers, equipped with education

and relevant skills to cope with technological advancement, tend to experience wage increase, whereas low-skilled workers whose tasks are less automatable may retain employment at a relatively stable wage. However, middle-skilled occupations involve a lot of routine work, are particularly vulnerable to automation. The phenomenon of disproportional increase in the demand for high-skilled workers is known as skilled-biased technological change (SBTC), see (Acemoglu, 2002). Also, the workers who get displaced by technology face longer unemployment spells, and lose out on the income in the future (Bessen et al., 2023).

The countries with higher technology adoption often exhibit more polarized labor markets (Autor & Dorn, 2013). The SBTC hypothesis states that the returns to skills are biased due to technology, as the technology advancement disproportionally favors high-skilled workers over unskilled workers. Thus, widening the wage gap between the skilled and unskilled labor force dramatically exacerbates labor market inequality. On the other hand, technology also has the potential to mitigate some forms of inequalities in labor markets, particularly those influenced by family background. Based on one's skill level, technology reduces the impact of parental income on one's chances of being successful in the labor market (Arntz et al., 2023). By emphasizing skills over inherited socioeconomic status, technology can promote meritocracy, giving workers with relevant skills a greater chance of being successful in labor market, irrespective of their family status.

Technology has significantly increased the demand for high-skilled workers, resulting in a price surge of skilled workers, while simultaneously reducing the employment opportunities for unskilled workers. The rise in employment polarization and decrease in intergenerational mobility have been witnessed in several developed economies simultaneously (García-Peñalosa et al., 2023). SBTC may foster a more meritocratic society in which a person's skills, rather than inherited advantages, determine their economic success, if the labor market rewards individual talents regardless of parental background. However, SBTC may exacerbate income persistence over generations if one's family background limits access to the education and skills needed to prosper in a technology-driven economy.

The dynamics of intergenerational income mobility have been vastly studied in the literature, with various factors identified as contributing to the mobility or its persistence across generations. However, the impact of employment restructuring driven by technology remains underexplored. Recent studies by Hennig (2021) and Guo (2022) address this gap by analyzing the impact of employment restructuring on educational attainment in the US. They highlighted that the rise of job polarization leads to lower mobility because lower-income families are not able to afford costly higher education, and job polarization ends up creating education polarization as well. This educational polarization enforces the cycle of intergenerational immobility, as children from disadvantaged backgrounds are disproportionately excluded from high-skilled, higher-paying jobs. As a result, job polarization caused by SBTC not only restricts immediate labor market employment opportunities but also shapes long-term socioeconomic outcomes by limiting access of disadvantaged children to the necessary human capital investment required for upward mobility.

As SBTC reshaped the labor market by creating wage and job polarization, it not only influences the current labor force but also has profound implications for the coming generations. The increasing premium on skills[4] can exacerbate income inequality and limit the upward mobility of those coming from a lower-income family background. Though the core premise of SBTC suggests that technology-driven labor markets should make the skills of an individual the sole determinant of success in the labor market. Economic theory suggests that technological change could either enhance or restrict social mobility. On the one hand, SBTC could create a more meritocratic society, where economic success is primarily determined by an individual's ability rather than inherited advantages. On the other hand, if access to skills and education necessary to thrive in a technology-driven economy is constrained by family wealth, then SBTC may reinforce existing socioeconomic hierarchies, exacerbating income persistence across generations. By controlling for parental income, this study tests whether children's income is genuinely driven by skill-biased effects or merely by inherited socioeconomic advantages.

[4] The skill-premium hypothesis states that technological progress disproportionately increases wages for skilled workers

The impact of SBTC on one's income can vary across various regions within a country. High-skilled employment prospects tend to be more prevalent in areas with greater exposure to technology, which is frequently represented by a higher number of skilled individuals. On the other hand, areas where most of the workforce is employed in routinely demanding or low-skilled employment might experience exacerbated inequality and fewer opportunities for upward mobility. Consequently, technologically exposed areas attract skilled workers and offer higher wages, and also associated companies that pay well (Moretti, 2012).

To understand how SBTC impacts an individual's income requires isolating the impact of parental background on one's earnings. If technological advancements are truly driving income inequality, it is crucial to examine whether individuals from lower-income families have equal opportunities to benefit from the rising skill premium associated with SBTC. This chapter focuses on the impact SBTC has on an individual's income after accounting for the impact of parental income, focusing on the nature of tasks performed by individuals. Technological progress, particularly under SBTC, tends to boost demand for workers in high-skilled, while diminishing opportunities in routine-based jobs. However, if we do not account for parental influence, we risk overestimating the role of inherited wealth and underestimating the impact of individual skills in shaping labor market outcomes. By adjusting for parental income, this research aims to clarify how SBTC shapes one's earnings independently of family economic status.

The transfer of economic status across generations could differ across various regions within a country based on various economic factors and labor market conditions, see (Chetty et al., 2014). There are considerable regional differences across Turkey in terms of economic growth, industrial expansion, access to education, and labor market conditions, all of which likely impact mobility trends. For instance, Istanbul and other western provinces generate a substantial share of the country's economic output, with strong service and industrial sectors driving prosperity. On the other hand, the Southeast Anatolian region struggles with persistent socioeconomic disadvantages, including lower income levels, limited educational opportunities, inadequate healthcare, and high unemployment, all of which may restrict upward economic mobility (Karaalp-Orhan, 2020). Because of that, the analysis has been done

regionally. Since technology itself is not directly measurable, I will use a proxy variable to account for the regional exposure to technology. For instance, the regions that have more skilled workers in the workforce will be considered to have more job opportunities for the high-skilled workers, thus being more exposed to technology.

The chapter focuses on geographical variation in intergenerational mobility, drawing inspiration from studies such as Hennig (2021), García-Peñalosa et al. (2023), and Guo (2022). Each region's exposure to technology is quantified by the share of high-skilled workers, as technology complements high-skilled tasks while displacing routine and low-skilled tasks. Workers are categorized into three groups based on the nature of their tasks, aligning with the SBTC framework:

- High-skilled workers: individuals performing abstract tasks that require advanced analytical skills, creative, or decision-making skills. These workers benefit from technology the most, as such tasks are complemented by technology.

- Medium-skilled workers: the workers who are performing routine tasks that are more susceptible to automation. These include jobs with repetitive tasks that technology can easily replace.

- Low-skilled workers: the individuals who are performing manual tasks. These tasks often require physical labor or less technical expertise

By incorporating regional analysis, this chapter provides insights into how labor market conditions and technological advancements shape individual income outcomes, independent of inherited socioeconomic advantages. The findings have implications for regional policies aimed at reducing income inequality and supporting workforce adaptation to technological change.

While the literature on Skill-Biased Technological Change (SBTC) has extensively examined its impact on wage inequality, few studies have specifically addressed its influence on intergenerational mobility and children's future income perspective. Most research on SBTC and income inequality assumes that wages are primarily determined by individual human capital, often overlooking the role of family background. This

study addresses this gap by investigating whether SBTC exacerbates intergenerational inequality or rewards individual skills independently of parental income using the cross-sectional data, the survey of the labor force from Turk-Stat for the period 2006-2022. I have employed various econometric methodologies such as descriptive statistic, transition matrix, and OLS regression to achieve the research objectives. In this chapter, I introduce a new measure to quantify intergenerational mobility at the individual level rather than relying on aggregated cohort-based measures. A detailed description of the construction and application of this individual-level metric is provided in the data section.

The findings of this chapter contribute to the literature of the skilled-biased technological change hypothesis and intergenerational mobility. The findings of this section indicate that regions with higher exposure to technology, characterized by a higher share of abstract task-intensive occupations, provide more opportunities to children coming from disadvantaged family backgrounds, those with parents engaged in manual or routine-intensive jobs. The result from this section aligns with the findings of Arntz et al. (2023), who emphasized the role of technological progress in skill-based mobility. Though income inequality has been shown to exacerbate intergenerational wage mobility, both empirically (Corak, 2013; Chetty et al., 2014) and conceptually (Becker and Tomes, 1979; Solon, 1999). As a result, it seems that the two seemingly incompatible findings about income inequality conditions—improving skill mobility on the one hand, but decreasing wage mobility on the other—need to be reconciled in some way.

By analyzing the variation of IGM across various regions in Türkiye and their relation to skills, the findings of the study suggest a positive relationship between skill-biased technological change (SBTC) and intergenerational mobility. The mobility is positively correlated when children are in abstract jobs; the findings indicate that children of fathers in abstract and routine jobs exhibit different mobility patterns depending on their regional context. In technologically advanced regions, such as Region 1[5], children from manual job backgrounds have a 47.95% probability of advancing to routine jobs and a 15.85% chance of moving to abstract jobs, illustrating

[5] The classification of region is in appendix section, Table B.1

higher mobility opportunities in areas with greater technological exposure, these results also align with Aghion et al. (2019). While intergenerational mobility is negatively related to children being in routine tasks.

The rest of the chapter flows as follows: next, section 3.2 gives a literature review on the topic, followed by data and methodology used in the study in section 3.3, section 3.4 is results and discussion, and then the last section, section 3.5, is the conclusion.

3.2. Literature Review

Skilled biased technological change (SBTC) has reshaped the returns to different skill levels. Katz & Murphy (1992) analyzed the wage structure of the US for the period 1963-1987 and found that the increase in the demand for skilled workers and the female labor force was the driving force of the sudden restructuring of the wage structure. Autor et al. (2003) extended on this by analyzing how technology caused the change in the demand of workers' skills. Their findings suggest that technology replaced tasks performed by low-skilled workers, known as routine tasks, while complementing the workers performing high-skilled tasks, known as abstract tasks. Goos et al. (2014) analyzed that workers in non-routine, highly skilled positions (such as programmers and managers) command rising wage premiums as automation and digitization transform labor markets, whereas those in manual or routine employment see stagnant or decreasing incomes.

The economic results of children are becoming more and more dependent on their capacity to learn skills that complement new technology, which has significant ramifications for intergenerational income dynamics. For instance, studies in the U.S. and Germany show that technological adoption raises returns to education, disproportionately benefiting children from high-skilled families who inherit both cognitive and socio-economic advantages (Goldin & Katz, 2008; Arntz et al., 2023). Conversely, in regions where middle-skill jobs—critical pathways for upward mobility—disappear due to automation, children from disadvantaged backgrounds face diminished opportunities (Guo, 2022; Wang et al., 2024).

Meschi et al. (2016) investigated the impact of technological advancement and globalization on skilled and unskilled labor force employment and wages in the Turkish manufacturing sector between 1992 and 2001 using the GMM-SYS approach. The study's conclusions demonstrated that technology and trade have a beneficial impact on job creation in the Turkish industrial sector. Additionally, the study's overall findings were reported to be consistent with the theory of skill-biased technological evolution. Thus, it was revealed that the impact of technical advancements has led to a significant increase in the demand for skilled workers and their salary level, which is higher than the demand for unskilled workers and their wage level.

Considering the employment polarization and decrease in intergenerational mobility spiking at the same time, especially in developed countries, García-Peñalosa et al. (2023) analyzed how the disappearance of middle skill jobs has impacted the upward mobility of children, especially coming from disadvantaged family backgrounds. They used the data of two cohorts in the UK, who entered the labor market at different times and were thus exposed to technology and employment polarization differently. They analyzed the impact of family income of these two cohorts on the children's upward mobility using an IV strategy. Their findings suggest that regions that are more exposed to technology have a higher influence of parents' income on children's economic outcomes.

Regarding the displacement of routine workers due to technology, Chiacchio et al. (2018) looked at how industrial robotics affected employment and earnings in six EU nations (Finland, France, Germany, Italy, Spain, and Sweden). They found that for every 1,000 workers, the employment rate drops by 0.16% to 0.20% when one more robot is used. They stated that the growing prevalence of industrial robots has an impact on workers, particularly those who are young and have completed middle school.

Eder et al. (2022) investigated the quantitative and qualitative impact of digital technology adoption on employment in Austria. The study concluded that, as a result of digitalization, there would likely be more jobs lost over the next ten years than created, and overall employment would drop by 0.80–4.81% relative to present employment levels. They emphasized that as robots replace human work and the need

for skills changes, the occupational and sectoral structure of employment would also change.

Though technology can worsen off some workers, but it also weakens the impact of family's status on ones' economic outcomes, a study done by (Aghion et al., 2019), who analyzed the effect of innovation on social mobility using cross sectional regression for the US at the commuting zone level suggest that areas with higher innovation exhibits higher social mobility as well. Türkiye, contend with dual labor markets: a small, technology-intensive formal sector offering high returns to skills, and a large informal sector dominated by low-skilled, routine work is an interesting case to analyze how does the change in return to skills have impacted the earnings dynamics of children irrespective of what family background they come from. This chapter, by linking SBTC to children's income through a regional lens, challenges the assumptions that technology fosters mobility. Instead, it demonstrates how SBTC runs the danger of solidifying intergenerational disadvantage in the absence of fair access to education and highly skilled employment.

3.3. Data & Methodology

The data used in this research is the Labor Force Survey taken from the Turkish Statistical Institute (TUIK) for the period 2006-2022. The data is a repeated cross-sectional data, and the survey covers questions on individuals' education, income, career, and parental background. The survey has information on those working children who are staying with parents, having the same household ID, so I have not considered working children who are living under a separate household ID. The age group of children has been restricted between 28 to 45 years old, only full-time working children and those with a positive income have been considered. The nominal wages are converted to real wages by using the consumer price index (CPI).

Technology can impact the intergenerational mobility differently across various regions, and based on that, the cities are grouped into six distinct regions[6]. The classification has been done according to the NUTS-2 classification. This

[6] The detail of the classification is in appendix.

classification has been done on cities' geographic location and their proximity to each other. Each districts have homogeneous cities in terms of development and socio-economic characteristics. Regional analysis is more suitable in this case as each region is classified on the basis of similar labor market conditions and labor market structure. I have only focused on the place of residents, the geographic location where children are active in the labor market.

The children, based on their occupation, have been divided into three groups: high-skilled children performing abstract tasks, medium-skilled children performing routine tasks, and low-skilled children performing manual tasks. In the survey, individuals are asked to write the two-digit ISCO08 codes[7] for tasks they perform. Before 2012, the data contains the ISCO88 two-digit code. To identify whether an area is technologically exposed, the number of skilled workers over the total number of workers in a region as a proxy has been used, which is inspired by the measures of technology by Bartel & Sicherman (1999)[8]. A region that is more exposed to technology would have a higher share of skilled workers employed in that region.

3.3.1. Methodology

In this chapter, a variable has been created to estimate an individual's income through a measure based on intergenerational elasticity (IGE). This measure, let's call it 'individual's estimated income', is calculated to estimate individual earnings, which separates the impact of a family's background on children's economic outcome.

To analyze the individuals' estimated income dynamics of each region, individuals' earnings have been estimated for each region separately by estimating individual IGE elasticity first. As the focus is on an individual's earnings, the following calculation method has been used to achieve that:

[7] The International Standard Classification of Occupations (ISCO) is a job classification system established by the International Labour Organization (ILO). It categorizes occupations based on required skills and job functions.

[8] They have used as number of STEM (science, technology, engineering and mathematics) workers as the proxy variable for technology, I have broadened the category based on all the workers performing abstract tasks according to ISCO08 codes.

$$y_{ir} = \alpha + \beta I_{ir} + u_r \quad (3.1)$$

Equation (3.1) is the formula used to calculate an individual's absolute intergenerational mobility elasticity, where y_{ir} is *i* child's income in region *r*, and I_{ir} is the father's income in region *r*, where coefficient *i*=1,2,3,4,5, & 6. The coefficient β shows the impact of parents/family income on children's income thus representing intergenerational income immobility but this doesn't represent individual mobility; it rather shows macro level mobility which is average of all individual β, higher the β, lower the mobility. As purpose of this research is to analyze the variation across regions, I analyze individual earnings by isolating the component of a children's income for each region that is independent of their father's economic influence. This is achieved using the following specification:

$$u_{ir} = Y_{ir} - (\alpha + \beta I_{ir}) \quad (3.2)$$

Where u_{ir} represents an individual's estimated earnings in region r. The right-hand side shows how the individual's estimated income has been calculated. It has been calculated by subtracting the impact of the father's income $(\alpha + \beta I_{ir})$ from children's total income Y_{ir}. While I_{ir} is the father's income, the expression $\alpha + \beta I_{ir}$ estimates the component of the children's income attributable to the father's earnings, where α and β are parameters determined from a regression of the children's income on the father's income within the same region. Notably, β indicates how closely a children'sincome is linked to the father's income and functions as an indicator of intergenerational persistence. By subtracting this inherited portion from the total income, the resulting measure, u_{ir}, isolates the income generated by individual-specific factors, therefore offering a more precise indicator of personal economic mobility.

The normalization of fathers' and children's income is a crucial component of this approach to ensure that the analysis concentrates on relative mobility rather than absolute income disparities. Relative mobility refers to the movement of individuals across income ranks (e.g., percentiles) relative to their parents, capturing whether children from low-income families can ascend the economic ladder compared to their

peers. For example, a child born into the bottom 20% of the income distribution achieving a position in the top 40% signifies upward relative mobility. Absolute income disparities, in contrast, measure differences in actual income levels between groups (e.g., the gap between the richest and poorest households) without accounting for positional shifts. For instance, even if absolute incomes rise for all due to economic growth, relative mobility may remain low if children's income ranks mirror their parents'.

Normalization adjusts for differences in income scales across regions or periods, enabling meaningful comparisons of socioeconomic mobility. The normalization formula is as follows:

$$Normalized\ Income = {(y - \overline{y})}/{\sigma}$$

Where,

- y is the individual's income (child or father)
- $\bar{y}$ is the average income of the reference group in the region r
- σ is the standard deviation of income in that region

This transformation centers the data around zero and scales it by variability, ensuring that income differences reflect relative positions within the distribution rather than absolute monetary gaps. For each region, the resulting model evaluates estimated individual income by separating the confounding factors like inflation or regional cost-of-living differences.

Having obtained individuals' earnings using the approach above, the following model has been used to test the hypothesis of the chapter:

$$EI_i = \beta_0 + \beta_1 Education_{3i} + \beta_2 D_{1i} + \beta_3 D_{2i} + \varepsilon_i \qquad (3.3)$$

Here EI_i is the individual's estimated income for the region i which has been calculated using equation (3.2). β_1 captures the impact of children's education on their estimated income, father's education has been used as an instrumental variable to

address the potential endogeneity in the child's education. D_1 is the dummy variable showing whether the child works in an abstract job? If he works in an abstract job, the values assigned to the dummy variable are 1; otherwise, 0. While D_2 is the dummy variable representing whether the child works in a routine job? If the child is in a routine job then D_2 is 1, otherwise 0. The base dummy variable is when child is in manual jobs; the dummy variable for manual jobs has not been added to the model to avoid the dummy trap. The instrumental variable approach has been used to estimate equation (3.3). The results of the estimation have been reported in Table 3.5.

3.4. Results & Discussion

Table 3.1 presents summary statistics of all the variables used for the empirical analysis. The summary statistics include the mean and the standard deviation of the variables used, including gender, experience, children's education, dummy for children being in abstract and routine jobs, individuals' income, fathers' income, and fathers' education. The statistics are shown as the average for all the years for each region. The last row has a number of observations. The variable 'Gender' is binary: 0 is for male and 1 is for female. The highest ratio of females in the labor force is in regions 1 and 2.

Looking at the summary statistics of education, it is quite evident that regions where there are more educated people also have a higher number of abstract jobs. Regions 3 and 5 have the highest education level among children, which confirms the SBTC hypothesis, as the number of abstract jobs/high-skilled jobs is also quite high in these regions; also, the fathers' education is highest in these two regions. The highest children's mean income is in region 1, which is a highly developed region as compared to other regions in the analysis, and it could be due to the fact that high-skilled workers are paid in more advanced regions as compared to skilled workers in less developed regions.

These findings highlight the importance of regional context in understanding the dynamics of intergenerational mobility, particularly as technological changes reshape labor markets and educational outcomes (Goldin & Katz, 2008). For policymakers, these results suggest that targeted investments in education and skill-building programs in less developed regions could help reduce disparities in income mobility and foster more equitable economic opportunities.

Table 3.1. Descriptive Statistics

		Gender	Experience	Education	Abstract	Routine	Income	Father's Income	Father's Education	No. of obs
Region 1	Mean	0.324	2.517	3.396	0.213	0.493	2.71	2.759	2.16	12299
	Std	0.468	3.013	1.339	0.409	0.5	0.255	0.241	1.32	12299
Region 2	Mean	0.3297	2.427	3.406	0.199	0.447	2.661	2.734	2.256	5274
	Std	0.47	3.18	1.32	0.4	0.5	0.27	0.27	1.42	5274
Region 3	Mean	0.27	2.33	3.46	0.22	0.42	2.67	2.79	2.43	8229
	Std	0.446	2.96	1.313	0.414	0.494	0.281	0.264	1.466	8229
Region 4	Mean	0.29	1.99	3.21	0.17	0.46	2.56	2.68	2.15	2503
	Std	0.45	2.64	1.33	0.38	0.5	0.3	0.28	1.41	2503
Region 5	Mean	0.28	2.51	3.53	0.23	0.37	2.67	2.8	2.46	3438
	Std	0.45	3.11	1.27	0.42	0.48	0.26	0.25	1.47	3438
Region 6	Mean	0.241	2.043	3.037	0.206	0.43	2.651	2.776	2.059	3719
	Std	0.43	2.85	1.41	0.41	0.5	0.26	0.26	1.41	3719

Table 3.2. has the results of the transition matrix, representing the dynamics of the task (occupation) mobility among fathers and children, showing the probability of a child occupying a job given the father's occupation. The diagonal values show the probability of children staying in the same jobs as their fathers, and the off-diagonal values show mobility. The higher diagonal values here show that there is high persistence of tasks performed through generations in Türkiye. The highest persistence is in routine jobs[9]: 52.29% of children end up in routine jobs if their fathers are in routine jobs. Then followed by abstract jobs, where 48.36% of children whose fathers are in abstract jobs end up being in abstract occupations. The lowest persistence is in families where fathers are performing manual tasks. The off-diagonal values show occupational/task mobility across generations. The highest mobility among the children is when the fathers are in manual jobs. There is a 42.42% chance of upward mobility towards routine jobs from manual jobs and a 14.58% chance of moving from manual jobs to abstract jobs when the fathers are in manual jobs. The highest downward mobility among children is to move towards routine jobs, is when there are fathers in abstract jobs; the probability is 30.06%.

Table 3.2. Tasks Transition Matrix

Father's Occupation	Children's Occupation			
	Abstract	Routine	Manual	Total
Abstract(high skilled)	48.36	30.06	21.57	100.00
Routine(medium)	17.68	52.29	30.02	100.00
Manual (low-skilled)	14.58	42.41	43.01	100.00
Total	21.05	44.92	34.03	100.00

Notes: The table reports the percentage distribution of children's occupational task categories (abstract, routine, and manual) conditional on their fathers' occupations

[9] The terms tasks and jobs have been used interchangeably in the chapter

3.4.1. Regional Transition Matrix

Table 3.3 has the regional transition matrix of tasks among fathers and children. In all the regions, diagonal values are higher than the off-diagonal values, representing high persistence of tasks performed across generations. The highest persistence in the abstract job is in regions 1 and 3, which makes sense, as region 1 is highly developed and more exposed to technology. Regarding the high persistence of abstract jobs in region 3, this can be observed from Table 3.1 that region 3 also has one of the highest averages of education obtained, which explains more children following their fathers and are in abstract jobs.

Routine jobs are a safe haven for middle-income and sometimes low-income families (Guo, 2022). Region 1 has the highest share of children being in routine jobs if their fathers are in routine jobs, 55.5%. The persistence in manual tasks is the highest in region 5. From the table, it is evident that region 5 has a high number of educated children, and the number of abstract jobs is also high, as higher education is a channel to high-skilled jobs, which fathers in manual tasks failed to provide to the next generation, thus leading to higher persistence in the region.

The upward mobility in routine jobs across generations is notable in region 5, children of fathers in routine jobs have 22.09% chances of moving upward to abstract tasks; while upward mobility when fathers are in manual jobs is the highest in region 1, where children have 47.95% of probability to move to routine jobs and 15.85% chance to move to abstract jobs. The downward mobility of children when fathers are in an abstract job is highest in regions 4 and 6. The downward mobility when fathers are in routine jobs is highest for children in region 3; children have a 33.59% chance of moving to manual jobs in region 3 if their fathers are performing routine tasks.

Table 3.3. Regional Tasks Transition Matrix

Region 1				
Father's Occupation	Children's Occupation			
	Abstract	Routine	Manual	Total
Abstract	50.10	29.99	19.91	100.00
Routine	18.39	55.55	26.06	100.00
Manual	15.85	47.95	36.20	100.00
Total	21.27	49.30	29.43	100.00
Region 2				
Abstract	48.07	27.71	24.22	100.00
Routine	15.40	53.25	31.35	100.00
Manual	13.84	41.76	44.41	100.00
Total	48.07	27.71	24.22	100.00
Region 3				
Abstract	50.14	30.34	19.52	100.00
Routine	16.89	49.51	33.59	100.00
Manual	15.23	38.90	45.87	100.00
Total	21.91	42.06	36.03	100.00
Region 4				
Abstract	44.75	30.56	24.69	100.00
Routine	14.04	52.63	33.33	100.00
Manual	11.84	44.88	43.29	100.00
Total	17.02	46.26	36.72	100.00
Region 5				
Abstract	47.13	29.31	23.56	100.00
Routine	22.09	44.78	33.13	100.00
Manual	12.81	34.64	52.55	100.00
Total	23.30	37.43	39.27	100.00
Region 6				
Abstract	43.43	33.56	23.01	100.00
Routine	19.04	51.29	29.67	100.00
Manual	13.74	38.13	48.13	100.00
Total	20.62	43.05	36.33	100.00

Table 3.4. shows the dynamics of the intergenerational income mobility of all the regions for children based on the occupations of their fathers, whether they are in abstract, routine, or manual jobs. These measures are calculated from the children and fathers' real income. The sample of children has been restricted to the children who

are between the ages of 28-45. Overall, the intergenerational mobility coefficient is not very high in all the regions of Türkiye, which shows there is a high-income mobility in Türkiye. Region 6 shows the highest persistence among children when their fathers are in abstract jobs; persistence among children whose fathers are in manual jobs is also quite high in this region.

Table 3.4. IGM Based on Father's Occupation

Father's Occupation	IGM					
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Abstract	.290*** (.0242)	.355*** (.0311)	.334*** (.025)	.263*** (.0584)	.303*** (.0363)	.436*** (.0425)
Routine	.394*** (.0157)	.389*** (.0224)	.348*** (.0205)	.262*** (.0421)	.303*** (.033)	.332*** (.0377)
Manual	.3445*** (.0164)	.343*** (.02674)	.274*** (.0223)	.285*** (.0377)	.466*** (.0343)	.421*** (.0357)

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 3.5 is the instrumental variable regression result from equation (3.3). The independent variable is the individual's estimated income calculated from equation (3.2). The dummy variable for routine tasks and the dummy variable for abstract tasks[10] captures the impact of children being in abstract jobs and routine jobs on children's estimated income.

Table 3.5. Individual's Estimated Income Across Regions

	Region 1	**Region 2**	**Region 3**	**Region 4**	**Region 5**	**Region 6**
Education	.115***	.127**	.074**	.246**	.121**	.014
Abstract Task	.259***	.136	.104	-.318*	-.001	.265***
Routine Task	-.101***	-.056	-.122***	-.177*	-.065	-.113**
Constant	.394***	.467***	.713***	.522*	.373**	.693***

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

[10] A dummy has not been created for manual jobs to avoid the dummy variable trap.

The positive coefficient on education indicates that an additional year of education significantly increases children's earnings, suggesting the importance of education as an indicator of economic mobility. In region 1, the coefficient on education is 0.115 suggesting that each additional year of education increases children's income by 0.115 units. Fathers' education was employed as an instrument to children's education attainment to address any endogeneity in the education variable, guaranteeing that the estimated impact of children's education on income is objective and represents a causal link, which is also consistent with Card (1999) who used instrumental variable approach to show the causal relationship between education and income.

Additionally, the findings indicate that children who work in abstract occupations—such as managerial, professional, or creative roles—earn substantially more than children who work in other occupations. This is consistent with the SBTC hypothesis, as abstract tasks—requiring problem-solving, creativity, and complex communication—are being highly valued with the rise of technology. Looking at the results for region 1, the coefficient on the abstract task variable is 0.259, indicating that abstract jobs are associated with a 0.259 unit increase in income premium relative to manual jobs. This confirms the SBTC hypothesis that technology disproportionately rewards workers in roles requiring abstract tasks.

Conversely, children in routine jobs (e.g., repetitive manual or clerical tasks) exhibit significantly lower incomes, reflecting the declining demand for routine labor due to automation and technological advancements. In region 1, the coefficient on routine job is -0.101, suggesting that routine jobs are associated with a -0.101 unit decrease in income as compared to manual jobs. These results emphasize the significance of abilities that support technological progress and the function of job type as a crucial factor in determining income. The demand for laborers performing routine jobs is declining due to automation, which suppresses wages in such occupations.

3.5. Conclusion

The rise in technology has led to higher wage disparities among workers. The skilled biased technological hypothesis says that technology complements certain skills while making some workers worse off. However, how this SBTC impacts individuals'

earning abilities irrespective of their family background, needs more attention. This study focuses on how SBTC impacts children's estimated income in Türkiye. The analysis reveals that SBTC exacerbates income inequality by reinforcing occupational persistence across generations, particularly in high-technology regions.

The analysis shows high persistence of occupation across generations in all the regions. However, the persistence in high-skilled occupations is higher in high-technologically exposed regions (e.g., Istanbul, Ankara), which shows that SBTC promotes immobility in abstract tasks. The results also suggest that children of fathers in abstract and routine jobs exhibit different mobility patterns. The children of fathers in manual jobs have more chances to move upward to abstract jobs when they are in areas that are more exposed to technology, thus having a greater share of abstract jobs. The positive relationship between intergenerational mobility and technology opens up an interesting avenue for discussion and future research. The results also show that SBTC reinforces income advantages for skilled workers but creates barriers for low-skilled families.

The study uses cross-sectional data for the analysis and thus has its limitations. More research can be done using longitudinal data to explore the long-term impact of SBTC on children's estimated income in Türkiye or other developing countries. To sum up, this study analyzed the role of the skilled-biased technological change hypothesis in shaping economic opportunities across generations in Türkiye. Focusing on regional disparities to technological exposure and economic opportunities, better access to education and skills development is essential to provide equality of opportunity, thus eradicating income inequality across generations.

CHAPTER IV

MULTI-DIMENSIONAL POVERTY AND MOBILITY

4.1. Introduction

An individual's success is closely tied to the socio-economic conditions of their parents' economic status, often serving as the foundation for their lifetime earnings and opportunities. Household poverty, encompassing monetary and non-monetary dimensions, is pivotal in shaping one's lifetime earnings. While monetary poverty reflects limited income resources, non-monetary poverty encompasses barriers such as restricted access to quality education, inadequate healthcare, substandard living conditions, and other factors constraining the development of essential skills for labor market success.

The implications of household poverty extend beyond immediate economic limitations, perpetuating disadvantages across generations. Severe deprivation across various dimensions within a household might restrict parents' ability to invest adequately in the human capital of their children, thereby influencing the intergenerational transfer of economic outcomes—a phenomenon conceptualized as intergenerational mobility (IGM). IGM posits that economic advantages or disadvantages are transmitted through generations largely via parental investments in education, health, and skill development. Consequently, household poverty emerges as a critical determinant in whether economic deprivations are perpetuated or mitigated across generations, highlighting its role in entrenching or disrupting cycles of inequality.

The economic well-being of a household is undeniably a key determinant of children's future economic prospects (Sano et al., 2021). Households entrenched in multidimensional poverty face compounded barriers that make it exceedingly difficult

to disrupt cycles of generational poverty. Understanding the nuanced impact of household poverty on children's income mobility and lifetime earnings is essential to addressing broader issues of income inequality within an economy.

Poverty, as noted by Sen (1999), transcends the mere absence of income; it encapsulates the lack of capabilities and opportunities to improve economic conditions. Multidimensional poverty reflects deficits in non-income dimensions of poverty, e.g., education, healthcare, and living standards, which can collectively stifle upward mobility. These deficits not only inhibit individual potential but also systematically reinforce structural inequalities, perpetuating poverty across generations. Hence, addressing multidimensional poverty is not merely a welfare concern but a cornerstone for fostering equitable economic growth and breaking entrenched cycles of disadvantage.

The understanding of poverty has evolved from a unidimensional perspective, primarily based on income or consumption, to a more comprehensive multidimensional framework. Iglesias et al. (2017) emphasize that the multidimensional approach to poverty offers a more nuanced and accurate depiction of an individual's socio-economic status by considering multiple facets of deprivation beyond income, such as education, health, housing, etc. By setting minimum thresholds across these dimensions, individuals falling below these standards are identified as multidimensionally poor.

The multidimensional poverty approach provides distinct advantages. Unlike absolute poverty measures, which may fail to capture contextual inequalities, the relative nature of multidimensional poverty accounts for societal norms and variations, offering a clearer representation of inequality within a society. This approach is particularly useful for policymakers, as it highlights various dimensions of inequality, enabling targeted interventions that address structural and systemic factors perpetuating poverty. Moreover, as Rodgers (2022) suggests, poverty is intricately linked to broader issues of inequality. Societies with higher levels of inequality are more susceptible to entrenched and widespread poverty. Thus, adopting a multidimensional perspective not only enhances the understanding of poverty but also fosters more inclusive and equitable strategies for mitigating inequality and its adverse effects.

Human capital theory, as established by Becker (1964), emphasizes that individuals' lifetime earnings are primarily influenced by the investments made in their human capital, such as education, skills, and health. In the realm of intergenerational mobility, this theory underscores the pivotal role of parents' investments in their children's development, which can serve as a crucial mechanism for breaking cycles of poverty and fostering upward mobility.

This chapter focuses on how the multidimensional poverty of a household impacts an individual's income prospects. There is a literature available on the inability of economically disadvantaged children to perform well in the labor market and have proper access to health as compared to their peers who belong to rich families.

Azariadis and Stachurski (2005) elaborate on this by highlighting the concept of poverty traps, wherein households experiencing poverty or going through multiple poverty traps form deprivation, such as inadequate education, insufficient healthcare, and substandard living conditions, find themselves unable to escape these conditions. Such deprivation not only hinders present economic mobility but also perpetuates a cycle of poverty across generations, despite potential increases in income. This scenario illustrates that income alone cannot address deeply rooted disadvantages, as multidimensional poverty encompasses a broader set of barriers that restrict individuals' upward mobility and economic progress.

In the literature, it has been proven in multiple studies that the economic status of children is highly dependent on the family income. Studies (Chetty et al., 2014; Cervini-Plá, 2015) have shown that there is a higher association between parents' income and their children's income. The poverty of a household can impact the future income prospects of children. Poverty is not only a monetary measure, but it also includes non-monetary measures to estimate the economic well-being of a household. Non-monetary aspects of poverty can be assessed through various dimensions such as psychological issues, lack of education, food, or lack of access to health systems (Alkire et al., 2015).

Despite the overall economic progress in Türkiye, multidimensional poverty persists in the country and is mainly concentrated in the Southeastern and Eastern Anatolia

region (Dönmez & Dereli, 2024). Şeker & Dayıoğlu Tayfur (2015) study on the poverty dynamics in Türkiye concluded that households facing multiple challenges are far less likely to achieve sustained income improvements. This study aims to clarify the structural causes of inequality and offer suggestions for more focused and efficient policy solutions by examining the connection between multidimensional poverty and economic mobility in Turkey.

This study investigates the impact of multidimensional poverty on children's income in Türkiye using data from Turk-Stat, emphasizing how variations in household deprivation across several dimensions, such as education, health, housing, and access to basic services, affect intergenerational income mobility. While unidimensional poverty measures only capture the extent of income deprivation, a multidimensional approach unveils the broader, more complex reality of household poverty. The significance of addressing these multiple dimensions is supported by literature (Sen, 1999; Alkire et al., 2015), which underscores that poverty cannot be fully understood through income alone, as it encompasses a wide range of human capabilities and living conditions. This holistic view is essential for capturing the full scope of deprivation and its long-term implications for wellbeing (Iglesias et al., 2017). By integrating multidimensional poverty metrics, the study advances our understanding of how inequality, in its many forms, perpetuates across generations. For the analysis, the data has been taken from the TurkStat Survey of Income and Living Conditions, and the children considered for the analysis are in the labor force.

Numerous methods in the literature have been introduced to measure multidimensional poverty, and the Alkire-Foster methodology is one of them and is the basis of calculating the global multidimensional poverty index, calculated by Oxford and Human Development Initiative (OPHI) in collaboration with the United Nations Development Program (UNDP). In this chapter, I have used the Alkire-Foster methodology (AF) developed by Alkire & Foster (2011) to calculate the multi-dimensional poverty index (MPI) using data from the Survey of Income and Living Conditions from TUIK. The MPI index provides a more detailed insight into household poverty across different dimensions, rather than just focusing on income. A household might have a high income but still faces deprivation across various dimensions, which are important for children's upward mobility, such as education,

health care, etc. The use of the MPI index is very crucial in analyzing how deprivations in different dimensions affect children's prospects of lifetime income. For example, children from a household facing deprivations in education and health care may face more barriers to upward mobility than children belonging to an income-poor household.

How does household multi-dimensional poverty affect children's income? Multi-dimensional poverty directly impacts the resources of daily consumption, which causes 'material hardship'. Material hardship is the failure to afford basic needs such as medical care, housing, nutritious food, etc. Material hardship is highly associated with family poverty (Iceland & Bauman, 2004) and thus linked with worse children's economic outcomes. Family poverty causes lower parental investment in their children's education and developmental outcomes (Chaudry & Wimer, 2016).

Health is another crucial aspect of son's development that gets affected by household poverty. Children from poor households face malnutrition, which leads to delayed development that affects their cognitive and physical abilities. These disadvantages affect their performance in the labor market and, skills acquisition. Besides education and health, household poverty can impact children's social capital because their parents do not have professional networks that can aid in their children's career advancement. On top of that, children who grew up in households facing multi-dimensional poverty are more prone to stress and low self-esteem, which could affect their motivation to pursue better career paths.

Multi-dimensional poverty could create a vicious cycle of disadvantage, repeating itself across generations. Households experiencing multi-dimensional poverty often produce human capital characterized by low education, poor health, and lower motivation to pursue high-skilled jobs. Thereby increasing the likelihood of individuals being trapped in low-paying jobs. This could result in poverty traps that could last across generations.

In this chapter, the ordinary least square (OLS) methodology has been used to estimate the impact of multi-dimensional poverty, fathers' income, and other control variables on children's income. This section contributes to the literature by incorporating multi-

dimensional poverty into the intergenerational mobility analysis, providing comprehensive insights on how different non-monetary dimensions of household wellbeing might influence children's mobility. As per my knowledge, this is the first attempt to use the multi-dimensional aspect of household wellbeing to see how family economic status impacts children's economic outcomes, rather than measuring household wellbeing by the household head's income only. This approach will broaden our understanding of the relationship between children's income and their parents' s by incorporating the non-monetary dimension of household wealth.

While the past studies on intergenerational mobility in Türkiye solely focused on the family income as the sole determinant of children's income and occupation mobility (Demirtaş & Torul, 2023), this study provides a more nuanced understanding of various factors contributing to economic outcomes across generations. The study aims to analyze to what extent does the multidimensional poverty of a household impacts the economic outcomes of their children. The poverty in multiple dimensions could act as a barrier for children to escape their parents' socio-economic outcomes. This chapter investigates the association between children's income and multi-dimensional poverty of a household, hypothesizing that deprivations across various dimensions of a household would limit the ability of children's upward mobility. Specifically, the following hypotheses have been tested in this chapter:

H1: Children from households facing severe multi-dimensional poverty will have lower income as compared to children from less deprived households.

H2: Multidimensional poverty has a negative impact on children's income mobility; the mobility is lower for children coming from households with a higher deprivation level

H3: Multi-dimensional poverty reduces the likelihood of income and educational mobility.

The findings of this study suggest that children's income is negatively related to the multi-dimensional poverty of the household. Children of households which is deprived across several dimensions earn lower lifetime earnings. As one's education level

provides a nuanced way to look at individuals' lifetime earnings rather than just looking at one's current income level (in this case, the average of the last three years income), I have also analyzed how multi faceted poverty of a household impact the education attainment of individuals in Türkiye. The results of this study also suggest that there is higher income persistence in lower-income quintiles of multi-dimensionally poor households as compared to the lower quintiles of multi-dimensional non-poor households. While the persistence is higher in the fourth and fifth quintiles of the multidimensionally non-poor household, as compared to the poor household.

The rest of the chapter is designed as follows: the next section explains the theoretical framework used in the study and followed by a discussion on how the MPI index has been created. Then there is a data methodology section, which is followed by results and discussion. Lastly is the conclusion and policy implications based on the findings of this chapter.

4.2. Theoretical Framework: Connecting Multidimensional Poverty and Intergenerational Mobility

Intergenerational mobility and household poverty are very closely knitted topics, and have profound importance due to their profound implications for inequality, economic development, and social cohesion. A higher degree of intergenerational mobility ensures higher equality of opportunity within a society (Corak, 2020). Household poverty further makes the intergenerational persistence phenomenon worse by limiting the families' ability to invest in their children's human capital. This leads to lower mobility by causing children from poor households to be trapped in the endless cycle of poverty.

The Alkire-Foster methodology provides a more nuanced approach to poverty by taking into account several dimensions of individuals' well-being, such as education, access to clean water, etc., breaking the traditional way of looking at poverty, which only considers the income aspect of a household. The multi-dimensional poverty index (MPI) developed using the Alkire-Foster methodology; analyses how deprivations in several dimensions affect households' ability to improve future economic outcomes.

The interaction of intergenerational mobility and multidimensional poverty can be seen through the lens of many theories. The first and foremost important is human capital theory by (Becker, 1964), which states that investment in human capital through education, skills acquisition, etc., leads to greater economic outcomes. Regarding intergenerational mobility, this means that children from high-income families would have better economic prospects because they are in a better position to have access to education and skill-acquiring opportunities.

Azariadis & Stachurski (2005) provided a thorough explanation of how poverty traps cause a lack of resources to invest in human capital, which leads to low productivity and income, which affects future investment, thus creating a cycle of poverty that could last across generations. Their study is highly relevant in understanding why individuals facing poverty in several dimensions, such as education, health, etc., find it difficult to achieve upward mobility. The existence of poverty traps could lead to lower mobility across generations, thus causing higher inequality. The findings suggest that children raised in deprived households face significant barriers to economic prosperity and higher lifetime earnings.

The household facing deprivations in a specific dimension needs targeted policy interventions to come out of poverty. Liu et al. (2023) analyzed the impact of a poverty alleviation through allocation (PAR) project on 1009 households facing multi-dimensional poverty in eight provinces of China. The study has its significance in understanding the targeted policy intervention to help households come out of income & multi-dimensional deprivations. The findings of their studies showed that household income poverty was reduced through higher wages, while multi-dimensionally deprived households came out of deprivation through policies targeted at improving the living standards of the households. The findings also suggested that in order to manage relative poverty, multi-dimensional poverty standards should be adopted along with income poverty.

However, despite these valuable insights, a gap remains in the literature regarding how multidimensional poverty directly influences income mobility across generations. While much has been done to show the effects of single-dimensional poverty on economic mobility (Chetty et al., 2014; Corak, 2013), where the first focuses on the

relationship between income-based poverty and intergenerational mobility in the United States, and concluded that sons belonging to disadvantage family background are less likely to achieve upward economic mobility. The second one highlights the association between income inequality leading to lower intergenerational mobility across countries, the phenomenon known as the ‘Great Gatsby Curve’.

Fewer studies have thoroughly examined how the intersection of multiple deprivations (education, health, housing, etc.) impacts children's income in the long term. This chapter aims to fill this gap by exploring the impact of multidimensional poverty (MPI) on children’s income, focusing on the direct relationship between deprivations across various dimensions and economic outcomes, specifically in the context of Türkiye.

The theoretical framework for this chapter comes from Becker's Human capital theory. It states that human capital is enhanced by education and the acquisition of skills. Becker (1964) says that investment in individuals' human capital through education, health, etc., increases their productivity and is positively related to their ability to generate income over time. Multi-dimensional poverty, which is a non-monetary aspect of investment in children’s human capital, is a barrier to the accumulation of human capital. Multi-dimensional poverty not only encompasses income deprivation, but also accounts for deprivation in other areas such as health, living standards, education, housing, etc. These deprivations limit one’s ability to invest in human capital accumulation and thus might cause the never-ending poverty traps for the coming generations.

Human capital theory states that children’s income is influenced by the human capital they inherit from their parents. Poverty across various dimensions that children experience while growing up can affect their ability to generate potential future lifetime income through not having access to quality education, health care, and other resources that one might need to live comfortably. These deprivations in several dimensions could severely affect children’s ability to develop the necessary human skills to succeed in life and acquire decent-paying jobs, which could result in lower economic mobility.

I am using the following model to express children's income (Y_i) as a function of father's income (Y_f). This model examines the intergenerational elasticity of income, a measure of economic mobility where higher elasticity implies lower mobility and a stronger linkage between the economic statuses of the two generations.

$$\boldsymbol{Y_i = \beta_0 + \beta_1} Y_i^f + \varepsilon_i \quad (4.1)$$

where,

$\beta_1$coefficient captures the impact of fathers' income on children's income. As in this chapter, the focus is on the impact of multi-dimensional poverty of a household on children's income; thus, the study aims to capture the non-monetary investment of the household head in his children's human capital accumulation.

So, here, father's income has been replaced with the multi-dimensional poverty index, and the model becomes,

$$Y_i = \beta_0 + \beta_1 MPI_i + \varepsilon_i \quad (4.2)$$

Where MPI includes seven dimensions of household wellbeing. Further details on the creation of the index have been explained in the next section.

4.3. Discussion on the Creation of MPI Using the Alkire Foster Methodology

Traditional poverty measures are usually unidimensional, using income or consumption, which cannot fully capture the extent and severity of one's poverty level. Considering that, this chapter employs a multi-dimensional poverty approach to conceptualize and measure several aspects of household poverty. The Alkire Foster Methodology, developed by Alkire and Foster (2011), offers a detailed approach to capturing the poverty level of an individual. This approach of measuring poverty is particularly beneficial in identifying and capturing the various poverty dimensions of households across various factors of wellbeing, such as Education, health, and living standards.

Alkire Foster Methodology (AF) is employed to capture the individuals' poverty level across several dimensions in Türkiye. How to decide someone's poverty status: whether he is poor or not, using the AF methodology? AF methodology is a dual cut-off identification method; the starting point is to assess each individual's achievement against dimension-specific cut-offs. The cut-off is decided based on the shortfall from a threshold on each dimension of each individual's wellbeing. I have used seven dimensions as per the availability of the data: children's education, health status, housing, sanitation, drinking water, air quality, and acquisition of assets.

Two identification approaches focus on dimensional shortfalls: the union identification method and the intersection method. According to the union identification method, an individual is considered to be poor if he is poor in at least one of the dimensions (k=1). While, according to the intersection method, a person is considered poor if he is deprived in all the dimensions (k=d). There are side effects to both approaches, the union approach might give a false sense of deprivation to someone who wouldn't be considered poor, for example, the deprivation in health might be due to other reasons and not directly related to poverty. Another problem with the union approach is that it might not accurately assess the extent of deprivation of an individual. The issue with the intersection approach is that it identifies individuals or households multi dimensionally poor only if they are deprived in all the considered dimensions simultaneously. It makes this approach impractical to use because it only identifies a small proportion of the population, which gets even smaller if more dimensions are considered. Put otherwise, k would identify a person i deprived if he is poor in all dimensions. An alternative to use here is a cutoff between the two extremes: 1 or d.

Alkire and Foster termed k as a dual cut-off technique of identification since it depends on both the within-dimension cut-off and across-dimension cut-off. The union and intersection procedures are included in this instance, k, as special situations when k=1 and k=d. The Alkire Foster methodology follows three steps to identify poverty. The first stage is the selection of dimensions. The dimensions and the indicators used in each dimension have been listed in Table 4.1. It has seven dimensions: education, health status, housing, sanitation, drinking water, air quality, and assets.

The education dimension includes an indicator showing the years of education obtained. The individual is considered deprived if the average education of the households is less than 8 years, which has also been considered as the legally required education in Türkiye since 1997-2012. The dimension of health has two indicators: general health status (a person is considered deprived if his health status is poor or very poor) and whether the individual suffers from any chronic illness (a person is considered deprived if he suffers from any chronic illness). Another dimension used is housing, there are three indicators used in this dimension: dwelling type (if an individual is not living in separate house is considered deprived), tenure status (a household is considered deprived if he doesn't have the ownership of the dwelling) and kitchen in the dwelling (an individual is considered deprived if there is no kitchen in the dwelling). The dimension of sanitation includes an indoor flushing toilet in the dwelling, and the household is considered deprived if it doesn't have one. The drinking water dimension includes one indicator of piped water in the dwelling (a household is considered deprived if it doesn't have piped water in the dwelling). The air quality dimension has one indicator; a person is considered deprived if the type of fuel used in the dwelling for heating is wood, coal, or dried cow dung. And the last dimension considered in the chapter is assets, which has seven indicators: possession of a television, washing machine, fridge, dishwasher, air conditioner, car, and the individual is considered poor if he does not possess these indicators. The second step is to identify a threshold, which is a deprivation cutoff for each dimension.

The third and final step involves the weighing and averaging of each dimension, where weights are assigned to each dimension. In this study, equal weights have been assigned to each dimension based on the importance of each dimension: a 1/7 weight is assigned to each dimension. Within each dimension, several indicators capture that dimension. In this study, I assigned equal weights to each of the indicators within each dimension. So, Alkire Foster's methodology has two cut-off points to capture the multi-aspects of poverty. Once deprivations are estimated for each household, they can be aggregated to calculate an aggregate multi-dimensional poverty index for the economy, however, this is outside the scope of this study as I am interested in the multi-dimensional poverty index at the individual level. A household is considered multi-dimensional deprived if the weighted sum of deprivations exceeds a certain

threshold, expressed as k. The standard k≥3 has been used here; this means a person is considered poor if he is deprived in 3 or more dimensions.

4.4. Data & Methodology

The data used in this chapter is the Survey of Income & Living Conditions (SILC) data taken from the Turkish Statistical Institute (Tuik). The data consists of three survey waves: 2010-2013, 2014-2017, and 2018-2021. The survey employs a rotating panel design in which approximately 25% of respondents are replaced each year. For this study, I include only individuals with continuous data across all years in each survey wave. So, this chapter uses data from a total of 968 individuals. The income of individuals and other parameters used in this study have been averaged over the available years. Only pairs where both father and children have non-missing, continuous income data are included to ensure the accuracy of mobility estimates. The nominal incomes of the children and the father have been converted to real income. The children considered in the analysis live with their parents.

I have constructed a multi-dimensional index to estimate the overall well-being of children using the Alkire-Foster (AF) methodology. The index incorporates variables capturing both children's well-being and that of their households, allowing for a comprehensive assessment of individual-level deprivation. An individual is considered multi-dimensionally deprived if they are poor in three or more dimensions.

The MPI index is calculated by assigning weights to dimensions depending on their significance in identifying one's poverty level. In this study, equal weights have been assigned to all seven dimensions, which is (1/7). The deprivation score has been assigned to individuals in each dimension: 1 if he is deprived in that dimension, and 0 if not. The scale of deprivation is explained in Table 4.1.

Following the strategy of the global definition of MPI, equal weights have been assigned to each dimension:

$$MPI_i = 1/7(Education + Health\ Status + Housing + Sanitation + Drinking\ Water + Air\ Quality + Assets) \quad (4.3)$$

The deprivation level of each individual is calculated by summing the weighted deprivations across the seven dimensions.

Table 4.1. Dimension & Indicators for Deprivation Calculation

Dimensions	Indicators
Education (1/7)	Number of years of education obtained (1/7)
Health Status (1/7)	General Health status (1/14)
	Suffer from any chronic decease (1/14)
Housing (1/7)	Dwelling type (1/21) Tenure Status (1/21) Kitchen in the Dwelling (1/21)
Sanitation (1/7)	Indoor flushing toilet in the dwelling (1/7)
Drinking Water(1/7)	Piped water system in the dwelling (1/7)
Air Quality (1/7)	Type of the fuel mostly used in the dwelling (1/7)
Assets (1/7)	If possess television (1/42) If possess washing machine (1/42) If possess fridge (1/42) If possess dishwasher (1/42) If possess air condition (1/42) If possess car (1/42)

To estimate the impact of multidimensional poverty on children's income, this study uses ordinary least squares (OLS) methodology, a logit model, and a transition matrix for the analysis. OLS methodology is used to estimate the linear relationship in equation (1), while the logit model is used to estimate the impact of multi-dimensional poverty on income mobility and education mobility. Children's income is the dependent variable, while the MPI index is the independent variable, along with control variables that have been used in the analysis. The average of children's income and the deprivation level of each individual have been taken across the years.

The logit model is particularly suitable for this analysis because it allows for the estimation of binary outcomes, such as whether children achieve upward income mobility (e.g., moving to a higher income quintile) or attain a certain level of education. Unlike OLS, which assumes a linear relationship, the logit model accounts for the non-linear nature of probability outcomes and provides odds ratios that are easier to interpret in the context of mobility.

$$\text{Income Mobility} = \begin{cases} 1 \text{ if there is mobility across generations} \\ 0 \text{ if there is no mobility across generations} \end{cases}$$

The logit model to predict the income mobility can be expressed as:

$$\pi = Pr\ (Income\ Mobility = 1|M, Y_f) = \frac{1}{1+exp^{-(\alpha+\beta_1 M+\beta_i X)}} \quad (4.4)$$

Where,

- π is the probability that a child experiences intergenerational income mobility
- M is the multidimensional poverty index
- Y_f is the father's income

Father's income (Y_f) has been added to equation 4.4 alongside the multidimensional poverty index. The approach is motivated by both theoretical and empirical considerations. Although this study's main goal is to examine the effects of multidimensional poverty (M), it is crucial to account for fathers' income to separate the special influence of M from the direct economic outcomes that are passed down through parental economic status. According to Corak (2013), neglecting to account for parental income runs the risk of confusing structural obstacles (such as poverty and illiteracy) with pure economic inheritance, hiding the real forces behind mobility.

The following logit model is used to estimate educational mobility. The dependent variable is educational mobility, a dichotomous variable.

Education Mobility= { 1 if there is educational mobility across generations
0 if there is no educational mobility across generations

The logit model to predict the education mobility can be expressed as:

$$\pi = Pr\ (Education\ Mobility = 1|M, Y_f) = \frac{1}{1+exp^{-(\alpha+\beta_1 M+\beta_2 Y_e)}} \quad (4.5)$$

Where,

- π is the probability that a child experiences intergenerational educational mobility
- M is the multidimensional poverty index
- Y_e is the father's education

4.5. Results & Discussion

Table 4.1. shows dimensions used to construct the multi-dimensional poverty index. Each dimension has a few indicators, which have also been shown in the Table 4.1. There were two cut-offs on the data; the first cut-off was placed on each indicator to identify the deprivation level. The second cutoff is on the index itself, to identify if the individual is deprived or non-deprived, which is $k \geq 3$. Which means a household is considered poor if it is poor in three or more dimensions.

Table 4.2 presents the descriptive statistics to understand the distribution of various deprivations across individuals in the data. The k-level in multi-dimensional poverty analysis refers to the number of dimensions one is deprived of to be considered as a deprived individual. The first column shows the number of deprivations in which an individual is deprived, ranging from 0 to 7. However, the data used in this chapter does not have individuals who are deprived of 6 or all of the 7 dimensions. The second column shows the frequency count of individuals corresponding to each level of the dimension's deprivation.

Table 4.2. Deprivation Level

Deprivation level	Frequency (for the whole data)
0	44
1	377
2	300

Table 4.2. (cont.)

3	183
4	53
5	11
6	0
7	0
Total	**968**

Notes: The data has been taken from SILC, and the table includes all three waves used in this chapter.

As per the data, as the deprivation level increases, the number of deprived individuals tends to decrease, which shows that fewer individuals meet the criteria for a higher level of deprivation. This suggests that in Türkiye, poverty is concentrated in fewer dimensions. So, if I increase the number of dimensions to consider an individual deprived, the proportion of the population considered poor would be smaller. This could help in policy making; policies targeting poverty should focus on the dimensions of poverty that are more common among deprived individuals.

Table 4.3 shows the descriptive statistics of the variables used in the analysis, including children's income, father's income, children's education, father's education, children's age, and deprivation status to present an overview of the sample's demographic and socio-economic characteristics.

Table 4.3. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Child's Income	968	9.06	1.077	5.736	12.032
Father's Income	968	9.872	.843	6.411	13.433
Child's Education	968	3.884	1.518	0	6
Father's Education	968	2.732	1.533	0	6
Child's Age	968	35.367	7.202	20	59
Deprivation Dimension	968	1.852	1.0299	0	5

Note: the data has been taken from SILC (Tuik).

Model 1: $Y_s = \beta_o + \beta_1 M + \varepsilon$

The first model shows the impact of multi-dimensional poverty of a household on children's income. Where Y_s is the children's income, while the coefficient β_1 reports the impact of the multidimensional poverty index of the household on children's income. The results show that multi-dimensional poverty has a negative impact on children's income. This confirms this chapter's hypothesis as well: children from households facing deprivations across various dimensions have lower prospects of upward mobility.

Model 2: $Y_s = \beta_o + \beta_1 Y_f + \varepsilon$

The second model shows the result of the father's income on the children's income. Where Y_s is the children's income, and the coefficient β_1 reports the impact of fathers' income on children's income. The coefficient of father's income is positive and significant for all the individuals, showing the positive association between children's income with their father's income. These results are in line with intergenerational immobility theory, which states that economic outcomes tend to be passed down from one generation to the next. A higher family income increases children's chances of having higher income as well because more likely they have access to better education, health system, etc. Human Capital Theory also supports this result; parents with higher income are more likely to invest in the human capital of their children. This relationship strengthens the income persistence across generations and makes it challenging to break the poverty cycle in disadvantaged families.

Model 3: $Y_s = \beta_o + \beta_1 Y_f + \beta_2 M + \varepsilon$

The third model estimates the impact of fathers' income and the multidimensional poverty index on individuals' income. Where Y_s is the children's income, the coefficient β_1 reports the impact of fathers' income, while the coefficient β_2 reports the impact of the multidimensional poverty index of the household on children's income. The coefficient of father's income is positive, while the coefficient on multi-dimensional poverty is negative. The positive and significant coefficients of fathers'

income show that individuals' income is associated with their fathers' income. The negative sign on the 'M' shows that there is a negative relationship between an individual's income and the multi-dimensional poverty of a household. Higher multi-dimensional poverty of a household would cause lower income for children. The child coming from a household experiencing multiple deprivations, such as inability to provide quality education, lack of nutritious food, no access to good health care, etc., might limit children's ability to possess the required skills to earn a higher income. The results suggest that multi-dimensional poverty constrains individuals' ability to escape poverty, which leads to the persistence of income inequality.

Model 4: $Y_s = \beta_o + \beta_1 Y_f + \beta_2 (M \times Y_f) + \varepsilon$

The fourth model shows the results of fathers' income and the interaction term between fathers' income and multi-dimensional poverty on children's income. Here, Y_s is the children's income, while the coefficient β_1 reports the impact of fathers' income and the coefficient β_2 reports the impact of the interaction term of the multidimensional poverty index and fathers' income on children's income. The coefficients on fathers' income are positive, showing the positive impact of fathers' income on children's economic outcomes. The coefficient for the interaction term of fathers' income and the multi-dimensional poverty index calculated for each household is negative. The negative sign represents a diminishing return on fathers' income in the household facing higher multi-dimensional poverty. The negative interaction term highlights that just high fathers' income cannot be sufficient to overcome the constraints imposed by multi-dimensional deprivations.

Table 4.4 presents the results of the four models mentioned above.

Table 4.4. Impact of MPI on Children's Income

	2010-2013	2014-2017	2018-2021
Model 1			
M	-4.28**	-1.069***	-1.237***
Constant	8.034***	9.394***	9.777***

Table 4.4. (cont.)

Model 2			
Father's Income	.192***	.303***	.141***
Constant	6.147***	6.266***	8.295***
Model 3			
Father's Income	0.167**	0.224***	0.119*
MDPI	-0.242	-0.813***	-1.114*
Constant	6.428***	7.159***	8.542***
Model 4			
Father's Income	0.171**	0.233***	0.120*
Indirect (Moderation)	-0.0273	-0.0857***	-0.116**
Constant	6.392***	7.064***	8.540***

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 4.5 analyzes the determinants of children's income across three periods (2010–2013, 2014–2017, and 2018–2021). Fathers' education exhibits a positive and strengthening association with children's income, supporting the IGM hypothesis. In 2010–2013, each additional year of fathers' education increased children' income by 0.076 units, rising to 0.108 units in 2014–2017 and 0.116 units in 2018–2021. This trend suggests educated fathers increasingly leveraged human capital investments (e.g., access to quality schooling, career networks) to enhance their children' earnings, particularly post-2014, as Türkiye's economy stabilized and tertiary education expanded.

The multidimensional poverty index (MPI) shows a growing negative impact on children' income over time. While MPI's effect was statistically insignificant in 2010–2013 (-0.295), it became strongly negative by 2014–2017 (-0.934) and remained significant in 2018–2021 (-1.028). This escalation reflects how overlapping deprivations (e.g., poor education, healthcare, housing) increasingly constrain children's earning potential, likely due to Türkiye's post-2013 economic volatility and rising inequality in access to high-skilled jobs. Children from multidimensionally poor

households faced lower income compared to non-deprived peers, underscoring systemic barriers to mobility.

Child age is positively associated with income, though its significance fluctuates. In 2010–2013, age had a weak, insignificant effect (0.0117), which strengthened in 2014–2017 (0.0285) before moderating in 2018–2021 (0.0139). This pattern aligns with labor market dynamics: the 2014–2017 surge may reflect post-recession opportunities for skill accumulation, while the 2018–2021 decline could signal saturation in returns to experience amid slower job creation.

These results highlight two critical trends: (1) parental education's growing role in shaping income mobility as Türkiye's economy modernizes, and (2) multidimensional poverty's escalating harm as systemic deprivation compounds over time.

Table 4.5. Determinants of Child's Income

Variables	2010-2013	2014-2017	2018-2021
	Child Income	Child Income	Child Income
Father's Education	0.0764*	0.108***	0.116***
	(2.42)	(3.95)	(4.32)
MPI	-0.295	-0.934***	-1.028*
	(-1.57)	(-4.71)	(-2.45)
Child age	0.0117	0.0285***	0.0139*
	(1.61)	(4.67)	(2.47)
Constant	7.357***	8.070***	8.986***
	(24.72)	(35.16)	(46.35)
N	263	382	323

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 4.6 presents the determinants of children's educational attainment across three periods (2010–2013, 2014–2017, and 2018–2021), using data from TUIK. The multidimensional poverty index (MPI) shows a consistently negative association with children's educational attainment. In 2010–2013, a one-unit increase in MPI reduced educational attainment by -2.429 units, reflecting severe barriers for deprived households. By 2014–2017, this effect diminished slightly (-1.909), and by 2018–

2021, it became statistically insignificant (-1.696, p > 0.10), suggesting structural improvements (e.g., poverty alleviation programs or expanded rural education access) may have mitigated deprivation's role. Fathers' education, however, remains a robust positive predictor: each additional year of paternal schooling increased children's attainment by 0.409 units in 2010–2013, dipped to 0.309 during 2014–2017, and rebounded to 0.379 in 2018–2021. Child age, while positive in 2010–2013 (0.323) and 2014–2017 (0.124), is statistically insignificant (p > 0.10) across all periods, indicating age alone does not systematically predict attainment once MPI and parental education are controlled for. The declining significance of MPI over time contrasts with the persistent influence of fathers' education, underscoring Türkiye's progress in addressing deprivation-related barriers while highlighting enduring inequalities tied to parental human capital.

Table 4.6. Education Attainment & MPI

Variables	2010-2013	2014-2017	2018-2021
	Child Education	Child Education	Child Education
MPI	-2.429*** (4.15)	-1.909** (3.11)	-1.696 (1.06)
Father's Education	0.409*** (6.57)	0.309*** (6.32)	0.379*** (7.48)
Child Age	0.323 (1.39)	0.124 (0.54)	-0.655 (1.09)
Constant	2.821*** (13.79)	3.321*** (20.07)	3.130*** (18.72)
N	263	382	323

Notes: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from TUIK.

Table 4.7 & Table 4.8 show the transition matrix of income quintiles among fathers and children to show the mobility pattern among children based on the family economic status. Table 4.7 shows the result for the child belonging to a deprived household. The poverty of a household has been decided based on the MPI index. The index cut-off point is 3, which means a household is considered deprived if it is poor

in at least three dimensions. Table 4.8 shows the result of the mobility for the non-poor household.

The transition matrices show that the percentage of households stuck in the lowest income quintile across generations is higher for households that are multi-dimensionally deprived, more as compared to the households that are non-poor according to the MPI index of this study. The overall trend of persistence across generations is higher for the lower three quintiles in 'multi-dimensionally poor' households: poor, lower middle class, and middle class. While the persistence of income in the fourth and fifth quintiles is higher for the household in the 'multi-dimensionally non-poor' household, upper-middle and rich households.

Table 4.7. Deprived Household Mobility Transition Matrix

	Children Income Quintile					
Father's Income Quintile	1	2	3	4	5	Total
1	46.79	24.77	20.18	6.42	1.83	100.00
2	36.76	35.29	16.18	10.29	1.47	100.00
3	16.67	38.10	28.57	11.90	4.76	100.00
4	23.81	23.81	9.52	**23.81**	19.05	100.00
5	28.57	28.57	0.00	14.29	**28.57**	100.00
Total	36.44	29.96	19.03	10.12	4.45	100.00

Notes :Author's own calculation. The data has been taken from TUIK.

Table 4.8. Non-Deprived Household Mobility Transition Matrix

	Children Income Quintile					
Father's Income Quintile	1	2	3	4	5	Total
1	34.12	17.65	23.53	20	4.71	100.00
2	23.62	21.26	29.13	16.54	9.45	100.00
3	12.42	14.38	20.92	30.07	22.22	100.00
4	10.00	18.24	18.82	26.47	26.47	100.00
5	6.99	11.29	13.44	21.51	46.77	100.00
Total	14.98	16.09	20.25	23.44	25.24	100.00

Notes: Author's calculation. The data has been taken from TUIK.

Table 4.9 shows the result of a logit regression for income and education mobility of children. The logit model has been used because both dependent variables, income mobility and education mobility, are binary variables showing two distinctive states- 1 shows across-generational mobility, while 0 shows immobility across generations. Left Table has the result of income mobility, where income mobility is regressed against multi-dimensional poverty of a household and the father's income. The coefficient on multidimensional poverty (M) is negative and statistically significant (β=0.96), indicating that a one-unit increase in multidimensional poverty reduces the likelihood of upward income mobility by approximately 96%. The increase in multi-dimensional poverty of a household reduces the likelihood of income mobility. Higher multi-dimensional poverty of a household acts as a barrier to achieving higher economic outcomes. A poor household has limited resources to provide quality education and comfortable living standards to their children, which ultimately would negatively impact children's future income. The coefficient on father's income is negative but insignificant.

The right panel shows the results of education mobility. Education mobility is a dummy variable where 0 shows educational immobility, while 1 shows educational mobility from one generation to the next. The negative coefficient of M shows a negative association between multi-dimensional poverty and educational mobility. The coefficient on multidimensional poverty (β=−2.693) shows that a unit increase in M causes decreases in log odds of educational mobility by 2.693. The coefficient on father's education (β=−0.606) is also negative and significant, signaling strong intergenerational persistence: children of highly educated fathers are more likely to mirror their parents' educational status. So, the children of highly educated fathers would most probably be more educated, just like their fathers, and the children of less educated fathers would be more likely to be, unfortunately, less educated.

Comparing both panels, multidimensional poverty exerts a stronger negative impact on income mobility than on education mobility, likely because education systems in Türkiye (e.g., centralized exams, scholarships) partially mitigate deprivation for some students, whereas labor market inequalities compound income disadvantages. Conversely, father's education matters more for educational outcomes than father's income, highlighting how non-monetary advantages (e.g., parental knowledge,

aspirations) shape mobility. These findings contrast with advanced economies like the U.S., where parental income strongly predicts both income and education mobility (Chetty et al., 2014)

Table 4.9. Income & Education Mobility Determinants

Income Mobility		**Education Mobility**	
M	-0.967** (2.73)	M	-2.693*** (6.71)
Father's Income	-0.131 (1.45)	Father's Income	-0.606*** (11.03)
Constant	2.154* (2.34)	Constant	3.356*** (14.87)

t statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variables, income mobility and education mobility, are dummy variables. 0 means immobility, which means children and fathers have the same income and educational level, while 1 shows mobility.

The results from Table 4.9 show that a household that is deprived in various dimensions would have less mobility among the children. The deprivations in accessing health care, education, and other living standards would create a barrier for the parents to invest in their children's human capital. This would eventually limit the children's ability to attain the skills and education required to earn a higher lifetime income. And this vicious cycle of poverty stays concentrated in certain families unless someone breaks through it with the help of external interventions such as educational subsidies.

4.6. Conclusion

This chapter is an attempt to dive into analyzing the impact of non-monetary poverty of a household on children's economic outcomes and also the intergenerational mobility dynamics in Türkiye. By examining the household non-monetary deprivations, this chapter contributes and presents new insights into the mechanisms through which socio-economic outcomes are transferred across generations. The chapter uses data from the Survey of Income and Living Conditions from 2010-2021 with three different waves: 2010-2013,2014-2017, and 2017-2021. Each survey wave

drops 25% of the sample size and is replaced by new individuals each year. So, only those individuals have been used for the analysis who are followed throughout each wave. Constrained by the absence of longitudinal data, I have employed various econometric techniques: OLS, logit model, and transition matrix to explore how multi-dimensional deprivation of a household limits the mobility of individuals. For that purpose, I have also looked at the educational mobility besides looking at the income mobility, because education provides valuable insights into the potential for future upward socioeconomic mobility (Chetty et al., 2014).

The findings of the chapter reinforce the intergenerational mobility hypothesis that parents' education and income are positively associated with children's educational attainment and lifetime earnings. However, multi-dimensional poverty of a household is a substantial barrier to children's successful economic outcomes. The negative relationship shows that poverty is not only an economic deficit but multifaceted deprivations affecting various dimensions of an individual's success in the labor market. Children from deprived households have fewer opportunities to earn higher future earnings because they lack the necessary skills and education required to have high-paying jobs. The persistence of income status is considerably higher in the 1st, 2nd, and 3rd quintiles of multi-dimensionally deprived households, indicating strong intergenerational poverty traps. In contrast, the 4th and 5th quintiles of deprived households exhibit lower persistence compared to their non-deprived counterparts. These results emphasized that children born in multi-deprived households face challenges in escaping poverty and achieving upward mobility.

This chapter shifts the focus from the classical measure of intergenerational mobility, where only fathers'/family's socio-economic status is considered to be the determinant of children's socio-economic outcomes, to multi-dimensional poverty. By moving beyond the conventional reliance on fathers' income as the sole predictor of intergenerational outcomes, this chapter incorporates a comprehensive assessment of household deprivation across various dimensions such as education, health, housing, and basic living conditions. This approach allows for a more nuanced understanding of how poverty, in its multifaceted forms, constrains upward mobility and perpetuates socio-economic inequalities across generations. The chapter contributes to the literature by highlighting the significance of multidimensional poverty as a critical

factor in shaping children's future economic trajectories, particularly in contexts where traditional income-based measures may overlook key aspects of deprivation that influence long-term mobility.

As per the findings of this chapter, the economic outcomes of children are explained by more than just the income of their parents. Policies aiming to improve mobility in an economy should address the multiple deprivations households face, simultaneously. Early intervention in education and healthcare is especially important in limiting the impact of multiple deprivations of a household on the children's future earnings and opportunities.

Policies aiming at reducing income disparities, such as a progressive tax, would give children from disadvantaged families greater opportunities and resources to break the poverty cycle. The government should include more policies to get more direct progressive taxes. In Türkiye, indirect taxes are more than direct taxes; 70% of taxes are indirect taxes, and only 30% of taxes are direct taxes. By narrowing down the income inequality in a society, policymakers can create a fairer society where the economic outcomes of children are free from the economic outcomes of their parents, leading to an economy where there is high economic mobility.

CHAPTER V

CONCLUSION

Lack of intergenerational mobility exacerbates income inequality within an economy, creating a cycle where economic disparities persist across generations. This persistent inequality not only undermines the principle of equal opportunity but also cultivates a sense of disenfranchisement and mistrust, particularly among children from disadvantaged family backgrounds. Such dynamics can perpetuate systemic barriers, hindering the upward mobility necessary for economic and social cohesion.

Numerous studies on intergenerational mobility in developed countries provide valuable insights into how parental economic status influences future wages and opportunities. Previous research has repeatedly demonstrated that parents' financial status and professional roles have a major impact on their children's long-term earnings and career paths. Furthermore, comparative studies show significant differences in mobility trends across countries and regions, emphasizing the influence of regional economic conditions and structural inequalities on social mobility. These results highlight a consistent relationship between growing income disparity and decreased mobility, underscoring the vital need to remove the systemic obstacles that impede upward economic mobility and perpetuate generational inequalities.

In this context, examining intergenerational mobility in developing countries or emerging economies becomes crucial, as these regions often face unique socio-economic challenges that differ from those of developed nations. Expanding the research lens to include multidimensional poverty and its interplay with mobility could provide a more comprehensive understanding of the barriers to economic progress and inform targeted policy interventions.

Türkiye serves as an ideal case study for examining intergenerational mobility and the impact of technological change, as its unique socio-economic landscape encapsulates

the challenges often faced by emerging economies. In Chapter Two, the analysis of intergenerational mobility in Türkiye is particularly pertinent because the country exhibits significant regional disparities—ranging from economically vibrant urban centers to more underdeveloped rural areas—that directly influence career trajectories and income outcomes. This heterogeneous environment provides an excellent opportunity to investigate how family background, in the form of parental income and occupational status, shapes the long-term prospects of children. Similarly, Chapter Three leverages Türkiye's dynamic economic transformation, where rapid technological adoption coexists with persistent structural inequalities, to explore how shifts toward high-skill and abstract occupations affect individual earnings. By focusing on Türkiye, the study not only extends the existing literature beyond the context of developed nations but also generates policy-relevant insights that address the multifaceted barriers to economic progress in an emerging market setting. The fourth chapter focuses on the impact of the multidimensional poverty of the household on the intergenerational mobility of children. Türkiye is characterized by significant disparities not only in income but also in access to quality education, healthcare, and adequate living conditions. These overlapping deprivations create a multifaceted form of poverty that can severely constrain the upward mobility of individuals across generations. This chapter investigates how these varied dimensions of poverty interact to impede intergenerational advancement, thereby offering a comprehensive understanding of the structural barriers that perpetuate inequality. By incorporating a multidimensional poverty framework, the study provides critical insights into the compounded effects of economic, educational, and health-related deprivations on mobility in an emerging market setting.

The second chapter establishes a robust empirical connection between human capital theory and intergenerational mobility, underscoring the mechanisms through which investment in education, skills development, and health influences children's economic trajectories. The theoretical framework of human capital theory elucidates how disparities in parental resources translate into differential economic outcomes for children, mediated through access to critical human capital inputs.

The findings reveal notable gender disparities in intergenerational mobility, with daughters exhibiting higher income elasticity relative to sons, indicating lower

mobility among women and reflecting persistent economic structures that constrain female economic advancement. Moreover, the analysis indicates a U-shaped pattern of mobility across income quantiles, where families in the medium-income ranges exhibit lower mobility compared to their counterparts in the highest and lowest quantiles. This highlights the "stickiness" of socio-economic status in middle-income families, which may be attributed to limited access to upward mobility pathways.

Additionally, the research identifies a stronger correlation between parental income and children's income during the latter's mid-career stage, signifying that the impact of familial socio-economic status persists and even intensifies over time. Occupational mobility analysis further complements these findings by demonstrating that children from lower-income households display greater occupational mobility and stronger incentives for upward movement compared to those from wealthier families. This suggests a higher degree of responsiveness in occupational attainment among economically disadvantaged groups, potentially driven by aspirations for socio-economic advancement.

These insights collectively underscore that while parental financial resources play a pivotal role in shaping intergenerational mobility, other factors, including socio-economic background, gender, and access to education, exert significant influence. This nuanced understanding calls for policy interventions aimed at reducing barriers to education and enhancing equitable access to human capital investments to foster greater intergenerational equity.

The third chapter delves into the geographical variations of the skill-biased technological change (SBTC) hypothesis and its implications for intergenerational mobility (IGM) within Türkiye. Utilizing data from the Turkish Labor Force Survey, I computed IGM measures for various regions and assessed the differential impacts of technological exposure across these areas.

The findings reveal pronounced regional disparities in intergenerational mobility, underscoring the significant role of education and skill acquisition. While SBTC predominantly benefits high-skilled individuals, allowing them to capitalize on technological advancements, the analysis indicates that technology can also serve as a

transformative tool for children from disadvantaged backgrounds, enabling upward mobility. However, the extent of this benefit is highly contingent on the regional intensity of technological adoption and integration. In regions with higher skilled labor force, SBTC appears to facilitate upward mobility by expanding opportunities for skill-based employment. Conversely, in regions where access to education and skill-building is limited, technology may exacerbate existing inequalities, constraining mobility.

The chapter emphasizes the critical need for targeted policies to enhance educational access and skill-building initiatives, particularly in technologically advanced regions. These measures are essential to ensure that the benefits of SBTC are equitably distributed and that children from all socio-economic backgrounds can leverage technological advancements to achieve upward economic mobility. The findings contribute to the broader discourse on the interplay between technological progress and social equity, offering nuanced insights into the role of regional dynamics in shaping intergenerational outcomes.

The fourth chapter delves into the relationship between multidimensional poverty and intergenerational mobility, emphasizing how various deprivations within a household hinder children's economic outcomes. Empirical findings underscore a negative relationship between multidimensional poverty and children' income, illustrating that households facing multiple deprivations severely limit their children's prospects for upward mobility.

The analysis highlights the inadequacy of conventional poverty measures focused solely on income metrics. Instead, the findings advocate for a broader framework that encompasses diverse aspects of household well-being, including education, health, housing, and basic living standards. This multidimensional approach provides a more holistic understanding of the barriers to intergenerational mobility.

The policy implications of this chapter are particularly significant. It calls for policymakers to address not just economic inequality but also the multifaceted nature of poverty. Strategies aimed at alleviating poverty must integrate interventions that improve access to education, healthcare, and other foundational services to dismantle

the structural barriers limiting upward mobility. These findings underscore the necessity of a comprehensive and inclusive approach to foster equitable opportunities across generations, thereby contributing to a more socially and economically just society.

In summary, the findings across the three chapters of this thesis collectively underline the multifaceted nature of intergenerational mobility and the diverse factors that influence it. The first chapter highlights the role of human capital investment and socioeconomic disparities in shaping mobility outcomes, demonstrating that gender, income distribution, and occupational pathways critically mediate mobility trajectories. The second chapter adds a geographical and technological dimension, showing that exposure to skilled-biased technological change (SBTC) can both facilitate and hinder upward mobility, contingent upon regional educational access and skill development. The third chapter underscores the pivotal role of multidimensional poverty as a barrier to mobility, emphasizing that holistic policy measures are essential to address the non-monetary dimensions of deprivation.

This research is a stepping stone in understanding the impact of multifaceted deprivations on children's economic mobility. Further analysis is required with longitudinal data to analyze how changes in various dimensions of poverty (non-monetary) impact the children's future lifetime earnings. One constraint this study faced is richer longitudinal data to analyze children when they were young and then compare their current income to see how the deprivations of the household when they were young, impacted their lifetime earnings.

The convergence of the findings from the analysis points to an urgent need for integrated and regionally tailored policies. Enhancing access to education, fostering equitable technological opportunities, and mitigating the multidimensional aspects of poverty are key strategies to break the cycle of persistent inequality. This thesis contributes to the broader literature by offering a nuanced understanding of intergenerational mobility, with implications that extend beyond income-based metrics to embrace a multidimensional framework of social and economic well-being. These insights pave the way for future research and policy action aimed at fostering inclusive growth and equitable mobility across generations.

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APPENDICES

APPENDIX A

COHORT ANALYSIS FOR ROBUSTNESS CHECK (CHAPTER I)

To test the robustness of the model, by utilizing one wave of the rotational panel data of survey income of living condition from 2014-2017 we have used empirical Bayesian methodology along with the methodology which is usually used in intergenerational mobility studies when panel data is available, OLS. The analysis has only been done on the 1,251 individuals whose data was available for at least consecutive 3 years-for SILC data, the maximum data available for an individual is 4 years. The results from Bayesian methodology and OLS both have the same signs on the coefficients, and most of the coefficients are very close to each other. For instance, the coefficients for father's income are closely aligned in both methodologies, indicating that the relationship between father and son incomes remains consistent regardless of the estimation method used. Bayesian and OLS coefficients are of almost similar magnitude across different age groups, quantiles, and career stages confirming the effectiveness of methodology used to capture the core dynamics of IGM.

Table A.1. IGE at Different Career-Level

	26-35		36-45		46-55	
	OLS	Bayesian	OLS	Bayesian	OLS	Bayesian
Father Income	0.331***	0.345***	0.321***	0.347***	0.557***	0.363***
Constant	6.20***	6.094***	6.496***	6.125***	4.032**	5.934***
N	710		389		89	

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table A.1.provides result of intergenerational mobility of sons divided in 3 age groups, from OLS estimation and Bayesian methodology. The direction of the association

between sons' income and fathers income from both methodologies is same. The estimates shows that fathers' income have significant and positive impact on sons' income. If the coefficient is close to 1, it shows immobility, coefficients closer to 0 represent mobility.

Table A.2. IGE for Different Quantiles

	1st quantile		2nd quantile		3rd quantile		4th quantile	
	OLS	Bayesian	OLS	Bayesian	OLS	Bayesian	OLS	Bayesian
Father Income	0.0369***	0.235***	0.940***	0.284***	0.370	0.283***	0.485***	0.336***
Constant	8.918***	7.152***	0.194***	6.665***	5.834	6.693***	4.644**	6.183***
N	273		402		337		238	

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table A.2. reports the result of OLS and Bayesian regression estimates of IGM based on fathers' income, e.g., fathers are being divided based on their income. So, 1st quantile father's income group refers to children belong to low-income group and 4th quantile is the richest-income group. Fathers' income has positive impact on sons' income irrespective of the family status.

Table A.3. Determinants of Sons' Income

Variables	**Child Income Beginning of Career**		**Child Income Mid-Career**		**Child Income At Peak of Career**	
	OLS	Bayesian	OLS	Bayesian	OLS	Bayesian
Father Income	0.254***	0.230***	0.125*	0.194***	0.182	0.211***
Education	0.160***	0.175***	0.191***	0.187***	0.248***	0.190***
Gender	-0.181**	-0.182***	-0.0805	-0.167***	-0.372	-0.195***
Marital Status	0.118*	0.118***	-0.0253	0.080***	0.211	0.136***
Constant	6.408***	6.617***	7.832***	7.010***	7.135***	6.766***
N	710		389		89	

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table A.3. reports results of OLS regression and Bayesian on the impact of various variables on sons' income at different career level. Fathers' income has significant positive impact on sons' income at all career stages. Besides fathers' income, education and being single has positive impact on sons at all career stages. The gender (1=male) coefficient is negative representing being male is negatively related to income, the sign of the gender coefficient is same for both methodologies for all career level.

Table A.4. Occupational Mobility

Variables	1st and 2nd Quantile		3rd and 4th Quantile	
	OLS	**Bayesian**	**OLS**	**Bayesian**
Income	0.0878	0.178***	0.397**	0.006***
Education	-0.0282	-0.044***	-0.137	0.001***
Gender	-0.0492	-0.095***	-0.127	0.015***
Marriage	0.292*	0.142***	-0.157	0.007
Constant	-2.369	-2.806***	-3.900**	0.557***
N	675		575	

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table A.4. shows the result of occupational mobility regression using OLS and Bayesian, both yielding coefficients with same sign for 1st and 2nd quantile income-group.

APPENDIX B

CHAPTER II

Table B.1. Categorization of the Regions

No.	Regions
1	Istanbul
	Edirne-Tekirdağ-Kırklareli
	Balıkesir-Çanakkale
	Bursa-Eskisehir-Bilecik
	Kocaeli-Sakarya-Düzce-Bolu-Yalova
2	Izmir
	Denizli-Aydın-Muğla
	Manisa-Afyon-Kütahya-Usak
	Antalya-Isparta-Burdur
3	Ankara
	Konya-Karaman
	Nevsehir-Aksaray-Niğde-Kırıkkale-Kırsehir
	Kayseri-Sivas-Yozgat
	Zonguldak-Karabük-Bartın
	Kastamonu-Çankırı-Sinop
4	Adana-Mersin
	Hatay-Kahramanmaras-Osmaniye
	Gaziantep-Adıyaman-Kilis
5	Samsun-Tokat-Çorum-Amasya
	Trabzon-Ordu-Giresun-Rize-Artvin-Gümüshane
	Erzurum-Erzincan-Bayburt
	Kars-Ağrı-Iğdır-Ardahan
6	Malatya-Elazığ-Bingöl-Tunceli
	Van-Mus-Bitlis-Hakkari
	Diyarbakır-Sanlıurfa
	Siirt-Mardin-Batman-Sırnak

APPENDIX C

CHAPTER III

Table C.1. Impact of MPI on Children's Income

	2010-2013	2014-2017	2018-2021
Model 1			
M	-.604***	-1.225***	-8.65***
Constant	8.125***	9.534***	9.839***
Model 2			
Fathers Income	.192***	.303***	.141***
Constant	6.147***	6.266***	8.295***
Model 3			
Fathers Income	0.159***	0.213***	0.13**
MDPI	-0.355	-0.935***	-0.827***
Constant	6.566***	7.375***	8.493***
Model 4			
Fathers Income	0.169***	0.234***	0.38**
Interaction Term	-0.04	-0.096***	-0.08***
Constant	6.474***	7.161***	8.406***

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table C.1. results are the robustness check for the Table 4.4. The magnitude of the relationship for all models is same when the deprivation level was 3. Hence, the robustness result shows the relationship between children's income and multi-dimensional poverty does not change when the multi-deprivation poverty threshold (k) has changed.

Table C.2. Determinants of Children's Income

Variables	2010-2013	2014-2017	2018-2021
	Child Income	Child Income	Child Income
Father Education	0.073** (2.32)	0.101*** (3.61)	0.121*** (4.57)
MPI	-0.432* (-1.87)	-1.023*** (4.62)	-0.909*** (3.37)
Child age	0.011 (1.56)	0.028*** (4.59)	0.015*** (2.47)
Constant	7.447*** (24.30)	8.218*** (34.78)	8.995*** (46.83)

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table C.2. shows the results for determinants of children's income. The magnitude of the coefficient is same as of the variables in
Table 4.5., hence proving that the nature of the effect of control variables on children's income does not change when the threshold of multi-dimensional poverty (k) changes.

Table C.3. Education Attainment & MPI

Variables	2010-2013	2014-2017	2018-2021
	Child Education	Child Education	Child Education
MPI	-2.732*** (6.15)	-1.929** (5.41)	-1.788*** (3.54)
Father Education	0.445*** (8.44)	0.302*** (6.72)	0.41*** (8.24)
Child Age	-0.015 (1.25)	-0.001 (0.08)	-0.032*** (3.04)
Constant	3.652*** (7.14)	3.595*** (9.46)	4.19*** (11.64)

Note: *** p<0.1, ** p<0.05, * p<0.01. The data has been taken from SILC.

Table C.3. presents the results of the impact of MPI and other control variables on children's education attainment when the household is deprived in more than 2 dimensions. The results confirm the magnitude of the relationship estimated in Table 4.6.

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