

ESSAYS ON THE EMPLOYMENT IMPACT OF TECHNOLOGICAL
INNOVATION

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

BİLGEN CEBİR BENLİ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
THE DEPARTMENT OF ECONOMICS

MARCH 2025

Approval of the thesis:

**ESSAYS ON THE EMPLOYMENT IMPACT OF TECHNOLOGICAL
INNOVATION**

submitted by **BİLGEN CEBİR BENLİ** in partial fulfillment of the requirements
for the degree of **Doctor of Philosophy in Economics, the Graduate School of
Social Sciences of Middle East Technical University** by,

Prof. Dr. Sadettin KİRAZCI
Dean
Graduate School of Social Sciences

Prof. Dr. Elif AKBOSTANCI ÖZKAZANÇ
Head of Department
Department of Economics

Assoc. Prof. Dr. Hakan ERCAN
Supervisor
Department of Economics

Examining Committee Members:

Prof. Dr. Erol TAYMAZ (Head of the Examining Committee)
Name of University
Department of

Assoc. Prof. Dr. Hakan ERCAN (Supervisor)
Middle East Technical University
Department of Economics

Assist. Prof. Dr. Eren GÜRER
Middle East Technical University
Department of Economics

Prof. Dr. Meltem DAYIOĞLU TAYFUR
TED University
Department of Economics

Prof. Dr. Burak GÜNALP
Çankaya University
Department of Management Information Systems



I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: Bilgen CEBİR BENLİ

Signature:

ABSTRACT

ESSAYS ON THE EMPLOYMENT IMPACT OF TECHNOLOGICAL INNOVATION

CEBİR BENLİ, Bilgen

Ph.D., The Department of Economics

Supervisor: Assoc. Prof. Dr. Hakan ERCAN

March 2025, 163 pages

The employment impact of technological innovation has long been debated in economic literature. This Thesis explores this issue in developing countries in two different contexts. Using firm level survey data collected by World Bank, the first essay examines the employment impact of technological innovation by applying the methodology of Harrison et al. (2014) and extended by Cirera and Sabetti (2019) with the same data set we use. We extend the model in a different way by controlling the potential employment impact of business obstacles perceived by the firms. Our findings align with most of the literature in the sense that product innovation enhances labor and this result is robust under various specifications or in different regions whereas the impact of process innovation is not so visible. For the pooled sample, the process innovation is labor-saving. On regional base, we obtain a robust result for labor-saving effect of process innovation only for Africa. On the other hand, controlling the perceived business obstacles improves the statistical significance of labor-saving impact of process innovation for South Asia, ECA and MENA in some cases. The second essay examines how pre-shock technological innovation affects firm-level employment during that shock, with a reference to

COVID-19 Pandemic. By using WBES and its COVID-19 Follow-Up surveys, we estimate the employment impact of pre-COVID technological innovation during the Pandemic. The results indicate that firms engaging in product innovation in pre-Pandemic period have been more resilient in maintaining employment levels during the Pandemic while process innovation reveals no significant impact.

Keywords: Technological Innovation, Employment, Product Innovation, Process Innovation, Economic Shocks



ÖZ

TEKNOLOJİK YENİLİĞİN İSTİHDAM ETKİSİ ÜZERİNE MAKALELER

CEBİR BENLİ, Bilgen

Doktora, İktisat Bölümü

Tez Yöneticisi: Doç. Dr. Hakan ERCAN

Mart 2025, 163 sayfa

Teknolojik yeniliğin istihdam üzerindeki etkisi ekonomik literatürde uzun süredir tartışılmaktadır. Bu tez, gelişmekte olan ülkeler bağlamında bu ilişkiyi iki farklı makale aracılığıyla incelemektedir. İlk makale, Dünya Bankası tarafından toplanan firma düzeyindeki anket verilerini kullanarak Harrison ve diğerleri (2014) tarafından önerilen ve daha sonra Cirera ve Sabetti (2019) tarafından aynı veri setiyle uygulanan yapısal modeli kullanarak, teknolojik yeniliğin istihdam üzerindeki etkisini değerlendirmektedir. İlk makaledeki farklılaştırma, modele firmalar tarafından algılanan iş engellerinin istihdam etkisinin kontrol edilmesidir. Bulgular, ürün yeniliğinin farklı spesifikasyonlar ve bölgeler arasında istihdamı destekleyici etkisi olduğunu tutarlı bir şekilde göstermektedir. Öte yandan, süreç yeniliğinin istihdam üzerindeki etkisi daha belirsizdir. Tüm örnekleme süreci yeniliğinin istihdam azaltıcı bir etkisi olduğu görülmekte ve bölgesel olarak da özellikle Afrika bölgesinde daha belirgin olduğu görülmektedir. Ancak, algılanan iş engellerinin modele dâhil edilmesi, bu istihdam azaltıcı etkinin Güney Asya ile Avrupa ve Orta Asya bölgelerinde istatistiksel olarak daha anlamlı hale gelmesini sağlamaktadır. İkinci makale, şok öncesi teknolojik yeniliğin ekonomik şoklar sırasında firma düzeyinde istihdamı nasıl etkilediğini, özellikle COVID-19 pandemisine odaklanarak

incelemektedir. Dünya Bankası'nın firma anketleri ve bunlara baēlı COVID-19 Takip Anketlerini kullanarak yapılan analizler, kriz öncesinde ürün yeniliēi yapan firmaların istihdam seviyelerini korumada daha dirençli olduğunu göstermektedir. Buna karşılık, süreç yeniliēinin pandemi sırasında istihdam üzerinde anlamlı bir etkisi olmadığı tespit edilmiştir.

Anahtar Kelimeler: Teknolojik Yenilik, İstihdam, Ürün Yeniliēi, Süreç Yeniliēi, Ekonomik Şoklar



*To my grandmother, Mebrure Aras, who had lived her whole life
as a manifest of the principle “Either independence or death”*

And

*To my mother, Tülay, to whom I owed everything and
who taught me to believe, to resist and to hope...*

ACKNOWLEDGMENTS

I wish to express my deepest gratitude to my supervisor Assoc. Prof. Dr. Hakan Ercan for his tolerance, guidance and motivation throughout my Dissertation studies. I also want to thank to the members of my Thesis Defense Committee; Prof. Dr. Erol Taymaz, Prof. Dr. Meltem Dayıoğlu Tayfur, Prof. Dr. Burak Günalp and Assist. Prof. Dr. Eren Gürer. They provided me precious comments and guidance to improve my Thesis.

Throughout this long journey, my family and friends provided me priceless support and motivation. I especially want to express my gratitude to my grandmother Mebrure, who passed away recently and my mother Tülay, for their endless help in every area of my life. My uncle Adnan Yaşar and aunt Sakine Benan Yaşar contributed to our life too much and made life easier to my family; therefore, I could be able to catch an opportunity to focus on my graduate study, I am grateful for all they did. I would also like to extend special thanks to my father Tahir, and father-in-law Sabri, for the motivation they provided me as both parents and long-time educators throughout my doctoral journey.

I want to thank to my superiors and my colleagues in Ministry of Treasury and Finance for their support and help since the beginning of my PhD education. To name them separately; I thank to Mehmet Alper Batur, Mücahit Duman and Necmettin Mete Sakallıoğlu for being very supportive as my superiors throughout these years. Also, I want to thank to Veysel Ergenç, Serhat Şeflek, Utku Şen, Neziha Pınar Kurtulan, Zümrüt Türkoğlu, Gülin Begüm Ünal, Hatun Burcu Turan and Elif Cansu Cengiz as my colleagues for their extra efforts they had to give when I was out of office for my doctoral studies.

I also thank to Kübra Öcal Danış and Hazel Büşra Hastürk for being an excellent listener whenever I need them.

My special thanks belong to my good friends Öznur Özbek Değirmenci, Onur Koca and Cumhuriyet Çiçekçi for them to believe in me and convince me to continue whenever I feel exhausted and close to giving up. I also want to thank to my long-time friends since our undergraduate studies in METU; Başak Tekçam, Derya Bostancı, Selin Seçil Akın Montecino and Özlem Bayraktar Yıldırım.

I also thank to one of my best friends Semiha Kara Koçer who holds and will hold a special place in my heart for all my life despite the physical distance between us.

Finally, I want to extend my very deep gratitude to my husband Assist. Prof. Dr. Onur Benli for always being by my side during this process both as a spouse and a scientist and supporting me both professionally and emotionally. Last but not least, I want to both thank to my little sweet daughter İdil Benli for being so patient and with full of love and apologize from her at the same time since I had to steal from the time that I should dedicate to her as a mother. I wish and hope that we will have enough time to compensate this for the rest of our lives.

TABLE OF CONTENTS

PLAGIARISM	iii
ABSTRACT	iv
ÖZ	vi
DEDICATION	viii
ACKNOWLEDGMENTS	ix
TABLE OF CONTENTS	xi
LIST OF TABLES	xiii
LIST OF ABBREVIATIONS	xv
CHAPTERS	
1. INTRODUCTION	1
2. LITERATURE REVIEW ON INNOVATION AND LABOR DEMAND.....	9
2.1. The Concepts of Innovation	9
2.2. The Theoretical Framework on Innovation and Labor Demand.....	12
2.3. The Empirical Evidence on Innovation and Labor Demand.....	16
2.3.1. Empirical Studies at the Aggregate Level.....	19
2.3.2. Empirical Studies at the Sectoral Level	20
2.3.3. Empirical Studies at the Firm Level	22
3. THE IMPACT OF TECHNOLOGICAL INNOVATION ON LABOR	
DEMAND: AN EMPIRICAL ANALYSIS AT THE FIRM LEVEL	27
3.1. Introduction	27
3.2. Literature Review	29
3.3. Data	36
3.4. Methodology	45
3.5. Estimation Results.....	51
3.5.1. Baseline Estimation Results.....	51
3.5.2. Extension: Controlling for the Employment Impact of Business	
Obstacles	53

3.6. Conclusion.....	60
4. THE EMPLOYMENT IMPACT OF TECHNOLOGICAL INNOVATION PRECEDING AN ECONOMIC SHOCK: AN EMPIRICAL ANALYSIS WITH REFERENCE TO COVID-19 PANDEMIC	66
4.1. Introduction	66
4.2. Literature Review	69
4.3. Data	76
4.4. Methodology	84
4.5. Estimation Results.....	91
4.5.1. Baseline Estimation Results	91
4.5.2. Extension: Controlling for the Impact of Government Supports	94
4.5.3. Robustness Checks	102
4.6. Conclusion.....	103
5. CONCLUSION	110
5.1. Main Findings	110
5.2. Main Limitations	113
5.3. Policy Implications.....	114
5.4. Future Research.....	115
REFERENCES.....	117
APPENDICES	
A. SECTORAL DECOMPOSITION.....	128
B. COUNTRY LIST FOR WBES 2013-2014 DATA	129
C. COUNTRY LIST FOR WBES 2016-2019 DATA AND COVID FOLLOW- UP SURVEYS.....	130
D. EFA RESULTS FOR THE POOLED SAMPLE	133
E. CURRICULUM VITAE.....	137
F. TURKISH SUMMARY / TÜRKÇE ÖZET	138
G. THESIS PERMISSION FORM / TEZ İZİN FORMU.....	163

LIST OF TABLES

Table 3. 1. Sample Description	41
Table 3. 2. Employment and sales growth of innovators and non-innovators	43
Table 3. 3. Employment and sales growth of innovators and non-innovators	44
Table 3. 4. Effects of innovation on employment (OLS), all countries and by region	61
Table 3. 5. Effects of Innovation on employment (IV), all countries and by region	61
Table 3. 6. First Step Regression Summary Statistics for 2SLS Estimation reported on Table 3.4	62
Table 3. 7. Effects of Innovation on employment when business obstacles controlled (IV), all countries and by region	63
Table 3. 8. Effects of Innovation on employment when business obstacles controlled according to EFA (IV), all countries and by region	64
Table 4. 1. Outcome of Re-contacting the Baseline Survey Sample for Round 1 Follow-Up Surveys	80
Table 4. 2. The status of firms during the conduction of Round 1 Follow-Up Survey.....	81
Table 4. 3. The status of firms whether they are ever temporarily closed or permanently closed due to COVID-19 outbreak (Round 1)	82
Table 4. 4. Firm distribution according to size, age, sector and innovativeness.....	83
Table 4. 5. Firm distribution according to the government support taken or not taken	83
Table 4. 6. Effects of pre-COVID innovation on employment during COVID period.....	95
Table 4. 7. Multinomial Logistic Regression Results of the Equations (2)-(8) in Table 4.6.....	96
Table 4. 8. Effects of pre-COVID innovation on employment during COVID period, government supports are controlled.....	105

Table 4. 9. Effects of pre-COVID innovation on employment during COVID
period, government supports are controlled according to their types ... 106

Table 4. 10. Effects of pre-COVID innovation on employment during COVID
period, government supports are controlled according to their types
and with survey year dummies and different sectoral classification ... 108



LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CC	Cost Competitiveness
CIS	Community Innovation Survey
CIS3	CIS 2000
CIS4	CIS 2004
DMF	the methodology of Dubin and MacFadden (1984)
ECA	Europe and Central Asia
EFA	Exploratory Factor Analysis
ES	Enterprise Survey
EU	European Union
GCS	Google Consumer Surveys
GMM	Generalized Method of Moments
GMM-SYS	System Generalized Method of Moments
HJMP	the initial letters of the surnames of the authors Rupert Harrison, Jordi Jamandreu, Jacques Mairesse and Bettina Peters
ICT	Information and telecommunication technologies
IoT	Internet of Things
IS/LM	Investment-Saving/Liquidity Preference-Money Supply framework
ISIC Rev3.1	International Standard Industrial Classification of All Economic Activities, 2002 Version, United Nations Statistical Commission
IIA	Independence of Irrelevant Alternatives hypothesis
IMF	International Monetary Fund
IV	Instrumental Variable
MENA	Middle East and North Africa
ML	Machine Learning

OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
R&D	Research and Development
SSC	Social Security Contributions
SME	Small and Medium Enterprises
SPRU	Science Policy Research Unit (University of Sussex)
TC	Technological Competitiveness
TCC	Turkish Cypriot Community
UK	United Kingdom
USA	United States of America
2SLS	Two-Stage Least Squares
3SLS	Three-Stage Least Squares
WB	World Bank
WBES	World Bank Enterprise Survey

CHAPTER 1

INTRODUCTION

An important part of the economic theory evaluates the technical change as an indispensable part and reason of the economic growth. The neoclassical growth model and Solow's (1957) famous paper put the technological change forth as the only driver of the economic growth by providing a theoretical model where the upward shift of the production function is possible only with the existence of technical change. On the other hand, Schumpeter [1934] (2013) has defined the innovation as a "*creative destruction process*" leading to new ways of production, products and organizational structure which causes to the phasing out of the old ways of production and products. Therefore, the new growth theory has manifested itself in the works of Romer (1982) and Aghion and Howitt (1992) with the main idea that innovation and knowledge accumulation have the central role in the economic growth process.

Throughout the very beginning of the First Industrial Revolution, the world economy has witnessed various technological shifts. More recently, various studies have attempted to define a new upcoming industrial revolution; namely "Industry 4.0" or the Fourth Industrial Revolution, especially after the popular book of Klaus Schwab published in 2017, "The Fourth Industrial Revolution".

As mentioned in Schwab (2017) and Prisecaru (2016) like many more studies, the world economy has passed through three industrial revolutions which all have distinctive characteristics in themselves.

The First Industrial Revolution has covered more than 100 years beginning from 1760 up until 1840s according to Schwab (2017) and until 1900s according to

Prisecaru (2016). The major change in the production process came from the invention of steam power with the use of coal as the energy source to produce it. With the use of the steam power in the production process, the production process had begun to be transformed from the labor-intensive one where manpower is the basic production input to the mechanical one where the machine power accompanied it.

The Second Industrial Revolution which has begun in the late 19th century and continued through the early beginning of the 20th century up until 1960s, had used the oil and electricity as the main energy source and enabled the mass production with the “assembly line” (Prisecaru, 2016, pg. 57; Schwab, 2017, pg. 11), also named as Fordist mode of production named after Henry Ford (Farnes, 1993).

The Third Industrial Revolution covers the period between 1960 and 2000, and is characterized by the advent of semiconductors and mainframe computers in 1960s, personal computers until 1980s and internet in 1990s (Schwab, 2017, pg. 11) and welcomed the nuclear energy and natural gas as new energy sources (Prisecaru, 2016, pg. 57).

Finally, the Fourth Industrial Revolution, which has begun just at the turning point to the Millennium, has been and will be a much more complex phenomenon built on the digital revolution and represented by more widespread and mobile internet, smaller and more powerful sensors which can be produced cheaper, artificial intelligence (AI), Internet of Things (IoT), and machine learning (ML) (Schwab, 2017, pg. 12; Prisecaru, 2016).

All industrial revolutions have made a profound effect on the labor market¹. While societies expect more economic and social prosperity with the advent of new technologies; on the other hand, every technological transformation in the economy has created a new fear of technological unemployment.

One of the most widely known citation of a prediction of “mass unemployment” due to technological change in the literature belongs to David Ricardo where he has

¹ See, for example, Acemoglu and Restrepo (2019) for a further discussion.

underlined the technological unemployment as a concept in his book “*Principles of Political Economy and Taxation*”, published in 1891². From Ricardian conceptualization to Keynes, technological unemployment had been handled by different scholars of economic thought where Keynes has also mentioned the reality of technological unemployment especially in the short term in which the economy cannot have enough time to absorb the excess employment liberated from the technological change; however, he continues with the argument that “... in the long run, *mankind is solving its economic problem*” (Keynes, 1930; Campa, 2017, pg. 8).

Although there has always been a fear of massive unemployment since the First Industrial Revolution, there has not been a clear sign of massive unemployment due to technological change up until now (Vivarelli, 2014). Nevertheless, the debate on technological unemployment has been refreshed with the advent of the Fourth Industrial Revolution. Many studies and economists have drawn attention to the possibility of a radical transformation of jobs and tasks in the production process due to the distinctive characteristics of computerization, digitalization and automation of the Fourth Revolution era. One of the most resounding works in this area is Frey and Osborne (2017). Frey and Osborne (2017) attempts to classify and calculate the susceptibility of current jobs to the extinction risk due to the recent technological advancements and comes with a surprising conclusion revealing that nearly 47% of total US employment are at the high risk of being obsolete in the near decades due to the automation. However, some other scholars emphasized that the focal point should be the tasks rather than the whole job itself when analyzing the effect of automation in the labor market³.

While the suspicion of negative employment impact of technological innovation has been debated throughout the time; starting from the classical economists, many scholars of economic thought have mentioned the existence of “compensation mechanisms” alleviating the negative impact of technological innovation. Various

² The reader may apply Campa (2017) for further discussion on Ricardo’s view on “technological unemployment” as well as other scholars in the literature.

³ See for example, Acemoglu (2011), Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019) and Acemoglu and Restrepo (2020), for the task-based framework.

compensation mechanisms are described theoretically by two main perspectives, namely “Classical-Neoclassical Approach” and “Keynesian-Schumpeterian Approach” in the literature (Calvino and Virgillito, 2018). In the empirical literature, various studies have attempted to test the validity of those compensation mechanisms at macro or micro level.

Putting this picture summarized so far in the background, this Thesis is mainly composed of two different essays where both of them aim to answer the same old question whose history is briefly described above which is “how does technological innovation affect labor demand?”. However, these two essays aim to answer this question in different contexts. Both essays rely on firm level data provided by World Bank Enterprise Surveys (WBES), conducted in emerging and developing countries around the world since the beginning of 2000s.

From the beginning of the 2000s, many policymakers or international institutions like World Bank (WB) emphasized the importance of improving business environments as one of the key development strategies (Stern, 2002; WB, 2005; Xu, 2011). With this approach to the development problem, WB started to conduct firm level surveys all around the world to collect comparable data on investment climate. Xu (2011) discusses the effects of various business environment categories on firm performance by relying on the previous literature in this area. The review study conducted by Xu (2011) reveals some important facts. First of all, some elements of business environment have strong association with firm level economic performance. For example, protection of property rights at a basic level, labor flexibility, low entry costs, efficient legal systems or courts, good infrastructure are the factors which have an enhancing effect for firm growth. On the other hand, corruption, for example has a heavy burden for firm growth and new firm entrance to the market. Secondly, there is heterogeneity in effects of various elements of business environment among industries, according to accompanying complementary institutions and the initial conditions of business environments. To illustrate, the contracting institutions like access to finance or courts have more visible impacts as the economy gets more mature; or infrastructure is more crucial for the very poor developing countries. On the other hand, entry costs are especially important for the industries heavily

dependent on new ideas or technology intensive ones. The role of business environments and its increasing importance at the firm level brings us to the point where we face the need of taking into account the role of business environments on firm performance or firm behavior when measuring the employment outcome of technological innovation. With this motivation in mind, the first essay tries to answer the question “how does technological innovation affect labor demand in developing countries?” by controlling the potential employment effect of perceived business obstacles by utilizing the opportunities of the data we use.

As we are going to give place in more detail in the following sections of the Thesis, there are various studies in the literature examining the effect of product or process innovation on employment during business cycle or crisis periods (see for example, Dachs et al., 2017b; Arenas Diaz et al., 2020). Many of those studies reveal the fact that innovation increases resilience of the employment levels of the firms when compared to the non-innovative ones during crisis or bust periods. With this background information from the literature, the second essay is motivated to focus on the firm level employment impact of technological innovation that occurred before an economic shock during that economic shock with a special reference to COVID-19 period. COVID-19 provides a unique opportunity to study the dynamics of the relationship between innovation and labor demand by comparing and contrasting different economies during a worldwide economic shock.

The Thesis is outlined as five chapters. The second chapter is a comprehensive preliminary chapter which is built on three main parts. In the first part, we discuss the concept of innovation with a special emphasis on technological innovation and the types of it. We especially handle the definition of innovation as it is used in the national innovation surveys conducted all around the world to produce micro data. Putting forth the definitions regarding innovation paves the way for a more accurate understanding of the literature merging the concepts of innovation and labor demand. The second part of this chapter is a comprehensive literature review which discusses both the theoretical and empirical aspects of the relationship between innovation and labor demand. It starts with the theoretical approaches related to the employment outcome of innovation; especially technological innovation, and the alleged

compensation mechanisms put forth by different scholars of economic thought which may have counterbalancing role to alleviate the potential labor-saving effect of technological progress. Third part of this chapter introduces and discusses the empirical literature trying to provide evidence for the employment impact of innovation and potential compensation mechanisms that may be intact.

The third chapter constitutes the first essay of the Thesis. By exploiting the micro data provided by WBES conducted during the years 2013-2014 for 53 countries in our sample, we follow the empirical model proposed by Cirera and Sabetti (2019) which is built on the structural model proposed by Harrison et al. (2014) to measure the employment outcome of technological innovation in developing countries. Harrison et al. (2014) proposes an empirical model enabling the employment effects of product and process innovation to be estimated separately. The model enables the differentiation of the employment growth due to the production of new products or services from the employment growth due to the increased production of the old products stemming from the efficiency increase in the production process emerging with newly introduced process innovation. Moreover, it provides an opportunity to test the Schumpeterian view of compensation mechanism claiming that product innovation is the only compensation mechanism to alleviate the labor displacement effect of process innovation. Harrison et al. (2014) estimates their proposed model by using CIS data for four European countries. Cirera and Sabetti (2019), on the other hand, as in the case in this Thesis, apply the same model to WBES data and its linked Innovation modules conducted during the years between 2013 and 2014 for 53 developing countries and extend the model by including the organizational innovation which may also have an effect on labor demand and accounting for country-industry heterogeneity in their estimations.

Building on the methodology of these two papers; we follow the methodology of Cirera and Sabetti (2019) and extend the model by incorporating the business obstacles relying on the questions posed with the survey. We suspect that the perception of the business environment by firms may have an effect on the labor demand at the firm level and therefore accounting for its effect may be helpful to improve the estimation results. Building on the main finding of Cirera and Sabetti

(2019) revealing no significant effect of process innovation on the firm level employment, we propose that controlling for perceived business obstacles may change the outcome of the model of Harrison et al. (2014) to some extent for this country group. The survey data includes ordinal variables for business obstacles in sixteen categories varying their degrees from “no obstacle” to “very severe obstacle”. The survey also asks the question that which obstacle is the biggest one among the fifteen categories (one of the categorical variables are excluded in the “biggest obstacle” question; namely, “telecommunication”). Since we do not start with a theoretical relationship between business obstacles; we firstly control for the “biggest obstacles” perceived by the firms in our model and then continue with the sixteen separate categories of business obstacles which have the ordinal structure mentioned above. By conducting an exploratory factor analysis for the ordinal variables, we firstly determine the number of factors and the most representative obstacles for each factor both for the pooled sample and the regional decomposition. Secondly, we include the representative obstacles for each factor into our model. The results reveal that controlling for the business obstacles improve the statistical significance of process innovation to some extent.

The fourth chapter constitutes the second essay of the Thesis. As mentioned before, one of the motivations of this Thesis is to investigate the firm level employment impact of technological innovation that occurred before an economic shock during that economic shock. As a recent and worldwide health, social and economic crisis, COVID-19 Pandemic provides a unique opportunity to study this question. WBES Unit has started to conduct Follow Up Surveys as a continuation of the last Enterprise Surveys immediately after the Pandemic starts to appear in countries. Reaping the benefits of this micro data, we estimate a model for employment change between the period before the Pandemic and during the first round of the Pandemic including the case that the firm exits the market by using the wage level of the firm and the product and process innovation of the firm that occurred before the Pandemic as the main explanatory variables. However, it is important to note that a selection bias problem arises here because of the fact that when it is attempted to re-contact the sample for the Follow Up Surveys, some of the firms could not be obtainable, some of them confirmed they exit the market, some of them refused to answer the

Follow Up Survey as total, and some of them confirmed they are open and answered the Follow Up Survey. Therefore, we encounter four categories of firms according to the baseline Enterprise Survey; “unobtainable”, “discontinued business”, “refusal” and “confirmed open”. To correct for the bias stemming from the missing data of the first three categories above, we use the methodology of the selection bias correction based on multinomial logit model with the selection stage has a multinomial dependent variable named as “firm status”. At the outcome stage of the estimation, we estimate our labor demand equation attempting to measure the effect of product and process innovation on employment during the first round of the Pandemic. We also control for the effect of various kinds of government supports provided by almost all governments around the world to alleviate the adverse economic effect of the Pandemic.

The Thesis aims to determine the employment impact of technological innovation at the firm level in developing countries in differentiated context as mentioned in the previous paragraphs. Each essay is structured in itself as a brief introduction, a literature review narrowed down to the purpose of the essay, data, methodology, estimation results and conclusion. The last and fifth chapter is devoted to connect the results of the two essays and make a general conclusion on the answers found to the questions proposed at the beginning. It also discusses the delimitations of the Thesis and make suggestions for further research.

CHAPTER 2

LITERATURE REVIEW ON INNOVATION AND LABOR DEMAND

The relationship between innovation and employment has been studied in the literature from many aspects; both theoretically and empirically. Some prominent literature review articles collect these major theoretical approaches and empirical studies testing those approaches in a holistic manner. Vivarelli (2014) and Calvino and Virgillito (2018) are the most comprehensive examples of those literature review articles putting forth both the theoretical and empirical perspective on this area. Therefore, in this chapter, we mainly follow the pathways of these two articles for summarizing the main pillars of the theoretical and empirical literature.

Before discussing the literature on the relationship between innovation and labor demand, it would be appropriate to go over the basic concepts regarding innovation. After going over those concepts briefly, the literature merging the labor demand and innovation may be interpreted more correctly and meaningfully. Therefore, in this chapter, we firstly introduce the concepts regarding innovation and the types of innovation with a special emphasis on product innovation and process innovation. Then, we review the literature analyzing the relationship between innovation and labor demand both theoretically and empirically.

2.1. The Concepts of Innovation

At the very first beginning, the literature generally starts to provide a distinction between the term “invention” and “innovation”. According to Malerba (1997), the concept of *invention* refers to “a new idea, a new scientific theory or a new technological newness which has not been implemented and diffused”; on the other

hand, *innovation* means the materialized outcome of invention and is a tradable application of an invention.

According to Diaconu (2011), it is not always so straightforward to separate invention from innovation, especially for technological innovation (Diaconu, 2011, pg. 129). For example, there may be a long time lag between the emergence of invention and its transformation into innovation like several decades due to the lack of conditions for innovation to materialize. Besides, the innovation process may need or be composed of some consecutive inventions or innovations to be completed.

About the nature of technology, Pavitt (1987) argue against the view that claims technological information is rather costly to produce when compared to its diffusion and use. The underlying assumption behind this view is that technological knowledge reveals itself in the form of patents, blueprints, operating manuals etc. However, Pavitt (1987) mentions strictly that these assumptions are far from being true and most empirical studies reveal that “most technology is specific, complex, often tacit and cumulative in its development” (pg. 185). Diaconu (2011) expands this view by emphasizing that inventions may feed from various economic and social environments; on the other hand, innovation is mainly due to the firm’s own activity. Therefore, turning the invention to innovation requires for a firm to effectively “combine information, human, financial and material resources and existence of a functional distribution system is needed” (Diaconu, 2011, pg. 129).

Lastly, it is important to mention the types and classification of innovation. Schumpeter (1934) defines five types of innovation which are new produces, new production methods, exploitation of new markets, new ways to offer products on the market and new ways of business organization (Diaconu, 2011, pg. 133). Building on this classification of innovation types, Schmookler (1966) makes a differentiation between “technological product” and “technological production” where the former refers to the way to create or improve products whereas the latter one refers to how to produce them. Pavitt (1987) also makes a classification for technological innovation and says that “technology is specific to products and processes” (pg. 185), i.e., technological innovation refers to product or process innovation whereas the

other ones are categorized as “non-technological innovation”. In a similar way, Oslo Manual (2005) also used the approach where product and process innovations are counted as technological innovations whereas marketing or organizational innovation are counted as “non-technological” ones.

Following mostly the Schumpeterian typology of innovation, Oslo Manual (OECD, 2005) used four main types of innovation. Most of the innovation surveys around the world, as well as our data sets used in this Thesis, follow the categorization adopted by the Oslo Manual; therefore, it would be appropriate to mention its definitions here. The Oslo Manual (OECD, 2005) defines “innovation” at the firm level as “the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations” (OECD, 2005, pg. 46). Therefore, there are four main types of innovation included in the definition of “innovation”; namely, product innovations, process innovations, marketing innovations and organizational innovations, respectively (OECD, 2005, pg. 47).

Inspired by Schumpeterian view, the “product innovation” is defined as “the introduction of good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics” (OECD, 2005, pg. 48). On the other hand, the “process innovation” is defined as “the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software” in line with the Schumpeterian approach (OECD, 2005, pg. 49).

Aligned with the definitions of Schmookler (1966), Pavitt (1987) and Oslo Manual (OECD, 2005) recently; we focus on technological innovation which can be decomposed as product and process innovation and its employment impact at the firm level. In the next subsection, we present the literature on the main theoretical approaches as well as empirical studies related to the employment impact of innovation.

2.2. The Theoretical Framework on Innovation and Labor Demand

The labor-saving effect of technological innovation has been debated throughout the various periods of economic history. Different theoretical perspectives for the employment impact of technological change mainly include the possible negative or positive effects of technological innovation on employment as well as the counterbalancing mechanisms which may lead to crowding out effect of the initial negative or positive effect if any. Therefore, aligned with Calvino and Virgillito (2018) and Vivarelli (2014), the compensation mechanisms mentioned in the literature are revisited in the following paragraphs.

Both Calvino and Virgillito (2018) and Vivarelli (2014) group different compensation mechanisms under six different categories in total. Calvino and Virgillito (2018) attribute four of those to Classical-Neoclassical approach and the remaining two of them to Keynesian-Schumpeterian approach. As defined explicitly in Calvino and Virgillito (2018), “equilibrium perspectives” are reciprocated in neoclassical theory whereas “disequilibrium perspectives” manifest themselves in Evolutionary, Keynesian, Structural and Regulationist theories. The main difference between these two streams is the view that the former one claims that the higher the innovation the higher the employment through the mechanism of increased productivity and increased growth rate in turn whereas the latter one claims that due to the complexity of the concept of technological innovation, it is not so straightforward to differentiate the employment outcome of innovation.

These six compensation mechanisms can be summarized here as follows:

- i. **New machines:** Technological improvement leads to the introduction of new machines and this new physical capital substitutes for labor. However, a shift between sectors may reveal as a compensation mechanism as displaced workers in machine-using industries shifts to the machine-producing or capital ones (Say, 1836).
- ii. **Decrease in prices:** New technology leads to a decrease in production costs which may lead to a reduction in *prices* (in competitive markets). The

demand is triggered with the lower prices in the market and this may work as another compensation mechanism for higher demand for labor.

- iii. **Decrease in wages:** If some part of the workers is displaced with the technological advancement, there will be an excess supply of labor in the factors of production market. This excess supply of labor leads to a reduction in the general wage level. Labor demand increases as a response to the reduction in the wage levels and the excess supply of labor is absorbed in the market in this way. This compensation mechanism reveals itself as a reduction in general wage level in the factors of production market.
- iv. **New investments:** The reduction in unit costs of production stemming from technological improvement is transferred to the reduction in prices with a time lag. By reaping the increased profit margin during this time lag, firms may make more investments and expand their productive capacity and therefore increase their demand for labor.
- v. **Increase in incomes:** *The Keynesian compensation mechanism* works in this way: If the workers are able to acquire appropriate benefits from increased productivity with the technological innovation, their wages and hence their consumption increase. The aggregate demand increases in this case which in turn leads to the employment increases. Therefore, the initial displacement of labor is compensated via the increase in income with the technological innovation.
- vi. **New products:** With the advent of new products and/or new branches, the consumption increases and higher consumption leads to higher demand which in turn leads to higher employment. The *Schumpeterian approach* makes a distinction between product and process innovation. Product innovation is seen as labor-enhancing while the process innovation is seen as labor-saving. In *Schumpeterian compensation mechanism*, the product innovation is the one responsible for compensating the labor displacement stemming from the technological or, in other words, process innovation. However, a few points are worth to mention here: First, new product may replace the old ones and lead to the *cannibalization* of the sales of old products. The net effect of the product innovation on employment is ambiguous in this case. Second; if they meet the unmet needs of the consumers, product innovative firms may face a

market expansion at the industry level with a positive effect on employment. However, on the other way around, product innovators may steal markets shares of the non-innovator firms which may lead to the so-called *business stealing* effect, as old products become outdated. This may be the negative effect on employment. Third, there is a possibility that the new products may be produced more efficiently than the old ones if there is a complementarity between the product and process innovation strategies.

The six compensation mechanisms defined above reveal that there is a significant possibility that some market impulses may counterbalance the initial labor-saving effect of technological innovation. However, on the other way around, the effectiveness or dominance of these six compensation mechanisms is hard to predict ex-ante because of the fact that many of the mechanisms interact with each other or they may even not work sometimes due to this complexity.

If we start to discuss the potential reasons of the failure of the mentioned compensation mechanisms explained in the above paragraphs with the same order, the arrival of “new machines” may not necessarily lead to the absorption of the displaced labor from the mechanized industry to the others since the mechanization process may move across the other sectors too (Calvino and Virgillito, 2018, pg. 87). The pace of the diffusion of technical change may determine whether this mechanism is in force or not. On the other hand, new machines may replace the scrapped or obsolete ones; in this case, this compensation mechanism loses its significance (Vivarelli, 2014, pg. 127; Calvino and Virgillito, 2018, pg. 87).

The second mechanism, namely “decrease in prices”, may work under some necessary conditions such as high price elasticity of commodities, or existence of competitive market structures (Calvino and Virgillito, 2018, pg. 87). In the absence of these conditions, the aggregate demand may not increase or even decrease with the dismissal of some part of labor due to the reduced aggregate consumption.

The third mechanism, “decrease in wages”, may not work due to several reasons. First of all, compatible with the *Keynesian view of effective demand*, a decrease in

wages may lead to an increased demand of labor by firms on one hand, but on the other hand, due to the reduction in aggregate demand because of the income loss of some workers, firms may revise their expectations for the future and hire fewer workers (Vivarelli, 2014, pg. 128). Second reason is the “time irreversibility of technical change” put forth by Dosi (1988), Dosi and Nelson (2013) and Rosenberg (1976). The basic rationale behind the concept that if a firm professionalizes in production with a specific technology; then it is very unlikely that it will stop using it even if the price of the substitute of the technology; i.e. labor, decreases. Therefore, the hypothesis of perfect substitution between capital and labor; or, in other words, the movement along the isoquant is not valid in this case. Various extensions to the idea of the insubstitutability between capital and labor are summarized in the review articles Calvino and Virgillito (2018) and Vivarelli (2014).

The idea of the fourth mechanism, “new investments” relies on the assumption of Say’s law, which claims that extra profits gained due to technological progress are entirely channeled into additional investments without any time lag (Vivarelli, 2014, pg. 128). However, even if Say’s law functions, new investments may be directed to the labor-saving new machineries and in this case, the Keynesian channel, which assumes that new investments lead to an increase in production and in turn an increase in aggregate demand becomes obsolete (Calvino and Virgillito, 2018, pg. 88). On the other hand, the investment process evolves into the financial investment instead of real investment at the firm level especially during the last two decades as put forth in the Lazonick (2015). This stylized fact also needs attention when considering the counterbalancing effect of the “new investments” mechanism.

The functionality of the fifth channel, “increase in incomes”, depends on the bargaining power of the labor force due to unionization. This channel had been more visible in the past when the Fordist mode of production was common in 1950s and 1960s (Vivarelli, 2014). However, with the end of Fordist mode of production and the advent of today’s more competitive labor market structure, this mechanism may not work as before to compensate the negative effect of technological innovation on employment (Calvino and Virgillito, 2018, pg. 88; Vivarelli, 2014, pg. 128-129).

The last channel, “new products”, seem to be the most visible mechanism to counterbalance the labor-saving effect of the technological and/or process innovation according to Vivarelli (2014); while Calvino and Virgillito (2018) claim that its effect is also uncertain to predict. The main hindering mechanism, nevertheless, mentioned in both papers, is the fact that some innovations that can be categorized as product innovation in some sectors, they may reveal the characteristics of process innovation in some other sectors. One of the most common examples of this kind of innovation is the arrival of information and communication technologies (ICT). ICTs may form a product innovation for the industries that produce them whereas they form a process innovation in other industries which use ICTs as a part of their production processes.

Summarizing the main milestones of the theoretical perspective of the employment impact of innovation, we now move on with the studies testing the validity of those theories and compensation mechanisms mentioned above.

2.3. The Empirical Evidence on Innovation and Labor Demand

A bunch of studies in the literature have tried to find evidence for the various theoretical approaches related to innovation and labor demand. However, this task is not so straightforward to fulfill from various aspects. First of all, there are several problems to be tackled when it comes to the “measurement” of both innovation and its impact on employment.

Vivarelli (2014) defines three main problems that applied economists encounter in measuring the product innovation, process innovation, compensation mechanisms that remain intact and the final impact of innovation on employment.

The first problem is how to measure innovation. Applied economics has to find valid indicators for different kinds of innovations to test the validity of compensation mechanisms as well as the final impact of innovation on labor demand. Nevertheless, most indicators widely used in the literature have various deficiencies besides advantages and practicality they provide. Following Hagedoorn and Cloudt (2003), it

is beneficial to provide some discussions on the single indicators used to represent innovation. Hagedoorn and Cloudt (2003) discusses four commonly used single indicators in the empirical literature; namely, R&D inputs, patent counts, patent citations and new product announcements to measure different kinds of innovative activities and proposes using a combination of those single indicators in a composite measure for better measurement performance of innovation at the firm-level for high-tech industries. Now, we will summarize the advantages and disadvantages of those four indicators briefly below.

For the sake of R&D inputs as a proxy for innovation, not only R&D activities indicate the innovative capabilities of companies which may also affect their performances, particularly in high technological industries (Duysters and Hagedoorn, 2001; Henderson and Cockburn, 1994) but also they may not reflect the current innovation input of companies alone; they may be a result of the previous successes of companies in developing R&D strategies with a stable set of long-term projects (Hagedoorn, 1989). Moreover, the measurement of R&D efforts may suffer from country-specific reporting requirements in itself (Calvino and Virgillito, 2018).

Patents are also prone to criticism in various ways. First of all, patents represent only some part or percentage value in overall innovation activity of which may technically be patented and therefore they have a potential to deviate from the actual innovation output due to the firm-specific innovation strategies or requirements for patenting (Calvino and Virgillito, 2018). Moreover, there may be significant sectoral and/or international differences in patenting behavior, different sized firms may reveal different patenting behavior; or giving identical weights to patents without differentiating the importance degrees of them may create severe measurement bias in innovative activities (Hagedoorn and Cloudt, 2003). Despite those deficiencies mentioned, the raw counts of patents have been frequently used in the empirical literature and many researchers accept it to be useful in measuring the innovation activities.

When it comes to patent citations, it is not only a quantitative measure like raw counts of patents but also includes a measure of quality (Hagedoorn and Cloudt,

2003). The underlying rationale behind using patent citations as an innovation indicator is that the more a patent is cited, this shows the degree of its importance or influence of it. However, even if it is a better quality of indicator to measure innovation than just the number of patents, it is still based on the patents and does not still represent all innovation outcomes especially the ones that are not patentable.

The last widely used indicator mentioned in Hagedoorn and Cloudt (2003) is new product announcements. These announcements are generally referenced from the marketing departments of companies and the databases providing them have no screening mechanism to evaluate the product novelty announced unlike the evaluation mechanisms existing for patents. Moreover, it is found by Devinney (1993) that the existence of positive correlation between patents and new product announcements at the industry-level is not proven to exist at the firm-level.

Measuring the final impact of innovation and differentiating the final impact of innovation on employment from other factors constitute the second and third problems of measurement according to Vivarelli (2014). Final impact is strongly related to different institutional mechanisms and those may have different effects at micro-, meso- and macro-level as well as in different sectors or countries (Vivarelli, 2014, pg.132). Therefore, the employment outcome would be different dependent on those mechanisms. The third problem, on the other hand, is related to many other economic conditions like macroeconomic and cyclical conditions, labor market dynamics etc. (Vivarelli, 2014, pg. 132).

The literature has been struggling to find appropriate solutions those measurement problems above and therefore studying the employment impact of innovation goes hand in hand with putting forth various alternatives to those measurement issues. Empirical studies use various proxies for different types of innovation as well as various methodological approaches and control variables both to measure the final impact of innovation and disentangle the final employment impact of innovation from other factors. Now, after introducing the theoretical perspectives on the relationship between innovation and employment and basic measurement problems in the empirical literature, we can continue with the important papers in empirical

literature. Following Vivarelli (2014), we investigate the empirical literature under three main categories as aggregate, sectoral and microeconomic empirical studies.

2.3.1. Empirical Studies at the Aggregate Level

The aggregate level studies generally use a partial or general equilibrium framework to test the validity of compensation mechanisms (Vivarelli, 2014, pg. 133). Some of the preeminent examples of this literature may be counted as Sinclair (1981), Layard and Nickell (1985) and Vivarelli (1995).

The analysis of Sinclair (1981) is based on an IS/LM macroeconomic model with various assumptions. It intends to test whether the technological unemployment exists. Whether the classical view or Keynesian view is valid under the conditions where technical change occurs depends on the behavior of the wages. The main findings of the paper reveal that the effect of technical change on labor demand is dependent on the reaction of wages and the nature of the technical change. The key factors are the price-elasticity of labor demand and the capital-labor substitutability. However, the compensation mechanism that are in work is “via decrease in wages” not “via decrease in prices” to detect a positive employment outcome after technical change.

The quasi-general equilibrium model of Layard and Nickell (1985) shows that technical change leads to an increase in labor productivity and therefore has a labor-saving effect. Only if there is a sufficient level of elasticity of labor demand, it is possible to compensate the initial job losses according to the results. Their findings are consistent with the labor-augmenting technological progress approach and with a 0.9 value of the elasticity of labor demand and a sufficient level for compensation according to the authors, technical change is not the reason of the rising unemployment in the United Kingdom in the post-war period.

Another pioneer study worth to mention in this subsection is Vivarelli (1995). Vivarelli (1995) uses a three-stage simultaneous regression model to find the direct impact of process innovation (labor-saving effect), the compensation mechanisms at

work and the employment impact of product innovation (labor-enhancing effect). The data is for US and Italy and covers the period between 1960 and 1988. As far as the compensation mechanisms are concerned, the results point to the fact that “via decrease in prices” is more dominant in both countries; however, product-oriented US economy is more successful to compensate labor-saving effect of process innovation with respect to Italian economy.

The examples of macro level studies show that the elasticity level of labor demand is one of the key factors for technological innovation to have a positive outcome on employment and the compensation mechanisms may change according to characteristics of the economy or the time period concerned.

2.3.2. Empirical Studies at the Sectoral Level

The sectoral analyses may be helping to understand the sectoral differences in employment effect of innovation as well as sectoral shifts especially due to the technological change.

Vivarelli et al. (1996) analyzes the effects of innovation on employment based on Italian manufacturing data. It investigates the relationship both at the firm and sectoral level. At the sectoral level, the general macro relationships between value added, employment, investment and technology indicators are analyzed and the main findings reveal that in contrast to the general trends observed in advanced economies like Japan and USA, Italian manufacturing sector sees a decrease in employment with an increase in productivity. The authors attribute this result to the dominant role of process innovation and embodied technical change in firms' innovative activities in Italy.

Antonucci and Pianta (2002) uses CIS data of the years 1994-1996, merges this data with some structural and macro level data from OECD and conducts a sectoral level study for eight European countries; namely, Italy, France, Germany, Denmark, Netherlands, Finland, the UK, and Sweden. They find that the technological change has had a negative effect on employment of European industries at overall and claim

that this finding points to the unemployment observed during 1990s in Europe has an underlying nature of being technological.

If we come to the most recent studies conducted in after 2000s, Mastrostefano and Pianta (2009), Bogliacino and Pianta (2010), Bogliacino and Vivarelli (2012) are the other examples of preeminent studies in this area.

Mastrostefano and Pianta (2009) proposes a dynamic econometric model to estimate the effect of both product and process innovation on employment at the industry level by controlling the changes in demand, in cost of labor, in the diffusion of innovation and the economic impact of new products by using CIS2 and CIS3 data, capturing the years between 1994 and 2001, for ten manufacturing sector of European economies. The main findings of the analysis reveal that the innovation of both kinds have a positive effect on job creation in the countries and industries where they are accommodated by a growth in demand and a slow increase in labor cost. When it comes to the diffusion of innovation; new processes are compatible with the labor-saving effect whereas new products have a job-creating effect at the market level. And lastly, when it is looked at the high-innovation and low-innovation industries differently, it is seen that in low-innovation industries the process innovation has a more dominant impact and therefore the overall effect of innovation on employment tends to be negative.

Bogliacino and Pianta (2010) puts forth a comprehensive model to estimate the employment impact of innovation at the industry-level in eight European countries by using various CIS data conducted between the years 1994 and 2004. The most original perspective of the model is its usage of a sectoral taxonomy of industries; namely Pavitt taxonomy first introduced by Pavitt (1984) and extension of this taxonomy to the services sector to better understand the employment outcome of technological change by taking into account the different patterns of it. The paper analyzes the effects of different innovative strategies; namely, the *cost competitiveness* (CC) (stemming from process innovation) and *technological competitiveness* (TC) (stemming from product innovation), on employment for different sectors of manufacturing and services classified according to the

methodology of Pavitt taxonomy. Estimating an industry-level demand curve with the related CC and TC variables and including various control factors such as the change in labor compensation, industrial dynamism and productivity growth; the results reveal that CC has a negative employment effect whereas TC has a positive one. Moreover, they verify that different innovative strategies have different effects across different Pavitt classes which is a striking result to understand the sectoral outcomes of innovation.

Bogliacino and Vivarelli (2012) analyzes the effect of R&D investment on employment with a dataset constructed from fifteen European countries, twenty-five sectors and ten-year duration with a dynamic system GMM model. They mainly find that, as an important sign of product innovation, R&D expenditures may have a positive impact on employment in the European manufacturing and service sectors, especially in high-tech sectors.

The studies reviewed in this subsection so far indicates that the main sectoral decomposition is generally made between manufacturing and services sector but more granular differentiation is also possible depending on the different sectoral characteristics such as high-tech vs. low-tech or knowledge-intensive or not to better understand the employment impact of technological innovation. The sectoral evidence implies that product and process innovation may have different employment outcomes under different sectoral classification. Providing a general picture in this area, we continue with the microeconomic empirical studies as the last subsection of this chapter.

2.3.3. Empirical Studies at the Firm Level

As we see that from the subsections 2.3.1 and 2.3.2 above, the aggregate and sectoral level studies are concentrated more in the periods of 1980s and 1990s. However, with the pervasion of firm-level innovation surveys, the microeconomic empirical studies have begun to grow up from the beginning of 2000s to estimate the employment effect of different types of innovation at the firm-level. In this subsection, we touch upon some of the important papers in this area and close the chapter.

One of the important studies at the firm-level is van Reenen (1997). Van Reenen (1997) constructs a static input-oriented model of employment and many subsequent studies use that model to estimate the employment outcome of innovative activities such as Bogliacino et al. (2012, 2014), Pellegrino et al. (2019) and Dosi et al. (2021). The article constructs a panel data set for 598 firms covering the period 1976-1982 by matching the data from London Stock Exchange database of UK manufacturing firms with the SPRU innovation database and mainly finds that both kinds of innovation, i.e. product and process, have a positive impact on employment but the former has a more labor-enhancing effect. This positive effect is visible even after using long lags on innovation and controlling for fixed effects. The author suggests that the dominant effect of product innovation may be due to the fact that product innovations are more frequent than process innovations and the paper provides evidence for the causality of the relationship from technological change to jobs.

Another study worth to mention is Greenan and Guellec (2000). This article looks at the employment impact of product and process innovation both at the firm and sectoral level by using French microdata over the period of 1986-1990. The article reveals very interesting results: (i) without decomposing innovation as product and process, innovation is positively correlated with employment at both the firm and sectoral level. (ii) when the product innovation and process innovation is distinguished, it is found that the overall effect of process innovation is negative at the sectoral level whereas it seems positive at the firm level. The sectoral result may be due to the creative destruction. Therefore, the job transfer is more expected in case of process innovation. (iii) Last but not least, on the continuation of the nature of job transfers, the authors claim that product innovation creates more job transfers but less durable when compared to the process innovation.

On the other hand, Piva and Vivarelli (2005) finds evidence for a positive relationship between innovativeness (i.e., innovative activity through gross innovative investment) and employment at the firm-level by using a panel of Italian manufacturing data and applying a system GMM methodology even when the “business stealing effect” is taken into account by controlling for lagged values of employment and current sales of firms.

Based on Peters (2004), Harrison et al. (2008, 2014) developed a model connecting the effects of product and process innovation separately to the employment growth at the firm level. This model has opened a new strand of literature in terms of product innovation for firm level studies by differentiating the employment growth due to the old product from the employment growth due to new products. The model uses CIS data for the period between 1998 and 2000 for the four European countries Spain, Germany, France and UK. The paper mainly finds that product innovation has a labor-enhancing effect whereas process innovation tends to have the opposite effect. However, the authors argue for an indirect existence of a *price compensation mechanism*; i.e., increased productivity due to process innovation leads to an increase in the production of old products through the mechanism of reduced prices. The overall increase in employment owes its existence to this expansion in output. Harrison et al. (2008, 2014) and the studies following the same methodology in the literature will be discussed further in detail in the next chapter since the methodology we use is based on the one of Harrison et al. (2014).

Some other example of dynamic estimation structure belongs to Lachenmeier and Rottman (2011). For the 20-year period between 1982 and 2002, the authors estimate a dynamic employment equation with wages, gross value added, year and industry controls and current and lagged dummies for product and process innovation for German manufacturing firms with GMM-SYS estimation technique. The findings reveal positive effect of innovation on employment no matter whether innovation inputs or innovation outputs are taken into account in the model. However, their results contrast with most of the previous literature in the way that process innovation rather than product innovation tends to create more jobs.

Some articles have tried to estimate the effects of innovation on different types of firms in terms of their sizes (for example, Triguero et al. 2014) or their prior and after growth rates with respect to the occurrence of innovation (for example, Herstad and Sandven, 2015).

Triguero et al. (2014) uses data of Spanish manufacturing firms over the period 1990-2008 to estimate the employment impact of innovation persistence, especially

for SMEs. They use the GMM-SYS estimation technique to estimate the relative outcome of the persistence of product and process innovation on employment growth according to the different sizes of the firms. The findings reveal that the persistence of process innovation has a more promising outcome for labor; even if the contemporaneous year effect is also positive, this effect seems to increase with the number of lags. This finding signs to the fact that compensation mechanisms may be in tact with a delay in case of process innovation.

Herstad and Sandven (2015) uses Norwegian CIS data merged with public employment registers before and after the occurrence of innovation over 2004-2010 and studies the relationship between the prior employment growth rate in reference to the occurrence of innovation and the following innovation, innovation output and growth performance of the firms after the innovation event. There is a positive correlation between the existence of positive growth ex-ante and positive growth ex-post. Moreover, when both product and process innovation is introduced together, this probability of positive growth ex-post increases further. The paper contrasts to most of the previous literature in the way that process innovation adds more to the ex-post growth rather than product innovation, especially for the firms located at the upper tail of the distribution.

Another novel extension to this literature comes from Evangelista and Vezzani (2012). The paper extends the analysis of employment impact of innovation by including organizational change. They use CIS4 data for six European countries; namely, Czech Republic, Spain, France, Italy, Portugal and Slovenia. They use a three-step approach to identify the relationship between various kinds of innovation and employment. By estimating a model of two simultaneous structural equations with Three-Stage Least Squares (3SLS) approach, they mainly find that both product and process innovation has a positive impact on employment in manufacturing and services sectors whereas the negative impact of process innovation is directly seen in manufacturing sectors only when it is exerted with organizational innovation.

Last but not least, Roy et al. (2018) uses data of patenting firms over the period 2003-2012 for twenty-two European countries and uses patent information as a

proxy of innovation and non-dummy indicator. However, they also include a quality information for patents by looking at the forward citations of them as a sign of their importance and influence in the future innovation activities. They use a GMM estimation technique to estimate a labor demand equation including the lagged values of innovation as explanatory variable. Their finding reveal that increasing patenting leads to an increase in employment but this finding remains significant only in high-tech and medium-tech industries whereas it loses its significance in low-tech and services industries. This final result implies that the technological nature of the sectors constitutes a bias in this framework.

Although there are many more studies in this literature, we end this chapter here by giving an important clue about the milestones of this literature both theoretically and empirically. We see that theoretical approaches draw a picture of various possibilities of the employment impact of technological innovation as well as the potential compensation mechanisms whereas empirical studies are able to verify some of those to some extent. The most remarkable conclusion implied by the existing empirical literature so far is that the literature tends to reveal a positive effect of product innovation on employment whereas a more ambiguous effect of process innovation varying from the countries studied, factors controlled or the modeling approaches used. Many important empirical studies are cited here in this chapter; however, some others are examined in detail in the next chapters where they are more relevant to the context.

CHAPTER 3

THE IMPACT OF TECHNOLOGICAL INNOVATION ON LABOR DEMAND: AN EMPIRICAL ANALYSIS AT THE FIRM LEVEL

3.1. Introduction

According to some scholars, technological innovation has been the only engine for economic development since the arrival of First Industrial Revolution. Starting in Europe and spreading to all around the world, industrialization has brought a rapid transformation in the production processes due to the emergence of new technologies and energy resources.

Although the perpetual technological innovation has become both a desire and a target for countries all around the world, its employment effects have been debated over time. Most of the empirical studies in the literature have concentrated on advanced countries due to the fact that advanced countries have started to consolidate data long before the developing countries. Moreover, these countries have a long-time historical experience for innovativeness and the concreteness and uniqueness of the innovation in those countries create a fruitful background to study the interrelation between innovation and employment. On the other hand, the innovation-employment relationship is relatively less studied in developing countries and this relationship in developing world is in need of investigation.

Based on this background, in this essay, we aim to provide an answer to the question that “Does technological innovation have an effect on labor demand at the firm level in developing countries?”. To answer that question, we use a comprehensive data set for 53 developing countries based on WBES and its linked Innovation modules conducted during the years 2013 and 2014 and follow the methodology of Harrison

et al. (2014) and Cirera and Sabetti (2019). However, our extension to the baseline HJMP model diverges in terms of the fact that business environments may have an important effect in firms' behavior in various areas including the demand for labor.

As mentioned in the Introduction chapter of the Thesis, new millennium has led to revive the idea business environment improvement should hold place among key development strategies for countries (Stern, 2002; WB, 2005; Xu, 2011). Xu (2011) reviews the literature in terms of the role of business environments on firm development and collects the findings of various studies under some kind of stylized facts. The literature shows that describing and measuring elements of business environment is crucial in understanding firm level economic performance. Many elements like protection of property rights, labor flexibility, low entry costs, efficient legal systems or courts, good infrastructure are triggering factors for firm growth whereas corruption, for example, forms a heavy burden obstructing firm growth. Xu (2011) also touches upon the issue of heterogeneity in effects of business environments. At this cross-section of business environments and firm-level development, we are motivated to take into account the role of business environments on firm performance or firm behavior when measuring the employment outcome of technological innovation. Therefore, we conduct an analysis similar to the one of Cirera and Sabetti (2019) with an extension of business obstacles perceived by the firms to provide an evidence that the estimation results for process or product innovation may be affected by the uncontrolled effects of business environments and especially process innovation may have a statistically significant effect on labor demand after controlling for this effect.

The remaining part of this essay is structured as follows. Section 3.2 reviews a significant part of the literature relying on the structural model proposed by Harrison et al. (2014). Section 3.3 introduces data, sampling methodology used by WB and some basic properties and descriptive statistics of the sample. Section 3.4 explains the model that we use based on Harrison et al. (2014) and used also by Cirera and Sabetti (2019) with the same data set used in our analyses. Section 3.5 presents estimation results of our model and discusses the implications of main findings. Finally, Section 3.6 concludes.

3.2. Literature Review

After going over the theoretical and empirical literature on the relationship between technological innovation and labor demand in the previous chapter, we only focus on the literature on the papers which used the methodology by Rupert Harrison, Jordi Jaumandreu, Jacques Mairesse and Bettina Peters (2014), which is abbreviated as HJMP model from now on in this Thesis. A very recent paper, Arenas Diaz et al. (2024), conducts a meta-regression analysis to provide some empirical explanations accounting for the difference between the results revealed by various studies based on the HJMP methodology published so far. Although the approach of Arenas Diaz et al. (2024) is not in the scope of this Thesis, it provides an important reference for reviewing the literature on the applications of the HJMP model.

Among the 27 papers included in the Arenas Diaz et al. (2024), eight of them use EU data, six of them use data for a single European country, two of them use Latin American data, nine of them use data for a single Latin American country, one uses South African data and lastly, one paper, i.e. Cirera and Sabetti (2019), uses a comprehensive data set covering Europe and Central Asia (mostly Central or East Europe countries in the European side), Middle East and North Africa, Sub-Saharan Africa and South Asia data. This distribution of the studies shows that the studies applying various forms of HJMP model so far are concentrated first and for most on EU or European countries; and secondly on Latin American countries. CIS conducted regularly for European countries and national innovation surveys based on CIS conducted in Latin America might have enhanced the application of HJMP model frequently for those countries.

Although it is not possible and unnecessary to cover all those papers mentioned in Arenas Diaz et al. (2024), some important ones are worth to be mentioned here.

To start with, the pioneer paper affecting the followers, Harrison et al. (2008, 2014)⁴ proposes an output oriented model which enables to differentiate the employment

⁴ The literature has papers published before 2014 using Harrison et al. (2014) model since the model backs to Jaumandreu (2003), Peters (2005) and Harrison, Jaumandreu, Mairesse and Peters (2005).

impacts of product and process innovations. By using the CIS data of four European countries; namely, France, Germany, Spain, and the UK, for the period between 1998-2000, the authors estimate their proposed empirical model and their main results reveal that process innovation does not displace labor whereas gross effect of product innovation is labor enhancing. Although the common productivity trend reveal itself in all estimations as a sign of labor-saving nature of productivity increase as a general term, the increased demand for the old products seem to compensate this negative effect as well as the production of new products seem to create new jobs. The results are remarkable in the empirical literature in terms of confirming the validity of compensation mechanisms and the labor enhancing nature of the overall effect of innovation.

Going back to the preliminary foundations of the HJMP model; the first proposal for disentangling the employment impact of product innovation from process innovation in a single equation of labor demand has been made by Jaumandreu (2003). With this approach, by using CIS3 data of Spain for the period 1998-2000, Jaumandreu (2003) finds also no displacement effect of process innovation whereas labor enhancing effect of product innovation. Soon later, Peters (2005) uses the methodology proposed by Jaumandreu (2003) and uses German CIS3 data again for the same time period to measure the employment outcome of product and process innovations separately for the manufacturing and services sectors of Germany. Moreover, Peters (2005) makes two important extensions to the analysis such that: (i) product innovation outputs are classified according to their novelty degree; i.e., sales growth generated by market novelties and sales growth generated by firm novelties and (ii) process innovation is also classified in two different categories as *rationalization*⁵ and other types of process innovations. The analysis provides striking results. Peters (2005) shows that product innovations are labor enhancing both in the manufacturing and services sector. The employment growth is one-for-one as the sales growth and not only product innovations to the market but also product innovations only to the firm has positive impact on employment as the coefficients of both indicators are not statistically significantly different. Peters (2005) mentions that this last finding

⁵ *Rationalization* is defined as “Introduction of at least one process innovation intended for rationalization purposes in terms of reducing production costs in 1998-2000”.

contradicts the hypothesis that job creating effect of product innovation depends on product novelty. With regards to process innovation, process innovation has a net negative impact on employment in manufacturing firms where the displacement effect outweighs the compensation effect; however, rationalization category of process innovation is mostly responsible from job losses, i.e., not all types of process innovations destroy jobs.

Hall et al. (2008) uses Italian micro data and uses the HJMP model to answer a new question. Pointing the fact that the data signaling a trend for a lower productivity growth and lower innovative activity in the Italian economy with respect to its four European economies considered in Harrison et al. (2005) at that time, the authors try to find an answer to the question that whether this lower innovative activity may be responsible from the slower labor productivity growth in the manufacturing firms in Italy. The data used in the analysis covers the period from 1995 to 2003. They find that there is no significant employment displacement effect of process innovation; the product innovation contributes to employment growth but with a lower permeability when compared to other European counterparts and finally innovation makes almost no contribution to productivity growth.

Benavente and Lauterbach (2008) merely estimates the model proposed by Harrison et al. (2014) by just using Chilean micro data covering the period 1998-2001. Compatible with most of the previous papers of the same model mentioned in the paragraphs above, the authors find a positive impact of product innovation on employment whereas there is no significant effect of process innovation. Alvarez et al. (2011) extends the study of Benavente and Lauterbach (2008) in several ways. They use additional innovation survey data and reconduct the empirical estimations for skilled versus unskilled labor, small versus large firms, controlling for potential effect of different innovation strategies and technological intensity of firms. As an overall effect, their findings are consistent with the previous results of Benavente and Lauterbach (2008) implying an insignificant effect of process innovation and positive effect of product innovation. However, decomposing the analysis as high skilled versus low skilled labor, they find that process innovation has a negative effect on low skilled labor except for low-tech industries. On the other hand, the net

contribution of product innovation is positive for skilled workers for all firms and in high-tech industries whereas it is negative for low skilled workers. It is important to note that these conclusions are open to discussion since they are not validated by instrumental variable regressions and endogeneity bias may reveal misleading information.

Leitner et al. (2011) uses CIS4 data for 14 European countries which they group in three economic regions; namely, (i) a set of Central and Eastern Europe transition countries, (ii) a group of Southern EU member states and (iii) a pool of Core EU member countries and analyzes the employment impact of technological product and process innovations as well as organizational innovation as non-technical innovation in those three regions. Their results reveal remarkable and somewhat surprising findings with respect to previous literature especially in terms of the employment outcome of process innovation. To summarize, the product innovation and process innovation only in both manufacturing and services sector in the first two group of countries have labor enhancing effect whereas non-technical innovation have labor saving effect only in the first group of countries. In the third group of countries, only product innovation has a positive effect whereas process or non-technical innovation has no significant effect on employment.

Crespi and Tascir (2012) and Crespi et al. (2019) use microdata of four Latin American countries; namely, Argentina, Chile, Costa Rica and Uruguay, for years varying between 1998 and 2012 to measure the impact of product and process innovation on employment by using the HJMP model. The authors find that product innovation makes positive contribution to the employment whereas there is no significant sign of labor displacement stemming from process innovation for the sample concerned. The paper also attempts to test the validity of skill bias; the regression coefficients do not give a signal of skill bias whereas employment growth decompositions tend to reveal a tendency for product innovation to be skilled labor friendliness.

Dachs and Peters (2014) uses HJMP model to differentiate the employment impact of innovation on foreign-owned and domestically-owned firms for 16 European

countries and find that foreign-owned firms experience more job losses than domestically owned firms in case of process innovation and the existence of general productivity increase. On the other hand, their findings reveal that labor enhancing effect of product innovation are higher for foreign-owned firms. The compensation effect of product innovation seems to overwhelm the negative impact of process innovation but the overall net effect is smaller when compared to domestically owned firms.

Dachs et al. (2017a), on the other hand, extends HJMP model in four dimensions. First, they account for the effect of organizational innovation. Second, they extend the data set used in the analysis covering the years 1998-2010 for 26 European countries. Third, they classify sectors according to their technological intensity. Fourth, relying on 12 years of coverage, they estimate the displacement and compensation effects of innovation over the business cycles. They find that technological intensity of the sectors determines the magnitude of the gains and losses from innovation. The ranking of the sectors according to the magnitude of the effect of innovation on their employment outcome is as follows: high-technology manufacturing, knowledge-intensive services, low-technology manufacturing and less knowledge-intensive services. Moreover, in recession periods, the net contribution of product and process innovation on employment growth is negative for manufacturing industries in general whereas it is positive for others.

Aboal et al. (2015) and de Elejalde et al. (2015) are other two examples of the papers applying the HJMP model to analyze the employment impact of innovation on different skill types and sectors according to technological intensity by using Uruguayan micro data of the manufacturing sector and Argentinian micro data, respectively. Aboal et al. (2015) finds evidence for labor enhancing effect of product innovation whereas somewhat weaker evidence for labor saving effect of process innovation especially in high-tech firms; and that process innovation displaces unskilled labor rather than skilled labor. De Elejalde et al. (2015) finds evidence for positive effect of product innovation whereas no significant effect of process innovation on employment or skill composition; moreover, it finds no significant evidence for heterogeneous effects in different technological intensity or size.

Dachs et al. (2017b) tests pro-cyclicality or counter-cyclicality of different kinds of innovation using the HJMP model for 26 European countries from the period 1998 to 2010. They mainly find that product innovation is strictly pro-cyclical, its net effect is positive during upturn, boom or downturns except recessions in which its net effect has become negative signaling the labor displacing effect. Moreover, product innovators seem to be more resilient to recessions in terms of employment loss with respect to non-innovators since they seem to lose smaller amount of labor with respect to others. On the other hand, process and organizational innovation have labor displacing effect during upturns and downturns signaling to the fact that labor demand decreases by increased production efficiency.

Cirera and Sabetti (2019) uses a novel and unique data set, WBES and its linked innovation modules covering a huge set of developing and emerging countries from ECA, MENA, South Asia and Sub-Saharan Africa. The surveys have been conducted during 2013-2014. The paper extends the HJMP model in several ways. Firstly, it accounts for the country-industry heterogeneity and control for the employment impact of organizational innovation. In terms of process innovation, the authors disentangle the process innovation having characteristics of automation and other types. They also extend their model by controlling the degree of novelty of product innovation. However, neither their baseline nor the extended versions of the baseline models reveal a statistically significant employment effect of process innovation whereas the employment enhancing effect of product innovation in the short run seem to be robust to various model specifications. Although economic characteristics of countries included in the data set differ significantly from European countries, the results do not much deviate from most of the previous studies in this literature.

Hou et al. (2019) estimates an HJMP model by harmonizing micro data of France, Germany, Netherlands and China covering the period of 2002-2004 for European countries and the period 1999-2006 for China with only manufacturing industries. Similar to the Harrison et al. (2014), Crespi et al. (2019) and Cirera and Sabetti (2019), they find no significant effect of process innovation on employment whereas the net positive effect of product innovation manifest itself in the estimation results.

Arenas Diaz et al. (2020) estimates an HJMP model by using Spanish micro data in the manufacturing sectors for the period 2006-2014. The period covered in the model corresponds to a time period of the existence of huge employment losses in Spain. Therefore, the paper analyzes the employment outcome of innovation in manufacturing industry where there are negative economic conditions in the background. Moreover, they differentiate employment outcomes for different skill types. Similar to Dachs et al. (2017b), their findings confirm that innovative firms are less affected in crisis periods than non-innovative firms and this positive effect of innovation seems to be more sounding for high skilled labor. The impact of product and process innovations seem to be more exacerbated in high-tech industries. And finally, process innovation has a small effect both on low-skilled and high-skilled workers. Arenas Diaz et al. (2025), on the other hand, uses Spanish micro data again to estimate the employment outcome of product innovation on upstream and downstream sectors and on firms in the same sector by extending the HJMP model accordingly and find that firms making product innovation destroy jobs other firms in the same sector. Moreover, they find a detrimental effect of product innovation on upstream sectors. Those two findings are especially valid for low skilled labor. No significant effect of product innovation on downstream sectors are found.

Foronda and Beverinotti (2021) estimates an HJMP model with Bolivian micro data and find that there is no significant impact of process innovation on employment whereas there is a positive impact of product innovation on employment which is compatible with most of the previous results in the literature. Naidoo et al. (2023) estimates an HJMP model by South African micro data by extending it in two aspects. One is to account for export status of the firm and the other is to account for the degree of novelty of innovation. In contrast to most of the literature on this area, the paper finds that process innovation is more job creating than the product innovation in South African case. Moreover, both product and process innovations possess a larger job creating effect on employment for exporters in the manufacturing sector with respect to services sector or non-exporter manufacturers. On the other hand, with respect to the second extension, i. e., the degree of novelty, the findings show that radical innovations which are new to the market lead to more employment creation.

Rochina Barrachina and Rodriguez Moreno (2023) uses micro data for Ecuador, from a national innovation survey conducted in 2013 to estimate an HJMP model. The main extension of the paper is to include organizational and marketing innovation as non-technical innovation. Their results reveal that there is a clear sign of labor displacement effect of process innovation in Ecuador whereas the net effect of product innovation on employment growth is positive although there is evidence for cannibalization of old products because the gross effect is larger than the net effect which confirms the “creative destruction” theory of Schumpeter (1942). Organizational innovation is statistically insignificant whereas marketing innovation is responsible from labor enhancement.

The literature on the model proposed by Harrison et al. (2014) is mostly covered here. The general findings reveal that process innovation gives mixed results and the employment impact of process innovation may change according to the factors controlled, the extensions introduced, over the business cycles or the macroeconomic conditions playing on the background. On the other hand, the employment friendly nature of product innovation seems more robust under alternative specifications of the HJMP model or factors controlled although some exceptions may still exist. As national innovation surveys have started to become common around the world especially after 2000s, the search for micro evidence and re-estimation attempts for the HJMP model have increased substantially. The question still keeps its validity and the attempts to use HJMP model to test the effects of product and process innovations on employment at the firm level still continues. This essay attempts to introduce a new extension to the baseline analysis of Cirera and Sabetti (2019) with an aim to increase the robustness of the estimation results, especially for the process innovation for the county group under study.

3.3. Data

World Bank Enterprise Surveys (WBES) have been conducted across all geographic regions and cover small, medium and large companies. WBES are one of the most comprehensive firm level surveys due to the fact that both they cover more than 150 countries recently and provide comparable data for most of the countries since WB

has started to use Global Methodology since 2005-2006 enabling a comparable survey data across countries in which the survey is conducted and across time since then. The surveys cover a broad range of topics including the general information and performance indicators of the companies or information related to business environment such as corruption, infrastructure, competition and/or business-government relations. It constructs a representative sample of firms in the non-agricultural private economy with a stratified sampling methodology⁶ where three levels of stratification are used; namely, industry, size and location within the subject country. Implementation Notes are provided beside with the data and they include detailed information about how the surveys are conducted and their sampling methodology. The reasons for choosing stratified random sampling methodology are provided in those Implementation Notes⁷ and given place below:

- To obtain unbiased estimates for different subdivisions of the population,
- To obtain unbiased estimates for the whole population, which is non-agricultural private economy including all manufacturing sectors according to the group classification of ISIC Rev. 3.1 (group D), construction sector (group F), services sector (group G and H), and transport, storage, and communications sector (group I). Financial intermediation sector (group J) is excluded and only IT sector from group K (real estate and rental activities) is included,
- To guarantee that the final sample incorporates establishments from all different sectors and that it is not concentrated in one or two industries, sizes or regions,
- To exploit the benefits of stratified random sampling where population estimates becomes more precise in most cases with lower standard errors,
- Stratification methodology may produce a smaller bound on the error of estimation than would be produced by a simple random sampling methodology of the same size. This result is particularly true if measurements within strata are homogeneous.

⁶ A stratified random sample is a sample obtained by separating the population elements into non-overlapping groups, called strata, and then selecting a simple random sample from each stratum. (Richard L. Scheaffer; Mendenhall, W.; Lyman, R., "Elementary Survey Sampling", Fifth Edition).

⁷ Cochran, W., 1977, pg. 89; Lohr, Sharon, 1999, pg. 95.

The three levels of stratification are designed as follows: The universe is stratified into one manufacturing sector and two services sector as retail and other services. Size stratification is the standard classification of firm sizes as firms having 5 to 19 employees are small sized, those having 20 to 99 employees are medium sized and those having more than 100 employees are large sized. The firm size is calculated on the basis of permanent full-time employees. Finally, location stratification is defined according to the size and economic features of each country and therefore each country has its own unique regional stratification.

We use WBES data conducted during the years 2013-2014 which include an additional linked Innovation Module, in order to provide information about the innovation performance of the firms. Innovation Module includes four types of innovation which are product, process, organizational and marketing innovation. Innovation Module captures questions similar to CIS in some ways; for example, it includes information about the share of new products in nominal sales for the firms who have made product innovation. It also includes questions on process innovation. However, it is not totally same as the CIS; therefore, it is not possible to check for the estimation strategies that have been tried with for HJMP models in previous studies using CIS data. Still, the survey is suitable to estimate a model capable of differentiating the employment outcome of product and process innovation. Our sample is composed of micro data of 53 developing and emerging countries in four geographical and economic group; namely, European and Central Asia (ECA), Middle East and North Africa (MENA), South Asia and Africa. The whole list of countries is provided at Appendix B.

Table 3.1 provides a detailed information about the sample both for pooled data and for the four regions mentioned above. The table provides the percentage of firms according to age, size, industrial groups that we use in the model with respect to total observations in the sample. The number of observations in the sample is over 33,000 for 53 countries; however, there is a significant amount of observation loss in the estimations due to the missing values existing in each variable defined for our model to be estimated. The distribution of firms according to their size reveals that almost half of the firms in the overall sample is small (the number of employee is up to 19)

and only 15.17% constitutes the large firms (the number of employee exceeds 100). On regional base, Africa and ECA are the two regions having small sized firms exceeding one half. In terms of age structure, the overall sample is relatively representative of older firms since older than 5 year firms constitute almost 85% of the sample and on the regional base South Asia is the region which has the smallest share of young firms (younger than 5 years old) in its sample. Industrial distribution reveals that in the overall sample manufacturing and services sector have balanced representation; however, the regional distribution again varies. For example, South Asia is heavily represented by manufacturing firms followed by MENA region in the second place whereas ECA is the region which has the smallest share of manufacturing firms where the share of retail and wholesale services is almost equal to the share of manufacturing sector in this region. On the other hand, Africa has the services sector outweighing the manufacturing sector.

In terms of innovativeness, the rate of non-innovativeness is over 55% in the overall sample. When it is looked region by region, the highest rate of innovativeness is seen in South Asia whereas the lowest rate of innovativeness exists in MENA. The rates of product and process innovation is close to each other; product innovation slightly exceeds process innovation in the overall sample whereas process innovation highly dominates product innovation in Africa. In all other regions product innovation exceeds process innovation with 2 to 4 percentage points.

Table 3.2 gives the sample mean of employment and sales growth rates for the manufacturing sector. In terms of employment growth in the manufacturing sector, all firms whether they are innovative or not witnessed an employment growth during this 3-year period in the overall sample and regionally except MENA since non-innovative firms in MENA region witnessed an employment decline in this period. In ECA and MENA regions, we see that product or process innovative firms have grown by far with respect to non-innovators in terms of their employment level. On the other hand, there is not much significance between the innovators and non-innovators in terms of the employment growth rates in South Asia. Surprisingly, the employment growth of non-innovators far exceeds the innovators in Africa.

In terms of sales growth shown on Table 3.2, the sales growth of innovators outweighs the non-innovators significantly. In terms of product innovation, we see that when there is product innovation, the sales growth due to old products becomes negative and since product innovation exists in all regions, the same trend can be seen for all regions.

In the services sector; on the other hand, as can be seen on Table 3.3, both the employment growth and sales growth show a more even growth decomposition between innovators and non-innovators. However, it is important to keep in mind that the sales growth is in nominal terms and includes firm-level price effect. In terms of nominal sales growth, MENA is the only region which witnessed a negative growth rate in all items.

Now, after providing the basic properties of the sample, we continue with the detailed explanation of the methodology in the next subsection. After introducing the methodology, we provide our estimation results.

Table 3. 1. Sample Description

	All Countries			Africa			South Asia		
	Numbers	Total	Percentage	Numbers	Total	Percentage	Numbers	Total	Percentage
Total Sample Size		33,336	100%		5,504	100%		5,649	100%
Size									
Small	16,642		49.92%	3,513		63.83%	1,966		34.80%
Medium	11,636		34.91%	1,468		26.67%	2,295		40.63%
Large	5,058		15.17%	523		9.50%	1,388		24.57%
Age									
<5	4,992		14.97%	1,171		21.27%	460		8.14%
5-9	7,035		21.10%	1,306		23.72%	1,064		18.83%
10-14	6,690		20.06%	1,047		19.02%	1,010		17.87%
15-19	5,665		16.99%	646		11.73%	854		15.11%
20+	8,954		26.85%	1,334		24.23%	2,261		40.02%
Industry		33,302			5,502			4,188	
Manufacturing	16,722		50.21%	2,292		41.66%	4,370		77.36%
Construction	2,146		6.44%	196		3.56%	269		4.76%
Retail and wholesale	10,465		31.42%	2,070		37.62%	531		9.40%
Hotels and Restaurants	1,933		5.80%	615		11.18%	248		4.39%
Transport	1,584		4.76%	243		4.42%	132		2.34%
IT	594		1.91%	86		1.56%	99		2.36%
Innovation									
Non-innovators	18,600		55.79%	1,930		35.06%	1,373		24.30%
Innovators									
Product	10,538		31.61%	2,219		40.31%	3,142		55.62%
of which only product	4,446		(42.19%)	856		(38.57%)	1,265		(40.26%)
Process	10,009		30.24%	2,639		47.94%	2,987		52.87%
of which only process	3,946		(39.42%)	1,294		(46.76%)	1,116		(37.36%)
of which product and process	6,030		18.08%	1,330		24.16%	1,870		33.10%

Table 3. 1. (Cont'd) Sample Description

	ECA			MENA		
	Numbers	Total	Percentage	Numbers	Total	Percentage
Total Sample Size		15,883	100%		6,300	100%
Size						
Small	8,298		52.24%	2,865		45.48%
Medium	5,647		35.55%	2,226		35.33%
Large	1,938		12.20%	1,209		19.19%
Age						
<5	2,386		17.85%	975		15.47%
5-9	3,839		24.17%	826		13.11%
10-14	3,532		22.23%	1,101		17.47%
15-19	3,308		20.82%	857		13.60%
20+	2,818		17.74%	2,541		40.33%
Industry		15,858			6,293	
Manufacturing	6,336		39.95%	3,582		56.92%
Construction	1,398		8.82%	283		4.50%
Retail and wholesale	6,317		39.83%	1,547		24.58%
Hotels and Restaurants	671		4.23%	399		6.34%
Transport	785		4.95%	424		6.74%
IT	351		2.26%	58		0.98%
Innovation						
Non-innovators	10,919		68.74%	4,378		69.49%
Innovators						
Product	3,780		23.79%	1,397		22.17%
of which only product	1,717		(45.42%)	608		(43.52%)
Process	3,119		19.63%	1,264		20.06%
of which only process	1,057		(33.88%)	479		(37.89%)
of which product and process	2,052		12.91%	778		12.34%

Note: The percentage values in parentheses reflect the percentage with regards to product innovators and process innovators not with regards to the whole sample.

Table 3. 2. Employment and sales growth of innovators and non-innovators

	Manufacturing									
	All Countries		Africa		South Asia		ECA		MENA	
	Total	Percentage	Total	Percentage	Total	Percentage	Total	Percentage	Total	Percentage
Employment Growth										
All firms	14,983	6.60%	2,018	14.19%	4,176	8.62%	5,622	5.82%	3,167	0.49%
Non-innovators	6,885	4.22%	606	17.35%	925	8.94%	3,369	4.23%	1,985	-1.99%
Process-innovators only	1,998	9.25%	574	13.65%	720	8.97%	421	7.18%	283	4.09%
Product innovators	6,002	8.45%	824	12.35%	2,523	8.41%	1,780	8.56%	875	4.66%
Sales Growth (nominal)										
All firms	11,728	20.76%	1,441	48.23%	3,636	19.16%	3,904	24.78%	2,747	2.76%
Non-innovators	5,067	15.13%	402	35.03%	665	15.95%	2,248	22.78%	1,752	0.46%
Process-innovators only	1,637	30.94%	404	57.76%	674	20.83%	304	39.46%	255	5.03%
Product innovators	4,973	22.99%	627	49.47%	2,297	19.60%	1,331	24.76%	718	7.46%
of which: old products	2,772	-26.60%	312	-22.45%	1,539	-33.87%	898	-13.72%	23	-100%
of which: new products	2,772	47.10%	312	38.62%	1,539	53.44%	898	37.46%	23	113.21%

Note: The sample mean of employment and sales growth rates are calculated over 3-year period as asked in the survey. Employment growth is measured by only taking into account the full-time permanent employees. Sales growth is calculated in local currency. For product innovators, total sales growth, sales growth due to old products and sales growth due to new products are given separately.

Table 3. 3. Employment and sales growth of innovators and non-innovators

	Services									
	All Countries		Africa		South Asia		ECA		MENA	
	Total	Percentage	Total	Percentage	Total	Percentage	Total	Percentage	Total	Percentage
Employment Growth										
All firms	14,633	8.78%	2,715	12.95%	1,215	10.15%	8,300	8.31%	2,403	5.03%
Non-innovators	14,335	8.63%	2,662	12.78%	1,142	9.83%	8,153	8.21%	2,378	4.81%
Process-innovators only	14,154	8.68%	2,652	12.92%	1,134	9.98%	8,017	8.27%	2,351	4.63%
Product innovators	14,335	8.76%	2,678	12.87%	1,173	10.11%	8,114	8.36%	2,370	4.84%
Sales Growth (nominal)										
All firms	10,384	21.75%	1,801	39.97%	1,041	20.00%	5,580	24.59%	1,962	-2.11%
Non-innovators	10,143	21.37%	1,763	38.33%	975	19.99%	5,467	24.66%	1,938	-2.63%
Process-innovators only	10,035	21.54%	1,760	39.43%	970	20.20%	5,389	24.61%	1,916	-2.86%
Product innovators	10,183	21.67%	1,777	39.81%	1,010	19.89%	5,462	24.62%	1,934	-2.41%
of which: old products	8,803	12.45%	1,328	22.46%	843	-1.16%	5,032	18.05%	1,600	-6.27%
of which: new products	8,803	7.53%	1,328	11.02%	843	21.41%	5,032	6.40%	1,600	0.89%

Note: The sample mean of employment and sales growth rates are calculated over 3-year period as asked in the survey. Employment growth is measured by only taking into account the full-time permanent employees. Sales growth is calculated in local currency. For product innovators, total sales growth, sales growth due to old products and sales growth due to new products are given separately.

3.4. Methodology

In this section, we explain the basic HJMP model and the extensions introduced by Cirera and Sabetti (2019). Then, we introduce our extension to the baseline model of HJMP.

Harrison et al. (2014) firstly puts forth a theoretical background paving a way to estimating the impacts of product and process innovations on employment outcome separately. In the literature, the input-oriented models, proposed firstly by Van Reenen (1997) where innovation inputs are used as a proxy for innovation such as R&D expenditures⁸ (Arenas Diaz et al., 2024), have been widely used so far. The structural model proposed by Harrison et al. (2014), on the other hand, is an output-oriented model diverging from the input-oriented models. Harrison et al. (2024) utilizes *commercial results* of product innovation in terms of sales due to new products as an indicator of product innovation whereas process innovation is represented by a dummy variable (Arenas Diaz et al., 2024, pg. 36). In the following paragraphs, we go over the model proposed by Harrison et al. (2014) which we call HJMP model throughout this Thesis.

The main assumptions of the HJMP model⁹ described in Harrison et al. (2014) can be listed as follows:

- There is a two-good and two-period production function.
- Two periods ($t=1$ and $t=2$), firms possibly introduce some new products in between.
- At $t=1$, old products are old ($i=1$). Outputs are denoted by Y_{jt} . Therefore, in year $t=1$, there is only Y_{11} .
- At $t=2$, firms may produce both old or new products [$j=1$ (old or marginally modified products) or $j=2$ (new or significantly modified products)]. Therefore, the firm may be producing Y_{12} and Y_{22} , but $Y_{22} = 0$ if the firm has not introduced any new products between the two years.

⁸ Sometimes patents are also used in this model as a non-commercial output variable (Arenas Diaz et al., 2024, pg. 36).

⁹ The model is explained with reference to Harrison et al. (2014) and Arenas Diaz (2024).

- The production technology has the property of CRS in capital (K), labor (L), and intermediate inputs (M), and can be divided into two separable production functions with different Hicks-neutral technological productivity indexed by θ_{jt} which indicates that productivity can change over time for old products:

$$Y_{it} = \theta_{it} F(K_{it}; L_t; M_{it}) e^{\eta + \omega_{it}} \quad (3.1)$$

- $\eta \rightarrow$ Firm fixed effect capturing firm idiosyncrasy.
- $e^{\eta + \omega_{it}} \rightarrow$ all the factors –non-observables– that make a firm more productive than the average firm using the same technology (in this case θ)
- $\omega \rightarrow$ unanticipated productivity shocks ($E(\omega_{it}) = 0$)
- It is assumed that firms conduct R&D to generate product and process innovations and that the predictable efficiency effects of these investments are reflected in the changes in θ .
- New products can be produced with higher or lower efficiency than old products and process innovation may interact with the efficiency of production of either old or new products. This specification of the model enables to differentiate between the employment effects stemming from systematic change in efficiency of old products (θ_{12}/θ_{11}) and the relative efficiency (θ_{22}/θ_{11}) of producing new and old products.
- The labor demand equations are derived following the cost minimization problem and by applying Shephard's Lemma:

$$L_{1t} = c_{wL}(w_{1t}) \frac{Y_{1t}}{\theta_{1t} e^{\eta + \omega_{1t}}} \quad (3.2)$$

$$L_{22} = c_{wL}(w_{22}) \frac{Y_{22}}{\theta_{22} e^{\eta + \omega_{22}}} \quad (3.3)$$

where $c_{wL}(\cdot)$ represents the derivative of $c(\cdot)$ with respect to the wage.

- After obtaining the labor demand equations of (3.2) and (3.3) above, now the employment growth can be decomposed as below under the assumption of constant input prices:

$$\frac{\Delta L}{L} = \frac{L_{12} + L_{22} - L_{11}}{L_{11}} = \frac{L_{12} - L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \cong \ln \frac{L_{12}}{L_{11}} + \frac{L_{22}}{L_{11}} \quad (3.4)$$

where the employment growth rate brought by new products is L_{22}/L_{11} .

- Inserting the labor demand equations described in (3.2) and (3.3) into the equation (3.4) and taking the logarithm of both sides gives;

$$\frac{\Delta L}{L} \cong -(\ln \theta_{12} - \ln \theta_{11}) + (\ln Y_{12} - \ln Y_{11}) + \frac{\theta_{11}}{\theta_{22}} \frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11}) \quad (3.5)$$

- Equation (3.5) describes the employment growth in four components:
 - (1) $-(\ln \theta_{12} - \ln \theta_{11})$ is the change in the efficiency of old products in the production process.
 - (2) $(\ln Y_{12} - \ln Y_{11})$ is the rate of change of the demand of old products.
 - (3) $\frac{\theta_{11}}{\theta_{22}} \frac{Y_{22}}{Y_{11}}$ expresses the increase of production related to new products.
 - (4) $-(\omega_{12} - \omega_{11})$ is the impact of non-technological perturbation of productivity.
- Based on the equation (3.5), the structural equation in its reduced form can be written as follows:

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \quad (3.6)$$

where α_0 is the increase in the efficiency of the existing production process or in other words the efficiency change in the production process of non-innovators and it is expected to be negative in theory. The dummy variable d represents the existence or non-existence of a process innovation not associated with a product innovation and is associated with the parameter α_1 in terms of the additional efficiency effect of process innovation on the production process of old products. α_1 is expected to be negative according to the expectations of Schumpeterian growth theory. β captures the effect of relative efficiency of old and new products; it is expected to be positive according to Schumpeterian growth theory and if it is smaller than one this means that the new products are produced more efficiently.

- The problem in the equation (3.6) is that y_1 or y_2 are not directly observable. Since only the values of sales growth of old or new products are available, those values are used instead of the respective growth rates of old and new outputs. Therefore, the equation of (3.6) is rewritten as below:

$$l - g_1 = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon \quad (3.7)$$

- However, the equation (3.7) incorporates an important endogeneity problem: g_1 and g_2 include firm level price effects and unavailability of firm level prices leads to an endogeneity problem¹⁰. In order to correct for this problem, Harrison et al. (2014) proposes to deflate g_1 and g_2 with industry level prices as well as using instrumental variables which are correlated with the sales growth due to new products but uncorrelated with the firm level price change whereas Cirera and Sabetti (2019) uses only instrumental variable approach.

An additional note should be added here for how g_1 and g_2 are derived. Based on the explanation given in Harrison et al. (2014), the g_1 and g_2 are derived as follows:

$$\text{Total Sales Growth} = g = \frac{\text{Total annual sales} - \text{Total annual sales 3 years ago}}{\text{Total annual sales 3 years ago}}$$

Percentage of annual sales accounted for by new or significantly improved products $\equiv s$

Sales growth due to new products $\equiv g_2$

$$= s \left(\frac{\text{Total annual sales last year}}{\text{Total annual sales 3 years ago}} \right) = s(1 + g)$$

Nominal sales growth due to old products $\equiv \hat{g}_1$

$$\begin{aligned} &= \frac{\text{Total annual sales for old products} - \text{Total annual sales 3 years ago}}{\text{Total annual sales 3 years ago}} \\ &= \hat{g} - g_2 \end{aligned}$$

¹⁰ On the issue of this endogeneity and its implications on the interpretation of the estimation results if it remained uncorrected, refer to the details in Harrison et al. (2014).

$$\text{Real sales growth for all products} \equiv g = \hat{g} - \pi$$

$$\text{Real sales growth due to old products} \equiv g_1 = \hat{g}_1 - \pi$$

where π represents the price level. When the information on price level is not available, the instrumental variable approach is used to tackle with the endogeneity problem.

The main properties of the HJMP model is given above. Many studies discussed in Section 3.2 followed this basic approach and have added their own extensions according to the questions which they seek for an answer. Since the sample we use is the same with the one of Cirera and Sabetti (2019); we explain their estimation strategy in the following paragraph and introduce our extension to the baseline model.

Cirera and Sabetti (2019) is closely related to our study due to the fact that we use the same sample to estimate an HJMP model. They mainly introduce two important extensions to the basic HJMP model. The first one is to control for the employment effect of organizational innovation. The second extension is to control for heterogeneity at the country and industry level. They claim that unobserved heterogeneity may play a role at the country and industry level given existing technology differences. Following Rabe-Hesketh and Skrondal (2012), they include random intercepts and coefficients for different clusters defined by pairs of country and sectors and estimate a random effects model in addition to the standard OLS and 2SLS approach in the case of IV use. For further information about their estimation strategy, the reader may apply to Cirera and Sabetti (2019), pages between 3-5.

Based on the details of HJMP model above, we use the equation (3.7) mentioned above to estimate a baseline model with our data set. We use country and industry controls as in Cirera and Sabetti (2019). We collect all industries under six groups which are available in Appendix A. To account for endogeneity embedded in the sales growth due to new products, i.e. g_2 above, we use the same instrumental

variables of Cirera and Sabetti (2019) which are *whether the firm invests in R&D* and *whether the new product is completely new to the firm*. The main reason is that the WBES does not provide alternatives existing in CIS to be used as IV for g_2 .

Our main extension to the basic HJMP model is to account for the employment effect of “business obstacles” perceived by the firm. At the very beginning, we start with a baseline analysis similar to the one of Cirera and Sabetti (2019). However, we expect that business environment perceived by the firms may have an effect on the firm’s decisions about the labor demand. Therefore, controlling its effect on employment growth may result in a change in the magnitude and statistical significance of product and process innovations. With this assumption, firstly we control for the effect of “biggest obstacles to business environment” categorized in 15 different categories and see whether there is a sign of validity of our hypothesis. Then, with the information the survey provides; we control for each obstacle having an ordinal value varying from the degree of “No obstacle” to “Very severe obstacle” in five degrees in total. The separate obstacle questions are categorized under 16 categories. Having too many categories to control in the second case, we first of all conduct an *exploratory factor analysis* (EFA) for those ordinal variables of business obstacles and choose the most important variables in each factor. We conduct this EFA for the pooled cross-sectional data set covering all countries in the data set and also region by region and make the choice of variables which have the most explanatory power in each factor according to the values of *factor loadings* and *uniqueness*. Although there are similarities across regions, EFA shows that the most representative business obstacle in each factor may vary according to the geographic and economic regional characteristics.

To sum up, we start with the estimation of equation (3.7) with country-industry controls and size dummies:

$$l - g_1 = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon \quad (3.7)$$

Then we continue with the extension that business obstacle dummies with two different forms summarized above:

$$l - g_1 = \alpha_0 + \alpha_1 d + \alpha_2 OBSTACLES_i + \beta g_2 + \varepsilon \quad (3.8)$$

After explaining the HJMP model in detail, summarizing the main extensions of Cirera and Sabetti (2019) and putting forth our contribution to the model; now we can provide the estimation results in the next sub-section.

3.5. Estimation Results

3.5.1. Baseline Estimation Results

We present the estimation results through Tables (3.4) to (3.8) below. We start with the OLS estimation results as a benchmark to check how severe the endogeneity problem is by comparing OLS estimation results with the IV estimation results.

OLS estimation results show a clear pattern for the labor-saving impact of process innovation accompanied by labor-enhancing impact of product innovation for the pooled sample as well as three out of four regional decompositions. Only in MENA region, we do see a statistically significant coefficient for process innovation even though the product innovation has a clear labor-enhancing impact in that region too. However, since we have not controlled for the endogeneity problem embedded in the nominal sales growth, these outcomes should be interpreted cautiously.

Following Cirera and Sabetti (2019), we use indicators *whether the new product is completely new to the firm* and *whether firms invest in R&D* as instruments for the explanatory variable *sales growth due to new products*. We present the results of 2SLS estimation in Table 3.5. The estimation results on Table 3.5 reveals more reasonable results with respect to the theoretical expectations of the HJMP model. As explained in Section 3.4 in detail, α_0 represents the efficiency change in the production process of non-innovators; α_1 represents the additional efficiency effect of process innovation on the production process of old products; β captures the effect of relative efficiency of old and new products, is expected to be positive and if it is smaller than one this indicates that the new products are produced more efficiently in equation (3.6). Keeping in mind those intuitions, we interpret the results on Table (3.4) as follows:

The column (1) represents the estimation results for the pooled sample. The constant term has a negative and statistically significant coefficient, indicating that there exists a general efficiency increase in the production process of non-innovators. The coefficient of the variable *process innovation only* (α_1) is also negative and statistically significant at 1 percent level indicating an approximate 9.8 percent decrease in employment level. The coefficient of *sales growth in new products* (β) points to a positive employment outcome for the product innovation. Moreover, its magnitude indicates to the existence of a slightly larger efficiency in producing new products. All in all, the estimation results of the pooled sample are consistent with the expectations of Schumpeterian growth theory.

On the other hand, the estimation results according to the regional decomposition through the columns (2) to (5) reveal an important fact that although the employment impact of product innovation seems to be more robust in different regions whereas the employment impact of process innovation is not so. Only the estimations for Africa give a labor-saving outcome of process innovation whereas the estimations for other regions reveal that process innovation has no impact on labor demand at the firm level. The product innovation, on the other hand, is still labor enhancing in all regions, only different outcomes appear in terms of the relative efficiency in the production of old products to new products. In Africa, the relative efficiency in producing new products is higher with respect to the other regions; in South Asia the magnitude of the coefficient of the variable *sales growth in new products* signs to an almost equal efficiency in producing old and new products since it is very close to 1; in ECA, the relative efficiency in producing new products does also not much differ from the one in old products. The divergent result in terms of product innovation comes from MENA region where the coefficient of the variable *sales growth in new products* signs to the fact that the old products are produced more efficiently than new products even though the product innovation still enhances labor at the firm level. It is important to return to the sample description and some basic statistics given on Tables 3.1 and 3.2, respectively at this point. As shown on Table 3.1, the ratio of *only process innovation* is highest in South Asia and Africa regions whereas in ECA and MENA it is relatively low. The same picture is the same for the product innovation, i.e., the product innovativeness is also higher in those regions. However,

in Africa, the ratio of product innovators among the group of innovators is far less than the ratio of the (only) process innovators. This may be one the reason that the labor-saving outcome of process innovation is more visible in Africa. On the other hand, even though the process innovators form the 52 percent of the sample, the ratio of product innovators exceed the (only) process innovators by a few percentage point which may be the cause of the employment impact of process innovation less visible in South Asia. Moreover, when we look at the average employment growth levels in the sample, we had mentioned that Africa is the only region witnessing higher employment growth in non-innovator firms with respect to the ones which are (only) process innovators or product innovators. Finally, MENA have already witnessed low employment growth in the time period concerned in general and a fall in the average employment levels of the non-innovators. In conclusion, the results make sense in terms of both the intuitions of the HJMP model and the data properties.

As a final note for this subsection, Table 3.6 shows the first step estimation results of 2SLS regressions reported on Table 3.5. The values on Table 3.6 confirms the validity and strength of instrumental variables, i. e., whether the new product is completely new to the firm and whether the firm invests in R&D.

3.5.2. Extension: Controlling for the Employment Impact of Business Obstacles

We have mentioned before that our main contribution to the work of Cirera and Sabetti (2019) is to control for *business obstacles perceived by the firms*. With the hypothesis that business obstacles perceived by the firms may be an explanatory variable of labor demand at the firm level, we control those variables to see whether the estimation results change or not. We start by including the “biggest obstacle” category into the estimations in the first place. In the ES data, the question below asks the biggest (or the most important) business obstacle for the establishment:

Which of the elements of the business environment included in the list, if any, currently represents the biggest obstacle faced by this establishment?

1-Access to finance

2-Access to land

- 3-Business licensing and permits
- 4-Corruption
- 5-Courts
- 6-Crime, theft and disorder
- 7-Customs and trade regulations
- 8-Electricity
- 9-Inadequately educated workforce
- 10-Labor regulations
- 11-Political instability
- 12-Practices of competitors in the informal sector
- 13-Tax administration
- 14-Tax rates
- 15-Transport

In order to decide which ones of those fifteen categories should be chosen, we conduct a PCA for those binary variables to see which ones explain the correlation most. However, PCA analysis shows that those fifteen binary variables almost evenly contribute to the cumulative correlation. Therefore, by choosing the base category as *business licensing and permits*, we re-conduct the previous estimations reported on Table 3.5 and report the new results on Table 3.7.

If we start with the constant term representing efficiency change in the production process of non-innovators (α_0); it loses its statistical significance in all specifications including OLS estimation. Therefore, when we control for *perceived business obstacles*, there is no evidence for the expected general increase in production efficiency of Schumpeterian growth theory. On the other hand, the statistical significance of the employment outcome of process innovation increases especially on regional base whereas both the statistical significance and magnitude fall in the pooled estimation with respect to the results provided on Table 3.5. On the other hand, however, the labor-saving outcome of process innovation still prevails in Africa and in addition the employment impact of process innovation gains statistical significance in MENA and South Asia. In MENA region, we see a positive employment impact of process innovation which is a contradictory result with

Schumpeterian growth theory. In South Asia, the process innovation has a labor-saving impact. As far as the employment impact of product innovation is concerned in the extended estimations, the results reveal not much change for the effect of product innovation except for Africa region. The relative efficiency in producing new products has increased significantly in terms of its magnitude (due to the fact that the value of the coefficient decreases from 0.838 to 0.598) in Africa. In other regions, we see that the employment impact of product innovation does not much differ from the previous results on Table 3.5.

Another model specification and estimation with the business obstacles controlled is conducted by using the separate questions for each obstacle category asked in the survey. In the survey, there is a question structure for sixteen categories of business obstacle as below:

To what degree is ... an obstacle to the current operations of this establishment?

<i>No obstacle</i>	<i>0</i>
<i>Minor obstacle</i>	<i>1</i>
<i>Moderate obstacle</i>	<i>2</i>
<i>Major obstacle</i>	<i>3</i>
<i>Very severe obstacle</i>	<i>4</i>

where “...” in the question above is filled by the following sixteen categories:

1-Access to finance

2-Access to land

3-Business licensing and permits

4-Corruption

5-Courts

6-Crime, theft and disorder

7-Customs and trade regulations

8-Electricity

9-Telecommunication

- 10-Inadequately educated workforce
- 11-Labor regulations
- 12-Political instability
- 13-Practices of competitors in the informal sector
- 14-Tax administration
- 15-Tax rates
- 16-Transport

As can be seen clearly, the question is in an ordinal structure and therefore, for the sixteen variables with five categories in an ordinal manner does not allow to apply PCA in this case. Therefore, we conduct EFA to see which business obstacles represent each factor the most and the factor number is determined according to the eigenvalues which are greater than zero.

It is appropriate to begin with a general definition of EFA. As explained in Norris and Lecavalier (2010), in multivariate statistics, exploratory factor analysis is defined as a statistical method which is used to explore the underlying relationship between measured variables. The researcher has no a priori knowledge about those relationships between the variables and therefore there is no a priori theoretical assumption when conducting EFA. However, it is important to mention here that EFA is a kind of statistical analysis method which has no standard and unique decision or practice mechanism. The studies Gaskin and Happell (2014) and Howard (2016) are the review papers discussing the alternative methods and decision mechanisms used in EFA. For the further discussion, the reader may apply to those studies.

We continue as follows: We apply EFA for the pooled sample and the four regions. We choose the Principal Axis Factoring (PAF) method as factor analytic method with *oblimin* rotation which allows the resultant rotating factors to be correlated. We use PAF as factor analytic method since we do not have any distributional assumption for the factors and *oblimin* as a rotation method seems more reasonable in our case since we do not have any reason to assume that our factors are orthogonal; on the contrary, the factors are most probably correlated with each

other¹¹. After conducting EFA with PAF method and *oblimin* rotation, we choose the most representative variable in each factor by looking at the values in the factor loading matrix for each sample. There are seven factors according to the EFA on regional base analyses but six factors in the pooled sample. We choose the most representative variable in each factor although some factors have no representative variable in South Asia and ECA region.

The most representative variables in each factor are listed below:

- **The pooled sample:** Corruption, telecommunication, tax rates, access to finance, labor regulations, customs and trade regulations.
- **Africa:** Tax administration, labor regulations, access to finance, political instability, courts, customs and trade regulations, telecommunication.
- **South Asia:** Tax rates, courts, inadequately educated labor force, labor regulations, access to finance, electricity.
- **ECA:** Telecommunication, political instability, tax administration, labor regulations, customs and trade regulations.
- **MENA:** Corruption, tax administration, telecommunication, access to land, customs and trade regulations.

Finally, we re-conduct the estimations on Table 3.7 and provide the results on Table 3.8¹². However, not all of the representative variables have a meaningful effect on labor demand according to the estimations provided on Table 3.8.

The estimation results on the pooled regression reveal that only labor regulations and customs and trade regulations have a significant impact on labor demand. On the other hand, the labor-saving outcome of process innovation is statistically significant at 1 percent level, product innovation still preserves its labor-enhancing outcome with an indication that the efficiency in producing new products is slightly higher

¹¹ See Howard (2016) for further discussion about the factor analytic and factor rotation methods.

¹² We provide the EFA results of the pooled example in Appendix D as an example of the analysis. The EFA is conducted by using the program Jamovi.

than the efficiency in producing old products as before. A general efficiency increase in the production process of non-innovators reveals itself in the negative and statistically significant constant term. The coefficient of process innovation and the constant term together indicates a general efficiency increase in all production processes leading to a labor-saving outcome. The columns through (2) to (5) on Table 3.8 show the estimation results for Africa, South Asia, ECA and MENA respectively. Africa has again confirmed the labor-saving outcome of process innovation and the magnitude of the coefficient shows that 1 percentage efficiency increase due to process innovation leads to 30 percent of employment decrease at the firm level approximately. The product innovation preserves its statistical significance at 1 percent level but we see that according to the factors controlled the magnitude of the coefficient of product innovation (i.e. *sales growth due to new products*) can change significantly. In this case, the relative efficiency of producing new products with respect to old products show a similar outcome with the pooled sample or South Asia and ECA estimation results. We see that MENA region still do not show any kind of efficiency increase – either in producing old products or new products – as well as any significant employment impact of process innovation on employment level; only product innovation leads to employment increase. As in the previous results for MENA, the results for product innovation diverges in the sense that new products are less efficiently produced than new ones. Finally, for MENA region, the business obstacle categories of *access to land* and *customs and trade regulations* show meaningful impact on labor demand. A surprising result is that the labor-saving outcome of process innovation in South Asia which has emerged when the *biggest business obstacles* are controlled vanishes in this case even though the efficiency increase in production processes of non-innovators still persists. In South Asia, the only business obstacle category which has a meaningful impact on labor demand is the obstacle category of *inadequately educated labor force*. The product innovation in South Asia shows a consistent estimation result with the previous cases. Another surprising result emerges for ECA region. After controlling for the business obstacles chosen according to EFA, we see that the labor-saving outcome of process innovation gains statistical significance at 10 percent level whereas the result for the product innovation is almost the same with previous results. The only significant obstacle for ECA region is *labor regulations*.

All in all, our extensions to the baseline model put forth some important results. First of all, for the pooled sample, there is a strong evidence that process innovation has a labor-saving impact in developing countries whereas the compensation mechanism through product innovation seems robust not only in the pooled sample but also in all regional specifications. However, the labor-saving nature of process innovation observed in the overall sample is mostly due to Africa effect in the pooled estimation. Secondly, as hypothesized at the beginning, the perception of business environment may have a significant effect on firm-level employment and therefore if it is not controlled, especially the employment impact of process innovation may be masked and seems to be statistically insignificant in a misleading way.

Thirdly, determining the latent factors and controlling for business obstacles which are most representative in each factor through EFA is important to account for the potential multicollinearity among the obstacles and paves statistically a more robust way of controlling business environment characteristics that may differ according to different regions although it does not totally alleviate the potential other endogeneity problems that may exist in terms of firms' perception of business environment. Fourth, controlling for business obstacles on regional base has made visible the labor-saving impact of process innovation on various regions to some extent. Africa is the only region showing labor-saving impact of process innovation among the others whereas the results differ in ECA and South Asia although the possibility of labor-saving impact cannot be ignored completely.

Finally, in terms of product innovation, we see that the labor enhancing effect of product innovation is robust under various specifications or in different regions. In terms of the relative efficiency of producing old and new products, we see that in the pooled sample and three of four regions (except MENA), new products are produced more efficiently than the old products. Only in MENA, the relative efficiency of producing new products is less than the one of old products. This result is expected in the sense that for the time period concerned, there is no significant sign of efficiency increase in MENA due to either innovativeness or non-innovativeness and sales and employment growth is lowest with respect to other regions.

3.6. Conclusion

In this essay, we have tried to answer the same old question that whether technological innovation has an effect on labor demand or not at the firm level but with a special emphasis on developing countries. To answer that question, we have used a unique and comprehensive data set for 53 developing countries based on WBES and its linked Innovation modules conducted during the years 2013 and 2014 and applied HJMP model proposed in the paper Harrison et al. (2014). Expecting that business environment “perceived” by the firms may have an effect on employment growth at the firm level, we have conducted an empirical analysis similar to the one of Cirera and Sabetti (2019) on the baseline but with an extension of controlling *perceived business obstacles* to provide an evidence that dissociating the employment impact of *perceived business obstacles* may improve the estimation results of HJMP model.

Our analyses reveal that the process innovation has a labor-saving impact on employment at the firm level for the pooled sample and only for Africa region according to the baseline specification of the HJMP model with IV estimation. On the other hand, controlling for the *biggest business obstacles* has pointed to a possibility that process innovation may have actually a labor-saving impact on employment although the evidence is relatively weak.

To investigate this relationship deeper, we have conducted an EFA to determine the factors and the most explanatory variables in each factor without imposing a priori hypothesis about the relationship between the business obstacle variables. After determining the most representative variables in each factor we have re-estimated the HJMP model with IV and shown that controlling for the *perceived business obstacles* have improved the estimation results and given a signal for the existence of labor-saving impact of process innovation. Perceived business obstacles do not make any difference in terms of the employment outcome of product innovation, only in Africa the magnitude of the coefficient of the variable *sales growth in new products* points to the fact that the relative efficiency of producing new products with respect to the one in old products is vulnerable to alternative specification. In Africa, the evidence

is strong in the sense that process innovation has saved labor during the time period studied. MENA, on the other hand, has not shown any signal of efficiency improvement in any way.

Table 3. 4. Effects of innovation on employment (OLS), all countries and by region

Dependent variable: Net labor growth (the labor growth minus sales growth due to old products)

	All Countries	By region			
	(1)	Africa (2)	South Asia (3)	ECA (4)	MENA (5)
Process innovation only	-0.202*** (0.034)	-0.438*** (0.126)	-0.123*** (0.022)	-0.118** (0.043)	0.038 (0.042)
Sales growth in new products	0.339*** (0.057)	-0.013 (0.096)	0.719*** (0.036)	0.306** (0.130)	0.825*** (0.073)
Size 20-99 (medium)	0.012 (0.020)	-0.081 (0.119)	0.033* (0.019)	0.033 (0.025)	-0.016 (0.029)
Size 100 and over (large)	0.054** (0.024)	0.141 (0.158)	0.029 (0.023)	0.080** (0.038)	-0.010 (0.039)
Constant	-0.852*** (0.329)	-0.693** (0.330)	0.015 (0.034)	0.046 (0.098)	0.020 (0.104)
N	17,985	2,360	3,692	8,330	3,603
R ²	0.0856	0.0902	0.3112	0.0550	0.0483

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors. All regressions include country-industry ummies.

Table 3. 5. Effects of Innovation on employment (IV), all countries and by region

Dependent variable: Net labor growth (the labor growth minus sales growth due to old products)

	All Countries (1)	By region			
		Africa (2)	South Asia (3)	ECA (3)	MENA (4)
Process innovation only	-0.098*** (0.036)	-0.315** (0.136)	-0.038 (0.025)	-0.066 (0.042)	0.044 (0.042)
Sales growth in new products	0.928*** (0.059)	0.838*** (0.221)	0.96*** (0.044)	0.911*** (0.117)	1.084*** (0.207)
Size 20-99 (medium)	0.017 (0.020)	-0.047 (0.119)	0.029 (0.018)	0.04 (0.025)	-0.021 (0.028)
Size 100 and over (large)	0.034 (0.024)	0.178 (0.159)	0.017 (0.023)	0.045 (0.038)	-0.021 (0.039)
Constant	-0.949*** (0.330)	-0.831** (0.328)	-0.085** (0.038)	0.059 (0.099)	0.017 (0.103)
N	17,863	2,351	3,682	8,246	3,584
R ²	0.0640	0.0613	0.29	0.0311	0.0461

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors. IV is an indicator whether the new product is completely new to the firm and whether firms invest in R&D.

Table 3. 6. First Step Regression Summary Statistics for 2SLS Estimation reported on Table 3.4

Explanatory variables: Whether the new product is completely new to the firm and whether firms invest in R&D

	All Countries (1)	By region			
		Africa (2)	South Asia (3)	ECA (3)	MENA (4)
R-squared	0.3097	0.1606	0.4847	0.1952	0.2905
Adjusted R-squared	0.2977	0.1364	0.4845	0.1775	0.2802
Partial R-squared	0.1861	0.1133	0.3510	0.1339	0.2673
F-value	F(2, 17557) =569.422	F(2,2284) =47.4755	F(2,3658) =1268.01	F(2, 8068) =152.887	F(2,3532) =21.6605
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000

Dependent Variable: Sales growth in new products. The explanatory variables are whether the new product is completely new to the firm and whether firms invest in R&D.

The findings put forth some important implications. First of all, no matter which location is the focus of the empirical study or factors controlled, the product innovation creates labor at the firm level. Secondly, the employment impact of process innovation is not so robust being compatible with most of the previous findings in the literature. On the other hand, we have evidence to some degree that process innovation may be labor-saving in developing countries noting the importance of finding and controlling the factors having an effect on employment. Some factors which have an effect on labor demand in developing countries may mask or absorb the effect of process innovation on employment at the firm level.

The results imply some important clues for the further research. The HJMP model may have a potential to shed light on the employment impact of technological innovation in developing countries. Although the national innovation surveys have become more common and repeatedly conducted for the last decades, comparable data sets across countries are not so much available. Therefore, the data collection consistent across countries is important to make comparable analyses. Moreover, the exact time of process innovation during the three-year time period would improve the estimation results by adding some sort of dynamic aspect to the HJPM model which actually is a static short run effect model. Innovation surveys had better to include such kind of information.

Table 3. 7. Effects of Innovation on employment when business obstacles controlled (IV), all countries and by region

Dependent variable: Net labor growth (the labor growth minus sales growth due to old products)

	All Countries (1)	By region			
		Africa (2)	South Asia (3)	ECA (4)	MENA (5)
Process innovation only	-0.049* (0.062)	-0.168** (0.078)	-0.063* (0.032)	-0.048 (0.049)	0.069* (0.038)
Sales growth in new products	0.875*** (0.064)	0.598*** (0.186)	0.898*** (0.053)	0.929*** (0.133)	1.092*** (0.208)
Size 20-99 (medium)	0.003 (0.018)	-0.141* (0.076)	0.032 (0.020)	0.043 (0.029)	-0.018 (0.029)
Size 100 and over (large)	0.019 (0.023)	-0.032 (0.097)	0.036 (0.026)	0.048 (0.044)	-0.016 (0.040)
Access to finance	0.048 (0.051)	0.157 (0.314)	-0.124* (0.065)	0.005 (0.078)	0.214*** (0.08)
Access to land	0.028 (0.064)	0.273 (0.324)	-0.175** (0.070)	-0.041 (0.107)	0.162 (0.116)
Business licensing and permits [base category]	-	-	-	-	-
Corruption	0.079 (0.050)	0.371 (0.319)	-0.164*** (0.063)	0.086 (0.082)	0.125 (0.079)
Courts	0.045 (0.078)	0.267 (0.350)	-0.125* (0.068)	0.070 (0.101)	-0.227 (0.391)
Crime, theft and disorder	-0.013 (0.088)	0.384 (0.334)	-0.201** (0.094)	0.022 (0.091)	-0.150 (0.215)
Customs and trade regulations	-0.057 (0.083)	0.316 (0.331)	-0.203*** (0.072)	-0.243 (0.162)	0.098 (0.098)
Electricity	0.082 (0.054)	0.267 (0.324)	0.112* (0.066)	0.060 (0.095)	0.166** (0.079)
Inadequately educated labor force	0.017 (0.053)	0.154 (0.462)	-0.186*** (0.066)	-0.017 (0.081)	0.116* (0.067)
Labor regulations	0.026 (0.062)	0.398 (0.412)	-0.140** (0.065)	-0.053 (0.111)	0.091 (0.135)
Political instability	0.044 (0.049)	0.103 (0.334)	-0.110 (0.081)	0.004 (0.080)	0.147** (0.063)
Informal sector	0.045 (0.053)	0.157 (0.324)	-0.110* (0.063)	0.024 (0.082)	0.135* (0.067)
Tax administration	0.016 (0.076)	0.111 (0.511)	-0.293*** (0.092)	0.045 (0.094)	0.074 (0.122)
Tax rates	0.036 (0.049)	0.218 (0.327)	-0.129** (0.063)	-0.004 (0.074)	0.138** (0.069)
Transport	0.033 (0.062)	0.232 (0.405)	-0.178* (0.100)	0.035 (0.085)	-0.019 (0.118)
Constant	-0.107 (0.141)	0.798 (0.517)	0.103 (0.071)	0.045 (0.125)	-0.126 (0.121)
N	13,710	1,599	2,395	6,259	3,457
R ²	0.0602	0.0821	0.2986	0.0300	0.0548

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors. IV is an indicator whether the new product is completely new to the firm and whether firms invest in R&D.

Table 3. 8. Effects of Innovation on employment when business obstacles controlled according to EFA (IV), all countries and by region

Dependent variable: Net labor growth (the labor growth minus sales growth due to old products)

	All Countries (1)	By region			
		Africa (2)	South Asia (3)	ECA (4)	MENA (5)
Process innovation only	-0.108*** (0.039)	-0.293** (0.149)	-0.039 (0.027)	-0.086* (0.046)	0.011 (0.045)
Sales growth in new products	0.912*** (0.065)	0.913*** (0.255)	0.968*** (0.046)	0.912*** (0.134)	1.112*** (0.213)
Size 20-99 (medium)	0.032 (0.022)	-0.030 (0.133)	0.036* (0.020)	0.052 (0.028)	-0.007 (0.027)
Size 100 and over (large)	0.037 (0.026)	0.289 (0.179)	0.021 (0.024)	0.027 (0.042)	-0.017 (0.042)
Access to finance	0.029 (0.022)	0.150 (0.131)	0.013 (0.018)	-	-
Access to land	-	-	-	-	0.091*** (0.034)
Business licensing and permits	-	-	-	-	-
Corruption	0.022 (0.022)	-	-	-	0.009 (0.031)
Courts	-	-0.422*** (0.133)	-0.003 (0.019)	-	-
Crime, theft and disorder	-	-	-	-	-
Customs and trade regulations	-0.090*** (0.028)	-0.311** (0.125)	-	-0.052 (0.037)	-0.073** (0.035)
Electricity	-	-	0.001 (0.016)	-	-
Inadequately educated labor force	-	-	-0.038** (0.018)	-	-
Labor regulations	0.059** (0.025)	0.139 (0.123)	0.017 (0.020)	0.094*** (0.035)	0.020 (0.034)
Political instability	-	0.251** (0.122)	-	-0.006 (0.028)	-
Informal sector	-	-	-	-	-
Tax administration	-	0.160 (0.113)	-	-0.010 (0.028)	-0.035 (0.031)
Tax rates	0.001 (0.020)	-	0.017 (0.018)	-	-
Telecommunication	0.004 (0.030)	0.069 (0.127)	-	-0.008 (0.034)	-0.059 (0.041)
Transport	-	-	-	-	-
Constant	-1.017*** (0.369)	-1.058*** (0.393)	-0.097** (0.043)	0.039 (0.107)	0.086 (0.113)
N	15,491	2,064	3,484	7,069	2,990
R ²	0.0664	0.0713	0.2889	0.0228	0.0529

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors. IV is an indicator whether the new product is completely new to the firm and whether firms invest in R&D.

In addition, some other factors like being an exporter, having a foreign ownership of the firm, the skill composition of the firm before the emergence of process innovation or the degree of integration into the global value chain may be important factors in the divergence of the results of employment impact of technological innovation. The WBES data and its linked Innovation Modules lack of information especially on the skill composition of the firms at the beginning of the time period concerned and the exact time of product or process innovation.



CHAPTER 4

THE EMPLOYMENT IMPACT OF TECHNOLOGICAL INNOVATION PRECEDING AN ECONOMIC SHOCK: AN EMPIRICAL ANALYSIS WITH REFERENCE TO COVID-19 PANDEMIC

4.1. Introduction

Beginning with the first case identified in the State of Wuhan, China in December 2019, the world encountered a global pandemic named as COVID-19 turning into a health crisis in a few months by spreading to all over around the world. To cope with this health crisis and minimize the deaths as much as possible, the governments all around the world started to take extreme measures not seen before in any case. Therefore, the health crisis turned into an economic and social crisis from many aspects. Lockdowns, mandated closures of workplace and businesses, social distancing, stay-at-home campaigns transformed economic and social life with an unprecedented speed. The extraordinary measures taken against the Pandemic endured for almost two years with profound effects on societies, economies and human life.

According to World Development Report (WB, 2022), the economic impact of the pandemic had been unequal within and between countries. In terms of within country inequalities, the disadvantaged groups were hit by the crisis disproportionately. Less-educated workers were affected harder from temporary unemployment in 2020 (Kugler et al., 2021). Bundervoet et al. (2021) reveals that young people, women, self-employed and casual workers had encountered more severe income losses. Women also were hit harder by the Pandemic due to the fact that both they had been more likely to work in the jobs affected more by the closures and social distancing and they had to undertake family care responsibilities with the closure of schools or

nurseries. According to the World Development Report (WB, 2022), high-frequency phone survey data conducted by WB show that during the period starting from the onset of Pandemic to July 2020, 42 percent of women lost their jobs while this ratio is 31 percent for men pointing the unbalanced gender impact of the Pandemic.

A similar unbalanced pattern emerges also between advanced and emerging economies (Adams-Prassl et al., 2020; Chetty et al., 2020; Crossley et al., 2021). Within-country inequality had gotten worse in emerging economies and the initial gap in job losses did not recover immediately after the relaxation of extreme measures especially for disadvantaged groups in emerging countries (Agrawal et al., 2021). The severity of the disparities between advanced and emerging economies also need to be paid attention since in many emerging economies informal economy forms a significant percentage of GDP; to illustrate, it is estimated that informal economy is responsible from 34 percent of GDP in Latin America and Sub-Saharan Africa or 28 percent in South Asia (Medina and Schneider, 2019).

Another important outcome of the Pandemic was the deterioration of global inequality and poverty. Mahler et al. (2022) tries to estimate the impact of Pandemic on global inequality and poverty and puts forth striking results. According to Mahler et al. (2022), the global Gini index increased by 0.7 point and pushed 90 million people into extreme poverty living with a daily income below \$2.15 per capita. This effect is the net impact of the Pandemic; the observed increase in the global Gini index from the year 2019 to 2020 is 0.5 Gini points and the number of people who started to live in extreme poverty increased by 71 million. However, if the Pandemic had not occurred, the global Gini index would have decreased by 0.2 point and 19 million people might move out extreme poverty. Therefore, the net impact is the sum of those (Mahler et al., 2022, pg. 3).

Putting this very broad picture into the background, we return to our main question to be answered in this essay of the Thesis which is “how does technological innovation emerging before an economic shock affect the labor demand during that shock?” The motivation of this question relies on studies examining the role of innovation on labor demand during bad times. For example, the papers Dachs et al.

(2017b) and Arenas Diaz et al. (2020) which are discussed in Section 3.2 put forth some important results on employment outcome of innovation during downturns of business cycles or crisis periods. Those studies demonstrate that innovative firms are more successful in preserving their employment during bad times when compared to the non-innovative ones. With this background information from the literature, this essay is motivated to focus on the firm level employment impact of technological innovation that occurred before an economic shock during that economic shock with a special reference to COVID-19 period. As the most recent and worldwide health, social and economic crisis, COVID-19 Pandemic period provides a unique opportunity to investigate this question.

WBES Unit has started to conduct Follow Up Surveys as a continuation of the last Enterprise Surveys immediately after the Pandemic starts to appear in countries. COVID-19, as its case numbers fluctuated by hitting some peak points and then starting to decelerate, had subsisted for approximately four waves almost in all countries. The WBES Unit had also conducted Follow Up Surveys in parallel timing to those waves in the subject countries; however, not the same number of surveys had been conducted in all countries. For over 40 countries, the Follow Up Survey data exists at least for one round, i.e. the first round of COVID-19. The second and third rounds diminish in numbers. Fourth round survey data exists for only a few countries. In this essay, we use the WBES baseline surveys and Round 1 Follow Up Surveys to investigate the effect of a pre-Pandemic product or process innovation on employment which constitutes a sample of over 20,000 observations covering 37 countries. The data set provides an opportunity for researchers to compare and contrast the firms' pre-Pandemic situations and during-Pandemic performances in various ways.

In the remaining part of this Chapter, the essay is structured as follows. Section 4.2 introduces the literature narrowed down to the COVID-19 impact on labor markets both from supply side or demand side. Section 4.3 introduces general properties of data, follow up survey structure and some descriptive statistics of the sample. Section 4.4 explains our methodological approach. Section 4.5 presents estimation results and discusses the implications of main findings. Finally, Section 4.6 concludes.

4.2. Literature Review

The labor market impacts of COVID-19 from both demand side and supply side have been wondered and started to be studied immediately especially with the availability of micro data collected through household or firm level surveys conducted in different phases of COVID-19.

After going over the literature on the relationship between innovation and employment in previous chapters from various aspects, we narrow down this literature review to studies elaborating on labor market impacts of COVID-19 in parallel to the main motivation of this essay.

As mentioned before, COVID-19 has exacerbated inequalities between advantageous and disadvantageous social groups, advanced and emerging economies, males and females, SMEs and large firms etc. (WB, 2022). It has made a deep and even irreversible impact on labor market from some aspects since new concepts has entered into labor market such as remote-work and digital adoption and/or digitalization has accelerated in businesses to cope with the restrictions related to the Pandemic.

Bartik et al. (2020) conducts a self-designed survey to American small businesses and analyze the effects of Pandemic on those businesses. They find that small businesses have been more affected by the Pandemic through many aspects. In labor market terms, their results reveal that even in the early periods of Pandemic, the damage has been extreme to small businesses. 43 percent of businesses across their sample have temporarily closed and nearly all of these closures are due to Pandemic and temporarily closed businesses reveal that the main reasons of their closure are the reduction in demand or health concerns in the business environment whereas the supply chain disruptions have been relatively less important. On the other hand, 40 percent of the businesses have reduced their employment since the beginning of Pandemic. Impacts vary across regions and industries. The businesses especially specializing in face-to-face services seemed to be more vulnerable to the Pandemic.

Couch et al. (2020) studies the impact of COVID-19 on unemployment rates among different ethnic groups in America and reveals that the racial gap in in the United States, especially between African-Americans and Whites have been expanded. Those effects may also have long term implications regarding the amount of earnings lost and wealth distribution among different ethnic groups. A similar study about the distributional consequences of the COVID-19 on employment has been conducted by Cortes and Forsythe (2022). The paper also points to the exacerbation of pre-existing inequalities and finds that Hispanic and non-White workers have faced more severe results and the probability of job loss has increased disproportionately for them.

Another study focusing on short-term impacts of COVID-19 on businesses including labor outcomes especially in developing economies is Apedo-Amah et al. (2020). The paper examines the effects of COVID on businesses from various aspects. The study covers more than 100,000 businesses from 51 developing countries with a data set obtained from various sources. The main findings point to severe and persistent decline in sales, smaller firms struggle with financial constraints more and relying on digital solutions to cope with the Pandemic have increased. On the labor terms, the employment outcome of Pandemic has been mostly on intensive margin not on extensive margin, i.e., most of the firms have preferred granted leave and reduction in working hours or wages whereas a small part of the firms have resorted to layoffs. According to their calculations, 57 percent of the firms in the sample adjusted their employment levels on the intensive margin, 12 percent on both intensive and extensive margin and 7 percent only on the extensive margin. Moreover, firms experiencing larger sales loss have also encountered larger reduction in their employment level.

Brynjolfsson et al. (2020) also studies the transformation in ways that people work with the onset of the Pandemic. The authors conduct a Google Consumer Surveys (GCS) for two consecutive waves to see how people respond to Pandemic with a very simple question structure across the states in the USA. In the first wave, they ask the question “Have you started to work from home in the last four weeks?” with the following response options:

1. “I continue to commute to work”
2. “I have recently been furloughed or laid-off”
3. “Used to commute, now work from home”
4. “Used to work from home still do”
5. “Used to work from home, but now I commute”
6. “None of the above/Not working for pay”

In the second wave, they have modified the question sentence as the following: “Have you started to work from home in the last 2 months?”. In both waves, 25,000 responses have been collected approximately from various states. By analyzing the survey data collected, the authors reach to those main findings: Across two waves of the survey, 1 out of 3 workers shifted to remote work while 10 percent of the workers were laid-off or furloughed. The share of people who have switched to remote work or the share of those who have continued to commute differ in states which is closely related to the sectoral composition of states. The young people have been more likely to shifting to remote-work with respect to older people and finally, the surveys reveal that most part of the transformation has occurred in the first wave which implies that the transformation has manifested itself immediately after COVID-19 have popped up. The States having business branches more concentrated in management, professional and related occupations have more flexibility to reorganize their business processes for remote work and therefore in those states there is a sign of employment persistence and fewer job losses. The paper emphasizes that the changes enforced by the Pandemic may have enduring effects on the organization of the work if especially firms can reorganize themselves and people adapt to new ways of working. This should be monitored in the future.

Beland et al. (2023) searches for the determinants of the outcomes of COVID-19 on employment and wages in the US with an attention to the possibility of more severe effects on certain occupations by constructing four indexes which are workers relatively more prone to disease, workers more dependent on co-workers; essential/critical workers and workers who are more suitable for remote-work. Their analysis reveal heterogeneous effects of COVID-19 across different professions and different types of workers according to their four main classifications of worker type

as mentioned. Firstly, they find that individuals who are more suitable to remote-work and essential workers are relatively less affected by the negative consequences of the Pandemic. Secondly, they put forth a key occupational task factor, which is “proximity to other workers”, explaining the broad effects of COVID-19 in labor markets since the workers in this category are seemed to more prone to the risk of job loss. Thirdly, job loss is less common in health related sectors and labor market effects are more severe in regions where there are seen larger number of cases and deaths.

One of the most important studies examining the inequality in the impact of COVID shock in the labor markets is the one of Adam-Prassl et al. (2020). The paper uses a real-time survey data collected as part of the COVID Inequality Project and conducted in the US, UK and Germany in March and April 2020 and analyzes the supply-side labor market impact of the Pandemic. They especially decompose the worker groups according to which kinds of workers face more risk of losing their jobs, of being furloughed or put on short-time work, of reducing their working hours and experiencing a decrease in earnings. They also dissociate cross-country differences and gender outcomes. Their results reveal that COVID-19 shock has unequal effects both within and across countries from various aspects. Firstly, they find that cross-country differences are significant in the sense of job loss; i.e., with a value of loss at 20 percent and 17 percent for the US and UK respectively, whereas this ratio is only 5 percent in Germany at the early arrival of the Pandemic. This underlines the importance of established properties of labor markets in different countries or policies implemented (or extended) during an economic shock since for example, this much less job loss may owe itself to the well-established short-time work (STW) scheme applied in Germany. Secondly, in all three countries, the job and worker characteristics lead to large within country differences; for example, the jobs more suitable to remote work or the workers who have a job with a high share of tasks that can be conducted from home have been at less risk of losing their jobs. Moreover, their estimations for job loss probabilities across countries reveal that the percentage of tasks workers can do from home is the most significant predictor of job loss when compared to other determinants such as industry, occupation or other job characteristics. In all three countries, permanent employees have been at much less

risk of losing job compared to temporary counterparts. On the gender and education side, the results reveal that there have been important differences between men and women and also having a university degree or not. Women and employees who do not have a university degree face a greater risk of losing job. The most remarkable fact revealing itself is the fact that the share of tasks which can be done from home and occupation fixed effects are able to account for the gap between educated and non-educated workers whereas the case is not so for the gender gap. The case for gender gap is also striking in the sense that most of the literature points to more job loss for men in usual recessions and also German case is different since gender factor or factor of having a college degree is not statistically significant for the prediction of job loss. The paper is important in the sense that even in advanced economies the labor market outcomes of COVID-19 Pandemic differs significantly which points to the significance of institutional differences or policy choices and it draws a general picture for the importance of job characteristics, gender and education in the prediction of job losses.

Albanesi and Kim (2021) have studied the gender effects of COVID-19, and similar to Adam-Prassl et al. (2020), the paper finds that women has lost their jobs with respect to men when compared with the previous four business cycles. The reason for this outcome is that the patterns of employment existing in the Pandemic period is not the same as the patterns existing in the previous business cycles both from the supply side and the demand side. The demand-side difference comes from the fact that women are more concentrated in services sector in general whereas men are more concentrated in the production sector which causes to more job losses for men during downturns in normal business cycle times since services sectors are less cyclical; however, in Pandemic, there has been a sharp decrease for services both due to health concerns and mandated measures by governments. On the supply side, the main asymmetry comes from the fact that during downturns, women in general try to save their jobs for the family maintenance and reduce the income loss risk; however, during the Pandemic period, the sharp reduction in childcare opportunities and mandated closure of face-to-face education in schools have led women to carry the burden of childcare.

Reichelt et al. (2021) also draws attention to the gender inequality due to the Pandemic as well as the changes in gender-role attitudes by analyzing a representative sample constructed from the US, Germany and Singapore. Their results also confirm that women have been more severely affected from the Pandemic and faced the risk of being unemployed, reduced work hours or enforced to part-time working. In addition, in terms of gender roles, women's transition to unemployment has revealed more traditional-like gender roles in case of their partners remaining in their jobs whereas men's transition to unemployment has seemed to be more egalitarian in case of their partners remaining in their jobs.

As can be seen from the studies discussed above, the COVID-19 Pandemic as a unique type of economic shock and recession has led to heterogeneous short-term impacts on businesses and labor from various aspects and a sharp transformation of work life with new business models heavily dependent on the task content of the occupations, the flexibility of industries and/or the digital capability of businesses etc. The researches in this area is mostly concentrated on supply side effects; however, our study investigates the demand side effect of COVID-19 on labor demand. Therefore, before closing this subsection, we touch upon two studies which are more closely related to our study in this essay.

Özşuca (2023) and Khan (2023) are two recent papers concentrating on firm-level impacts of COVID-19 Pandemic by using the WBES data and its COVID-19 Follow Up Surveys. Özşuca (2023) focuses on the firm survival during COVID-19 by taking into account the innovation performance of the firm and the moderating role of financial constraints in Central and Eastern European countries. She conducts her analyses by controlling for the firm characteristics like firm size, age, foreign ownership, exporter status, manager experience and female ownership which may have an effect on firm adaptability or survival capacity. Her results reveal that firm size and age are the most important factors enhancing firm survival during the Pandemic. She also finds empirical evidence for the hypothesis that innovative firms have higher survival probability during COVID-19 crisis as innovative firms have more ability to adapt and adjust themselves to changing environments. Although both product and process innovations contribute to the survival probability of firms,

especially firms which have introduced process innovation have higher probability to survive. Moreover, the empirical analysis finds out that internal R&D activity is also important for survival which points that internal knowledge generation has an enhancing effect for firm survival during bad times. Lastly, in terms of the role of financial constraints on the innovation and firm survival nexus, the findings reveal that being financially constrained mitigates the positive impact of innovation on survival probability.

Khan (2023) studies the firm-level employment impact of COVID-19 for 39 developing and emerging countries with WBES data and its COVID Follow Up Surveys for various rounds. The paper seeks to answer to three main questions which are: What determines the likelihood of a firm decreasing full-time workers, and the magnitude of the percentage decrease in employed workers (extensive margin)? What are the factors affecting a firm's decision to employ furlough as a buffer to economic shock induced by COVID-19 and workers' decisions to quit or take leave due to COVID-induced oppressions? What are the role of managers' expectations regarding a firm's viability, default risk and perceptions on financial performance in the short and medium term? Those research questions have been tried to be answered by using pre-pandemic firm heterogeneity and financial constraints, firm-level responses to the Pandemic including teleworking, temporary closures, adoption of digital technologies to switch to online businesses, adjustment to business operations etc., and country-level variables and governmental response measures to the Pandemic.

Khan (2023) mainly finds that pre-crisis credit constraints are important for employment decisions of the firms during the Pandemic even if he controls for the firm level characteristics before the Pandemic, i.e., credit-constrained firms in pre-Pandemic period have been more tended to reduce employment with respect to the non-constrained ones. This finding implies that firms which are dependent on external financing are more prone to vulnerable shocks especially at the beginning of the Pandemic. The paper also demonstrates that the existence of access to finance or bank loans during the Pandemic or government support to firms for enhancing their access to external finance alleviates the adverse effects of the economic shock

through preserving the labor. However, the author notes that the effect of financial constraint is only valid in the early phase of the Pandemic; in the following rounds, the economic shocks emanating from the Pandemic overtook the initial employment effect of external financial access. Another important finding is that firm-level adaptation and operational response to the Pandemic-induced working conditions such as temporary closure, adoption of online digital platforms, remote work arrangements etc. are significant predictors of employment outcomes during the Pandemic. Lastly, the findings also indicate that female workers have been more at risk in terms of losing job due to the sectoral concentration of women labor, firms' financial distress and digital transformation in the businesses.

The COVID-19 has drawn attention in terms of its labor market effects immediately after its arrival as a health, economic and sociological shock. The labor market impacts have been studied mostly from the supply side due to the fact that household surveys have begun to be conducted all around the world more easily. Due to the rapid and radical transformation in the business life and mandated closures and measures imposed by the governments all around the world, collecting firm-level data has become more tedious in some sense since reaching businesses have become less probable with a degree varying from sector to sector. The last two studies mentioned above uses WBES data for various country groups and rounds of the follow up surveys to examine the firm performances and labor market from the demand side. Our study is more closely related to those two studies; namely, Özşuca (2023) and Khan (2023), in terms of examining the firm performance during the COVID-19 with reference to some pre-COVID conditions. In the next subsection, we introduce data in detail.

4.3. Data

The World Bank Enterprise Analysis Unit has started to conduct follow-up surveys with the onset of the COVID-19 to understand the effects of the Pandemic on the private sector. The WB have conducted those Follow-Up Surveys to the countries which have recently completed the baseline ES and therefore the sample in each country is the same with the sample of the baseline ES. As mentioned before in the

previous chapter, enterprise surveys are conducted according to the stratified sampling methodology which we have provided detailed information on the construction of it in the Section 3.3. The follow-up surveys have been conducted by re-contacting all the establishments sampled in the standard ES before. The universal set of the sample is composed of the registered establishments with five or more employees and operating in the sectors defined using ISIC Rev. 3.1: manufacturing (group D), construction (group F), services sector (group G and H), transport, storage and communications sector (group I), and information technology (division 72 of group K).

The Follow-Up Surveys were conducted to 24 countries in Europe, 5 countries in Central Asia, 3 countries in MENA, 7 countries in Africa and 4 countries in Central America which means 43 countries were surveyed in total. However, not all of them are surveyed in all rounds. The Follow-Up Surveys were conducted maximum in four rounds; however, only two countries were surveyed in four rounds; namely, Armenia and Jordan. 25 of the countries in the sample were surveyed in three rounds and 32 of the countries were surveyed in two rounds. The details of the dates of the follow-up rounds and country list are provided in the Appendix C.

Our data set is constructed by merging the baseline surveys and only the first round follow-up surveys. The reason for constructing the sample in this way will be explained in the next paragraphs. Therefore, our sample is composed of 43 countries with regional distribution summarized above. However, Armenia and Lebanon is excluded from our sample since Armenia's first round follow-up survey was conducted only to micro-enterprises and Lebanon had lived another crisis concurrently with the COVID-19, namely, Port of Beirut explosion and therefore the first round follow-up survey conducted to Lebanon refers to those two crises which occurred simultaneously. Those two countries are excluded at the beginning of our analysis to avoid estimation bias which may arise from sample construction. A second point worth to mention here is the fact that the baseline survey years of the countries are different. European, Central Asian and MENA countries were surveyed mostly in 2019 and just a few ones in 2018 whereas African and Central American countries were heavily surveyed during the years 2016-2017. Therefore, the time

elapse between the baseline ES completion and Follow-Up survey conduction has not been the same for all countries in the sample. Especially, the variables representing the pre-Pandemic conditions should be cautiously interpreted in this aspect.

The second point worth to mention here is that a significant part of the firms which have been surveyed in the baseline ES could not have been reached to be surveyed for the COVID Follow-Up Survey with the onset of the Pandemic. Moreover, some of the firms existing in the baseline survey refused to answer the Follow-Up surveys. Therefore, the sample size obtained by merging the baseline survey and first round follow-up is not the same with the one of baseline survey itself. To correct for this selection bias, we propose an estimation technique which will be provided below.

Table 4.1 below provides the outcome of re-contacting the sample based on the universe of baseline survey. Unfortunately, the attempt to reach all firms had not been successful during period of Round 1 survey conduction. Therefore, the firms are categorized as follows: the firms which are *unobtainable*, which *discontinued business*, which *refused* to answer the follow-up and which *confirmed open* (obtainable) for Round 1 Follow-Up Survey. The total sample includes 21,700 observations including all the firms no matter they can be reached or cannot be reached. However, approximately 2,947 firms could not be reached in the first round, 799 of them stopped operating, 1,298 firms refused to answer the Round 1 Follow Up Survey and only 16,656 firms had answered the survey. Therefore, approximately 76.75 percent of the universal sample has been surveyed in the first round. On the other hand, the information on 19.56 percent of the sample (excluding the firms which are known to stop operating definitely) has been unavailable which indicates that there is a significant amount of information loss from the baseline sample.

Table 4.2 shows the operational situation of the firms in three categories as *open*, *temporarily closed* and *permanently closed*. *Discontinues business* category in the Table 4.1 includes the firms that exit the market due to COVID-19 or another reason whereas *permanently closed* firms refer to the firms which stopped operating due to COVID-19. The total number of observations in Table 4.2 is not the same as Table

4.1 since there is a significant amount of missing data for this question in the survey. The number of missing observations is provided in Table 4.3 in which the number of missing observations there is the same with the one of Table 4.2 (which is not reported in Table 4.2).

As can be seen from Table 4.2, the available 75 percent of the universal sample is decomposed as 88.3 percent is open, 7.2 percent is temporarily closed and 4.5 percent is permanently closed due to COVID-19 approximately. However, there is a significant number of missing status here which refers to over 5,500 firms in approximate value. Table 4.3 provides information about the firms' situation in more detail by additionally showing the number of firms which have been *temporarily closed for a while* and *still temporarily closed*. This indicates that as a response to COVID shock, a significant share of firms had been temporarily closed even if they operate normally in the moment that the follow-up survey was conducted.

For our interest of analysis, we provide information on the sample in Table 4.4 and Table 4.5 in terms of the firms' size, age, sector and innovativeness in the former one whereas their distribution according to the government support taken during the first round survey period. This information will shed light on our estimation results in the following sections.

Table 4.4 represents some important facts regarding our sample. First of all, the small and medium sized firms constitute approximately 78 percent of the sample which is an expected ratio in developing and emerging countries whereas the economy is dominated by SMEs. In terms of the age structure; however, the sample seems to be skewed towards old firms. If we count the firms which are 5 year-old and younger ones are young firms, only 9.19 percent of the firms are *young*. There exists a significant ratio of 20 year-old or older firms constituting 43 percent of the sample alone. Therefore, the interpretation of results should be treated keeping in mind this age distribution skewness towards older firms which may directly affect the firms' innovativeness, labor hoarding capacity during economic shocks and survival probability during the times of crisis. The sectoral distribution is given in

general terms in Table 4.4. With a ratio of nearly 52.5 percent of manufacturing sector and the remaining part is retail and other services; the sample is balanced between manufacturing and services sectors.

In terms of technological innovation performance of the firms (not non-technological innovation like marketing or organizational innovation), the sample reveals that innovativeness is less common with respect to the innovativeness since the former group of firms represents a ratio of approximately 64 percent whereas the latter group represents nearly 36 percent. This fact may reveal a common trend among developing and emerging countries since the non-innovativeness outweighs innovativeness

Table 4. 1. Outcome of Re-contacting the Baseline Survey Sample for Round 1 Follow-Up Surveys

Country	Unobtainable	Discontinued Business	Refusal	Confirmed Open	TOTAL
Albania	0	4	29	344	377
Azerbaijan	76	12	36	101	225
Belarus	11	26	0	563	600
Bulgaria	59	40	0	673	772
Chad	29	6	17	101	153
Croatia	44	12	0	348	404
Cyprus	38	8	7	187	240
Czechia	39	8	16	439	502
El Salvador	248	14	54	403	719
Estonia	32	8	16	304	360
Georgia	0	17	87	597	701
Greece	23	2	0	575	600
Guatemala	81	5	55	204	345
Guinea	35	1	11	103	150
Honduras	136	6	24	166	332
Hungary	133	12	0	660	805
Italy	65	37	3	655	760
Jordan	13	66	24	498	601
Kazakhstan	418	67	0	961	1,446
Latvia	78	8	9	264	359
Lithuania	40	1	104	213	358
Malta	8	0	3	231	242
Moldova	51	3	22	284	360
Mongolia	37	30	9	284	360
Montenegro	0	2	12	136	150
Morocco	194	92	0	810	1,096
Mozambique	209	14	155	223	601
Nicaragua	86	6	49	192	333
Niger	58	6	15	72	151
Poland	130	30	234	975	1,369

Table 4. 1. (Cont'd) Outcome of Re-contacting the Baseline Survey Sample for Round 1 Follow-Up Surveys

Portugal	148	84	7	823	1,062
Romania	120	21	74	599	814
Russia	5	46	111	1,161	1,323
Serbia	7	9	0	345	361
Slovakia	26	14	13	376	429
Slovenia	89	0	51	269	409
Togo	68	8	20	54	150
TCC	0	4	0	116	120
Zambia	0	45	22	534	601
Zimbabwe	113	25	9	813	960
TOTAL	2,947	799	1,298	16,656	21,700

Table 4. 2. The status of firms during the conduction of Round 1 Follow-Up Survey

Country	Open	Temporary Closed	Permanently Closed
Albania	300	44	3
Azerbaijan	92	9	4
Belarus	526	4	21
Bulgaria	511	10	38
Chad	18	83	6
Croatia	340	2	9
Cyprus	161	6	4
Czechia	398	0	7
El Salvador	298	93	14
Estonia	270	1	1
Georgia	463	134	17
Greece	510	20	2
Guatemala	166	33	4
Guinea	74	29	1
Honduras	113	50	6
Hungary	616	3	11
Italy	367	52	34
Jordan	471	27	66
Kazakhstan	752	54	65
Latvia	228	12	4
Lithuania	213	0	1
Malta	191	2	3
Moldova	245	38	3
Mongolia	257	27	30
Montenegro	135	1	2
Morocco	715	66	92
Mozambique	97	19	15
Nicaragua	174	10	6
Niger	59	9	4
Poland	912	63	30
Portugal	736	7	77
Romania	513	1	18
Russia	1,096	49	46
Serbia	306	7	5
Slovakia	324	1	13
Slovenia	247	2	0
Togo	41	10	5

Table 4. 2. (Cont'd) The status of firms during the conduction of Round 1 Follow-Up Survey

TCC	91	1	4
Zambia	442	91	30
Zimbabwe	717	96	25
TOTAL	14,185	1,166	726

Table 4. 3. The status of firms whether they are ever temporarily closed or permanently closed due to COVID-19 outbreak (Round 1)

Country	Temporarily Closed for a while	Still Temporarily closed	Permanently Closed	Never Closed	Missing data
Albania	178	44	3	122	30
Azerbaijan	53	9	4	39	120
Belarus	44	4	21	482	49
Bulgaria	127	10	38	384	213
Chad	2	83	6	16	46
Croatia	93	2	9	247	53
Cyprus	78	6	4	83	69
Czechia	90	0	7	308	97
El Salvador	172	93	14	125	315
Estonia	46	1	1	224	88
Georgia	243	134	17	219	87
Greece	155	20	2	355	68
Guatemala	108	33	4	58	142
Guinea	18	29	1	56	46
Honduras	89	50	6	24	163
Hungary	70	3	11	546	175
Italy	192	52	34	174	307
Jordan	450	27	66	18	37
Kazakhstan	346	54	65	402	579
Latvia	11	12	4	216	115
Lithuania	92	0	1	121	144
Malta	54	2	3	137	46
Moldova	110	38	3	135	74
Mongolia	102	27	30	154	46
Montenegro	40	1	2	95	12
Morocco	485	66	92	230	223
Mozambique	36	17	15	165	367
Nicaragua	44	10	6	130	143
Niger	12	9	4	46	79
Poland	130	63	30	782	364
Portugal	197	7	77	539	242
Romania	123	1	18	390	282
Russia	684	49	46	412	132
Serbia	54	7	5	252	43
Slovakia	116	1	13	208	91
Slovenia	87	2	0	159	160
Togo	5	10	5	36	94
TCC	67	1	4	24	24
Zambia	80	91	30	362	38
Zimbabwe	578	96	25	139	122
TOTAL	5,661	1,164	726	8,614	5,525

Table 4. 4. Firm distribution according to size, age, sector and innovativeness

		Total	Percentage
Total Sample Size		20,154	100%
Size			
Small (5-19)	9,201		45.65%
Medium (20-99)	6,453		32.01%
Large (100+)	4,500		22.32%
Age			
<5	1,854		9.19%
5-9	3,103		15.39%
10-14	3,313		16.43%
15-19	3,217		15.96%
20+	8,667		43.00%
Industry		12,994	
Manufacturing	10,394		52.57%
Retail	3,646		18.09%
Other Services	6,114		30.33%
Innovation			
Non-innovators	12,869		64.44%
Innovators			
Product	5,813		29.11%
of which only product	3,603		
Process	3,434		17.19%
of which only process	1,258		
of which product and process	2,147		10.75%
Total (exc. missing values)		19,969	

Table 4. 5. Firm distribution according to the government support taken or not taken

		Total	Percentage
Total		20,154	100%
Government Support			
No Support	9,325		46.26%
No but expected in 3 months	788		3.90%
Support	4,330		21.48%
Missing/Don't Know	5,711		28.33%
If government support is taken;			
Cash Transfers	1,502		34.68%
Deferral/Rollover of Payments	1,423		32.86%
New Credit Access	926		21.38%
Fiscal Exemption	1,582		36.53%
Wage Subsidy	3,352		77.41%
Other supports	240		5.54%
Total		4,330	

Note: Firms can obtain multiple type of supports, therefore all the ratios do not sum to 100%.

generally in those countries and therefore it may not be a representativeness problem of the sample but rather a reflection of a chronic fact.

As widely known, almost all governments around the world have declared various support programs for businesses as soon as the Pandemic showed up. Table 4.5 shows the firm distribution according to whether they benefit from government support or not. Surprisingly, only 1 out of 5 firms have benefited from government supports (21.48 percent) during the first round survey. This is way too low when compared to normal expectations especially in developing countries where conditions for access to external finance is less favorable or equity resilience of the firms to the external shocks is more vulnerable. Another striking fact is that giving no answer to the government support Yes/No question or not knowing whether the firm had already benefited from some support is quite common where “Missing/Do not know” category owes 28.3 percent share. Finally, among the 4,330 firms which were granted any kind of support, fiscal exemptions and wage subsidies were the most benefited categories among the firms.

Looking at the general properties of the data according to the purposes of our estimation strategy and methodology, we can now continue with the explanation of our methodology. By taking into account the selection bias emerging with the unobtainability of all the firms in the universal sample, the innovativeness of the firms before pre-Pandemic period and whether the firm has benefited from any kind of government support, we try to figure out the employment behavior by controlling the stratification levels (sector and region within the country).

4.4. Methodology

We estimate the following baseline regression to estimate the pre-COVID product and process innovation on employment outcome of the firm during the early phase of COVID-19 economic shock:

$$LCOV_{i,t} = \alpha_0 + \alpha_1 prod_{i,t-1} + \alpha_2 prcss_{i,t-1} + \beta_1 L_{t-1} + \beta_2 \omega_{i,t-1} + country\ dummies + sector\ dummies + region\ dummies + u_t \quad (4.1)$$

where the dependent variable $LCOV_{i,t}$ represents the logarithmic value of employment level during COVID-19 first round period, $prod$ is the dummy variable showing whether the firm had generated product innovation in the pre-Pandemic

period, *prcss* is the dummy variable whether the firm had generated a process innovation in the pre-Pandemic period, L_{t-1} and $\omega_{i,t-1}$ represent the logarithmic values of employment and total labor cost respectively in the pre-COVID period.

In the extension, we control for whether the firm has benefited from government support or not and if it has taken, we control for the effects of various kinds of government supports available as a choice item in the questionnaire. Therefore, we estimate the following equation as well:

$$LCOV_{i,t} = \alpha_0 + \alpha_1 prod_{i,t-1} + \alpha_2 prcss_{i,t-1} + \beta_1 L_{t-1} + \beta_2 \omega_{i,t-1} + \text{country dummies} + \text{sector dummies} + \text{region dummies} + \text{government support}_{i,t} + u_t \quad (4.2)$$

And on the condition that the government support is taken, the following equation is estimated:

$$LCOV_{i,t} = \alpha_0 + \alpha_1 prod_{i,t-1} + \alpha_2 prcss_{i,t-1} + \beta_1 L_{t-1} + \beta_2 \omega_{i,t-1} + \text{country dummies} + \text{sector dummies} + \text{region dummies} + \text{Cash transfers}_{i,t} + \text{Deferral}_{i,t} + \text{Credit Access}_{i,t} + \text{Fiscal Exemption}_{i,t} + \text{Wage Subsidy}_{i,t} + \text{Other}_{i,t} + u_t \quad (4.3)$$

We start with standard OLS estimation as a benchmark for all the equations above. As we explained in Section 4.3, the universal sample set is not available for the first round follow up survey of COVID-19. Some firms are unobtainable due to the unknown reasons (whether they are temporarily closed, stopped operating permanently or just did not want to answer) and therefore we have a significant amount of observation loss. Therefore, since there is a selection bias problem in the independent variable, we continue to our estimations with the selection bias correction based on the multinomial logit model. The selection bias correction based on the multinomial logit model provides a correction for this information loss in the independent variable and therefore it helps to estimate more accurate estimations.

Economists apply to the methodology proposed by Heckman (1979) when a selection bias problem arises from a binary choice outcome for the dependent variable. However, the methodology proposed by Heckman (1979) does not solve

the problem when the selection is based on exclusive choices more than two. Therefore, the Heckman methodology has extended in the literature to answer to this kind of need. Bourguignon et al. (2007) presents those different methodological approaches on selection bias correction available in the literature in the case where selection is specified as a multinomial logit model. Three approaches exist in the literature to correct for the selection bias for that kind of specification. These are proposed by Dubin and MacFadden (1984), Dahl (2002) and Lee (1983). Bourguignon et al. (2007) compares and contrasts those three methodologies by conducting some Monte Carlo experiments to compare the robustness of the results those three methodologies provide and finds that Dubin and MacFadden (1984) and Dahl (2002) methods give better results with respect to Lee (1983) in most of the Monte Carlo experiments.

We briefly introduce the theoretical background of the selection bias correction based on the multinomial logit model based on Bourguignon et al. (2007) in the following paragraphs.

General description of the model and definitions

Consider the following model:

$$\begin{aligned} y_1 &= x\beta_1 + u_1 \\ y_j^* &= z\gamma_j + \eta_j, \end{aligned} \quad j = 1 \dots M$$

(4.4)

where the disturbance term u_1 is not parametrically specified and meets the assumptions that $E(u_1 | x, z) = 0$ and $V(u_1 | x, z) = \sigma^2$.

For the model specification (4.4) above:

- j represents a categorical variable describing a choice set from M alternatives based on ‘utilities’ y_j^* for an economic agent.
- The vector z is the maximum set of explanatory variables for all alternatives.
- The vector x is all determinants of the variable of interest.

- The main assumption: The model is non-parametrically identified with the exclusion of some of the variables in the vector z from the variable of interest.
- Without loss of generality, the outcome variable y_1 is observed if and only if the first category from M alternatives is chosen which means;

$$y_1^* > \max_{j \neq i} (y_j^*) \quad (4.5)$$

- Now, based on the expression (4.4) above, we define;

$$\begin{aligned} \varepsilon_1 &= \max_{j \neq i} (y_j^* - y_1^*) \\ &= \max_{j \neq i} (z\gamma_j + \eta_j - z\gamma_1 - \eta_1) \end{aligned} \quad (4.6)$$

(4.6) implies that the condition (4.5) is equivalent to $\varepsilon_1 < 0$.

- Assuming that the (η_j) s are independent and identically Gumbel distributed¹³, the cumulative and density functions for (η_j) s are $G(\eta) = \exp(-e^{-\eta})$ and $g(\eta) = \exp(-\eta - e^{-\eta})$, respectively.
- The functional forms and assumptions given above brings us to the multinomial logit model as proposed by MacFadden (1973):

$$P(\varepsilon_1 < 0|z) = \frac{\exp(z\gamma_1)}{\sum_j \exp(z\gamma_j)}$$

where it is straightforward to obtain consistent estimates for (γ_j) s.

- The problem is the estimation of the vector β_1 given in (5.4).
- The correlation between u_1 and (η_j) s leads to inconsistent LS estimates of β_1 .
- Therefore, defining a functional form as $\Gamma = \{z\gamma_1, z\gamma_2, \dots, z\gamma_M\}$ and generalizing Heckman (1979) model, the selection bias can be corrected according to the conditional mean of u_1 as below:

$$E(u_1 | \varepsilon_1 < 0, \Gamma) = \iint_{-\infty}^0 \frac{u_1 f(u_1, \varepsilon_1 | \Gamma)}{P(\varepsilon_1 < 0 | \Gamma)} d\varepsilon_1 du_1 = \lambda(\Gamma)$$

¹³ This is called as Independence of Irrelevant Alternatives (IIA) hypothesis.

where $f(u_1, \varepsilon_1 | \Gamma)$ is the conditional density of u_1 and ε_1 .

- Let P_k be the probability that any alternative k is preferred:

$$P_k = \frac{\exp(z\gamma_k)}{\sum_j \exp(z\gamma_j)}$$

- The functional form for conditional mean of u_1 can be rewritten as

$$E(u_1 | \varepsilon_1 < 0, \Gamma) = \mu(P_1, \dots, P_M)$$

under the condition that the M components of Γ and the M corresponding probabilities is invertible.

- Consistent estimation of β_1 can be obtained from either form of the regressions below:

$$\begin{aligned} y_1 &= x_1\beta_1 + \mu(P_1, \dots, P_M) + w_1 \\ &= x_1\beta_1 + \lambda(\Gamma) + w_1 \end{aligned} \tag{4.7}$$

where w_1 stands for the residual representing the mean-independent of the regressors.

The important point about the estimation of representation (4.7) is that as the number of alternatives to be chosen increases, this will lead to an estimation of a very large number of parameters which is difficult to implement practically. Therefore, some restrictions over $\mu(P_1, \dots, P_M)$ or $\lambda(\Gamma)$ need to be imposed. The methodological differences for bias corrections existing in the literature stems from the restrictions imposed (Bourguignon et al., 2007, pg. 176).

We just give the general description of the theoretical model and definitions of the selection bias correction based on the multinomial logit model which take place on the pages between 175-177 in Bourguignon et al. (2007). We do not go further into the details of the different approaches proposed for the restrictions imposed over $\mu(P_1, \dots, P_M)$ or $\lambda(\Gamma)$. We just note that we estimate the equations (4.1), (4.2) and

(4.3) with linearity approach of Dubin and MacFadden (1984) (abbreviated as DMF) with the restriction that all correlation coefficients sum up to zero¹⁴.

In the first regression of multinomial logit model (selection equation); the multinomial dependent variable named as “firm status” has three choice outcomes; namely, firms which ANSWER, DO NOT ANSWER and STOP DOING BUSINESS (EXIT). After correcting the selection bias in the first step, we estimate the second regression (outcome equation) to estimate the employment effect of pre-COVID innovation on during COVID period. The excluded variables in the second step and used to correct for selection bias in the first step are “response reliability”, “calculation reliability” and “survey completion” which are defined below. Those three variables are constructed from some information provided by survey conductors at the end of the baseline survey.

The variable *response reliability* is constructed from the following statement which has three choices in an ordinal manner and the survey conductor chooses one of the alternatives:

It is my perception that the responses to the questions regarding opinions and perceptions were:

- *Truthful*
- *Somewhat truthful*
- *Not truthful*

The variable *calculation reliability* is constructed from the following statement which has four choices but not in a strict ordinal nature, the survey conductor chooses one of the alternatives:

The responses to the questions regarding figures (productivity and employment numbers) were:

- *Taken directly from establishment records*

¹⁴ For the details of the specific assumptions of Lee (1983), Dahl (2002) and DMF (1984), the reader may apply to Bourguignon et al. (2007) pages between 177-180.

- *Estimates computed with some precision*
- *Arbitrary and unreliable numbers*
- *In some case taken from books and in some case estimates*

The last variable of exclusion, *survey completion*, is constructed from the following statement which has three choices in a non-ordinal manner and the survey conductor chooses one of the alternatives:

The questionnaire was completed in:

- *One visit in face-to-face interview with one person*
- *One visit in face-to-face interview with different managers/staff*
- *Several visits*

The reason for those variables of exclusion to be chosen can be explained as follows. The dependent variable of the selection regression, i.e. the status of firms, may depend on the truthfulness of answers or calculation reliability of numerical data about the firms' economic activities. This is because of the fact that *response reliability* or *calculation reliability* may be a signal for firms' discipline in terms of their habit of answering the phone calls or e-mails by World Bank Enterprise Unit regularly, especially in an abnormal economic process. The firms providing truthful information before the Pandemic period are expected to be less reluctant to provide information during the following COVID shock whereas the firms providing misleading information during pre-Pandemic period may be more reluctant to provide information in general during bad times. A similar argument can also be considered for the firms providing more precise information regarding numerical data before the Pandemic period. The last variable of exclusion, i.e. *survey completion*, is to be considered to have a possibility for answering the dependent variable of the selection regression with the hypothesis that completing a survey during several visits or with different personnel of the firm during pre-Pandemic period may create some sort of consistency problem in terms of providing coherent answers to the survey as a whole. Therefore, the firms completing their surveys in partial periods or with different staff may be not so eager to answer the follow-up surveys during the COVID period. Therefore, under those assumptions those three

variable options are used in estimations of the selection regression. The first step regression can be written as a multinomial logit regression as follows:

$$\begin{aligned} Firm\ Status_{i,t} = & \alpha_0 + \alpha_1 prod_{i,t-1} + \alpha_2 prcss_{i,t-1} + \beta_1 L_{t-1} + \beta_2 \omega_{i,t-1} + \\ & country\ dummies + sector\ dummies + region\ dummies + \\ & Exclusion\ Variable_{i,t} + u_t \end{aligned} \quad (4.8)$$

After correcting for the selection bias with the estimation of equation (5.8) above with the exclusion variables of response reliability, calculation reliability and survey completion and their double or triple combinations to check whether they provide more robust corrections for selection bias, we estimate the outcome regressions of (4.1), (4.2) and (4.3) described above.

4.5. Estimation Results

4.5.1. Baseline Estimation Results

In previous section, we have explained our regressions to be estimated and the reasons why we have endorsed a methodology for selection bias correction based on the multinomial logit model. Now, in this section, we provide estimation results and their implications.

We have started to estimate our regression with 40 countries in our sample; however, we have ended up with 37 countries due to the fact that three countries (Azerbaijan, Cyprus and Mozambique) have too many missing observations, i.e. the number of missing values exceed the number of observed ones; therefore, the first step selection bias correction cannot be conducted in those countries (See Section 4.3 for the number of missing data on country base).

On the Table 4.6, we provide estimation results for the equation (4.1) which is our baseline regression as described in Section 4.4. We note here that all regressions from now on include country and industry dummies to control for heterogeneity at country and industry level which are not observed from the data (also region

dummies due to the stratification methodology used in the survey) but not reported in the results. The first column gives the standard OLS estimation results as a benchmark analysis to check for how much and in which way the selection bias correction improves the estimation results. The columns from (2) to (8) represent the estimation results of selection bias correction based on multinomial logit model with different combination of exclusion variables in the first step selection regression. As noted in the previous section, the multinomial dependent variable of the first step regression is “firm status” which has **three** categories; namely, the firms which ANSWER the survey, the firms which DO NOT ANSWER the survey and the firms which STOP OPERATING THE BUSINESS (EXIT).

The first column of Table 4.6, i.e. OLS estimation results of equation (4.1), show that the COVID-period employment level is mostly sticky to the pre-COVID period employment level at the firm level. Almost 82 percent of COVID period employment level is explained by the pre-COVID employment level. On the other hand, the results regarding pre-COVID labor cost seem surprising since the pre-COVID labor cost has a positive and statistically significant level on the COVID-period employment level. According to the standard theory of labor demand, the demand for a production input is negatively correlated with its price as mostly explained in textbooks in economics. However, in our estimation, the labor cost or aggregate wage level of pre-COVID period affects the demand for labor positively during COVID period. This may stem from the fact that high wage level may indicate high labor productivity and the firms having a higher labor productivity may consist their employment level during economic shocks more easily. In terms of product and process innovation, the estimation results of OLS reveal that pre-COVID product innovation signs a positive employment impact even the statistical evidence is not so strong whereas pre-COVID process innovation has no effect on COVID period employment level. Most of the coefficients of sector dummies are insignificant whereas an important ratio of the country and region dummies are significant in all eight regressions.

Now if we turn to the estimations where selection bias is corrected, we see that estimation results improve significantly. First of all, we see that in all regressions

(including the first column of OLS estimation), the constant term is negative and indicates a general downward trend during COVID-period employment level. Secondly, the statistical significance and value of pre-COVID employment level do not much change whereas the value of the coefficient of pre-COVID labor cost seems to increase from approximately 6.8 percent to over 8 percent. Thirdly and more importantly, the value of the coefficient and statistical significance of product innovation increases significantly with the selection bias correction whereas the status of the process innovation does not change. The estimation of our baseline results show that product innovation implemented before an economic shock helps to sustain for businesses their employment during that economic shock. This result may point to an underlying fact that product innovations ensure the demand for the firms' products being more resistant to external shocks by the additional revenue and profit generated with the introduction of new products (or services).

It is relevant to check here whether the first step regression actually corrects the selection bias or not. In the Table 4.7, we give the first regression results for the baseline regression to show that there is actually a correction for selection bias. As we mentioned in Section 4.4, the first step regression is a multinomial logit regression given in equation (4.8). In the estimation of equation (4.8), we use the three exclusion variables defined in the previous section separately as well as their double and triple combinations. As we see from the Table 4.7 below, *response reliability* is the most corrective variable for the selection bias whereas *calculation reliability* is also valid. However, the coefficients of *survey completion* are statistically insignificant and therefore this variable seems not to correct selection bias in any regression. The base category of the dependent variable is the firms which *answer* the survey. Therefore, we see the results for the firms which *do not answer* the survey and the firms which *stop operating the business (exit)* with respect to the firms which *answer* the survey. We see that the first step regression corrects the selection bias since the model specification of the first step gives meaningful results and also the variables of exclusion has statistically significant coefficients except the variable *survey completion*. The *response reliability* and *calculation reliability* reveal more corrective power separately or together. The use of "survey completion" as the variable of exclusion or any combination of use with *response*

reliability or *calculation reliability* does not give statistically significant coefficients for itself. Therefore, the specifications including *response reliability* or *calculation reliability* seems more reliable in terms of bias correction. Moreover, we see that the first step regression does not give meaningful results for the third outcome which refers to the firms which stopped operating business. This may make sense since the firms which exit may have exit due to various reasons and our variables of exclusion are probably not related to those factors. From now on, we do not show the first step regression results to avoid unnecessary repetition. We only continue with the results of the outcome regressions of the extended model in the next subsection.

4.5.2. Extension: Controlling for the Impact of Government Supports

As we explained in Section 4.4, the main extension to the model is to control for the effects of the government supports benefited by the firms. COVID-19 period is a unique example of a global economic shock because governments all around the world have reacted in an unprecedented speed and various macroeconomic and microeconomic policy tools to alleviate its adverse economic effects. *Policy Tracker* by IMF¹⁵ provides policy responses by governments to COVID-19 for 197 countries as of July 2, 2021 in three broad categories; namely, fiscal, monetary and macro-financial, and exchange and balance of payments. When we check for the available policy supply for different countries especially the ones existing in our sample, we see that the broadest category of the policy universe is the fiscal category. In this category, almost all governments had provided funding for health sector, support to businesses on different bases (size, sector, exporter vs. non-exporter etc.) and individuals or households including wage subsidies, partial coverage of salaries, SSC subsidies, reduction in business license fees, measures enhancing access to funding, tax deferrals or tax relief, employment support or promotion programs, short time work programs, cash transfers, deferment of public obligations, credit guarantee schemes etc.

¹⁵ See the website <https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19>

Table 4. 6. Effects of pre-COVID innovation on employment during COVID period*Dependent variable: Log of COVID-Round 1 Employment*

	Standard OLS	Selection Bias Correction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of pre-COV employment	0.818*** (0.012)	0.815*** (0.014)	0.809*** (0.015)	0.80*** (0.022)	0.82*** (0.013)	0.818*** (0.013)	0.817*** (0.013)	0.815*** (0.014)
Log of pre-COV wage level	0.068*** (0.008)	0.083*** (0.008)	0.088*** (0.009)	0.089*** (0.010)	0.082*** (0.008)	0.082*** (0.008)	0.083*** (0.008)	0.085*** (0.008)
Product Innovation (Dummy variable)	0.032* (0.016)	0.078*** (0.024)	0.097*** (0.029)	0.103*** (0.033)	0.076*** (0.023)	0.073** (0.023)	0.080** (0.023)	0.086*** (0.025)
Process Innovation (Dummy Variable)	0.01 (0.019)	0.027 (0.022)	0.036 (0.023)	0.043 (0.028)	0.024 (0.021)	0.024 (0.022)	0.027 (0.022)	0.030 (0.023)
_m1		1.376*** (0.404)	1.004** (0.419)	1.193*** (0.442)	1.103*** (0.385)	1.267*** (0.396)	1.195*** (0.392)	0.964** (0.409)
_m2		1.009 (0.756)	0.148 (0.898)	0.018* (1.271)	0.818 (0.692)	1.032 (0.738)	0.802 (0.721)	0.420 (0.828)
_m3		-0.336 (0.458)	-0.833* (0.486)	-0.672 (0.506)	-0.521 (0.438)	-0.376* (0.446)	-0.501 (0.450)	-0.763 (0.465)
Constant	-0.245*** (0.087)	-1.55*** (0.465)	-1.67*** (0.474)	-1.791*** (0.632)	-1.534*** (0.425)	-1.471*** (0.442)	-1.605*** (0.444)	-1.487*** (0.439)
N	11,783	11,780	11,781	11,781	11,780	11,780	11,780	11,781
R ²	0.7269	0.7276	0.7275	0.7276	0.7275	0.7275	0.7276	0.7167

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors. The values in parentheses are standard errors.

Selection Bias Correction: In all first step regressions, the dependent variable is “**firm status**” which has **three** categories; namely, the firms which ANSWER the survey, the firms which DO NOT ANSWER the survey and the firms which STOP OPERATING THE BUSINESS (EXIT).

(2) “Response reliability” in the baseline ES survey is the only exogenous variable used in the first step.

(3) “Calculation reliability” in the baseline ES survey is the only exogenous variable used in the first step.

(4) “Survey Completion” in the baseline ES survey is the only exogenous variable used in the first step.

(5) All three exogenous variables used in (2), (3) and (4) are used together in the first step.

(6) “Response reliability” and “Survey completion” are used as exogenous variables in the first step.

(7) “Calculation reliability” and “Survey Completion” are used as exogenous variables in the first step.

(8) “Response reliability” and “Calculation reliability” are used as exogenous variables in the first step.

Table 4. 7. Multinomial Logistic Regression Results of the Equations (2)-(8) in Table 4.6.*Dependent variable: Firm Status (firms which ANSWER, DO NOT ANSWER or EXIT)*

	(2)	(3)	(4)	(5)	(6)	(7)	(8)
For the outcome 2:							
Log of pre-COV employment	0.113*** (0.026)	0.115*** (0.026)	0.115*** (0.026)	0.114*** (0.026)	0.113*** (0.026)	0.113*** (0.026)	0.116*** (0.026)
Log of pre-COV wage level	-0.034* (0.02)	-0.034* (0.020)	-0.037* (0.019)	-0.032 (0.020)	-0.033* (0.019)	-0.032 (0.020)	-0.034* (0.019)
Product Innovation (Dummy variable)	-0.136*** (0.048)	-0.135*** (0.048)	-0.143*** (0.048)	-0.133*** (0.048)	-0.136*** (0.048)	-0.132*** (0.048)	-0.136*** (0.048)
Process Innovation (Dummy Variable)	-0.098* (0.057)	-0.104* (0.058)	-0.104* (0.057)	-0.100* (0.057)	-0.098* (0.058)	-0.100* (0.057)	-0.104* (0.057)
Response reliability		-	-				-
Truthful	-0.482** (0.190)			-0.483** (0.201)	-0.048** (0.190)	-0.484** (0.200)	
Somewhat truthful	-0.33* (0.189)			-0.355* (0.196)	-0.328* (0.189)	-0.354* (0.196)	
Not truthful	Omitted			Omitted	Omitted	Omitted	
Calculation reliability	-		-		-		
Are directly taken from establishment records		-0.160** (0.067)		-0.125* (0.069)		-0.125* (0.069)	-0.159** (0.068)
Are estimates computed with some precision		-0.048 (0.064)		-0.051 (0.064)		-0.051 (0.064)	-0.047 (0.064)
Are arbitrary and unreliable numbers		0.006 (0.102)		-0.089 (0.106)		-0.089 (0.106)	0.005 (0.103)
Are in some cases taken from books and in some cases estimates		Omitted		Omitted		Omitted	Omitted

Table 4. 7. (Cont'd) Multinomial Logistic Regression Results of the Equations (2)-(8) in Table 4.6.

	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Survey completion	-	-				-	
One visit in face-to-face interview with one person			-0.166 (0.116)	-0.157 (0.116)	-0.158 (0.116)		-0.164 (0.116)
One visit in face-to-face interview with different managers/staff			-0.224 (0.150)	-0.210 (0.150)	-0.214 (0.150)		-0.213 (0.150)
Several visits			omitted	omitted	omitted		omitted
Constant	-1.264*** (0.487)	-1.57*** (0.457)	-1.444*** (0.467)	-1.024** (0.510)	-1.102** (0.502)	-1.185** (0.496)	-1.401*** (0.473)
For the outcome 3:	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of pre-COV employment	-0.170*** (0.055)	-0.172*** (0.055)	-0.170*** (0.055)	-0.170*** (0.055)	-0.168*** (0.055)	-0.171*** (0.055)	-0.170*** (0.055)
Log of pre-COV wage level	-0.13*** (0.037)	-0.131*** (0.037)	-0.129*** (0.037)	-0.132*** (0.037)	-0.129*** (0.037)	-0.132*** (0.037)	-0.132*** (0.037)
Product Innovation (Dummy variable)	-0.519*** (0.131)	-0.526*** (0.130)	-0.517*** (0.130)	-0.522*** (0.130)	-0.516*** (0.130)	-0.525*** (0.130)	-0.524*** (0.130)
Process Innovation (Dummy Variable)	-0.139 (0.158)	-0.138*** (0.158)	-0.134 (0.157)	-0.138 (0.158)	-0.138 (0.158)	-0.140 (0.158)	-0.137 (0.158)
Response reliability		-	-				-
Truthful	-0.375 (0.301)			-0.345 (0.329)	-0.372 (0.301)	-0.347 (0.329)	
Somewhat truthful	-0.408 (0.295)			-0.354 (0.313)	-0.405 (0.296)	-0.355 (0.313)	

Table 4. 7. (Cont'd) Multinomial Logistic Regression Results of the Equations (2)-(8) in Table 4.6.

Not truthful	omitted			omitted	omitted	omitted	
Calculation reliability	-		-		-		
Are directly taken from establishment records		0.157 (0.148)		0.157 (0.153)		0.156 (0.153)	0.158 (0.148)
Are estimates computed with some precision		0.025 (0.135)		0.029 (0.135)		0.031 (0.136)	0.025 (0.135)
Are arbitrary and unreliable numbers		0.175 (0.189)		0.123 (0.200)		0.127 (0.200)	0.171 (0.189)
Are in some cases taken from books and in some cases estimates		omitted		omitted		omitted	omitted
Survey completion	-	-				-	
One visit in face-to-face interview with one person			-0.083 (0.241)	-0.077 (0.242)	-0.079 (0.242)		-0.079 (0.242)
One visit in face-to-face interview with different managers/staff			-0.309 (0.376)	-0.306 (0.377)	-0.305 (0.377)		-0.309 (0.377)
Several visits			omitted	omitted	omitted		omitted
Constant	0.084 (1.048)	-0.365 (1.00)	-0.235 (1.033)	0.057 (1.080)	0.157 (1.075)	-0.158 (1.052)	-0.289 (1.031)
N	16,506	16,507	16,507	16,506	16,506	16,506	16,507
Pseudo R ²	0.0948	0.0946	0.0943	0.0952	0.0949	0.0951	0.0948

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors.

Base outcome is the first outcome where the firm status corresponds to the firms which ANSWER the survey.

Table 4. 7. (Cont'd) Multinomial Logistic Regression Results of the Equations (2)-(8) in Table 4.6.

Country, sector, region dummies are used in all the regressions but not reported here. Most of the country and region dummies are significant whereas sectoral dummies constructed from sectoral classification used in stratification of the sample are insignificant in most case in the regression of the second choice of the dependent variable in the third choice most country, sector and region dummies lose their significance.

(2) "Response reliability" in the baseline ES is the only exogenous variable used in the first step.

(3) "Calculation reliability" in the baseline ES is the only exogenous variable used in the first step.

(4) "Survey Completion" in the baseline ES is the only exogenous variable used in the first step.

(5) All three exogenous variables used in (2), (3) and (4) are used together in the first step.

(6) "Response reliability" and "Survey completion" are used as exogenous variables in the first step.

(7) "Calculation reliability" and "Survey Completion" are used as exogenous variables in the first step.

(8) "Response reliability" and "Calculation reliability" are used as exogenous variables in the first step.

In terms of monetary and macro-financial measures; temporary suspension of loan classifications and provisioning for the banking system, regulations to allow banks to restructure loans, cuts for policy rates, liquidity injection to the banking system, suspending dividend distribution for banks are among the most applied ones. Finally, in some countries, interventions to the exchange rate market had also been observed as a macroeconomic policy reaction.

Controlling for the effect of government support is important in the sense that government supports provided during COVID-19 had especially aimed to alleviate the disadvantages among the sectors or firms especially for the ones which are more vulnerable to the business slowdown due to COVID-19. This may not only have an alleviating effect of the side effects due to the economic shock brought by the Pandemic but also a “masking” effect for some of the different structural weaknesses (or strengths on the other way around) of businesses existing before the Pandemic that could be visible if those supports had not been provided. Keeping in mind this possible fact, we control for the government supports. Table 4.8 provides the results where the effect of any kind of government support is controlled whereas Table 4.9 shows the results for the effects of various kinds of government support on the condition that the government support is obtained. Note that country, sector, and region dummies are used in all the regressions but not reported. Almost all coefficients of sector and region dummies are insignificant in all regressions.

As we see from the estimations through columns (2) to (8) on Table 4.8; government support, no matter which kind of support is provided, has a positive employment impact during the early period of COVID-19 and in every specification has a value of coefficient equal to 4.3 percent (3.9 percent in standard OLS estimation). However, controlling for the government support has not made any difference of the statistical significance or magnitude of the coefficients of other explanatory variables. The important result is that even after controlling the impact of government support, the positive employment effect of product innovation implemented in the pre-Pandemic period persists and also this effect is robust in terms of its magnitude. In this specification of our extension, we do not see a masking effect of government support on the employment outcome of product innovation.

On Table 4.9, we differentiate the different kinds of government support. In this case, the magnitude of the coefficient of the product innovation falls around 1 or 1.5 percentage point in every specification through (2) to (8) whereas its statistical significance is not affected. In the OLS estimation, column (1), the statistical significance of product innovation improves. In terms of the employment impacts of government supports, we see a weak evidence of positive effect of *wage subsidy* in OLS estimation and the selection bias correction estimation in regression (2) whereas in other specifications it is not significant. *Other kinds of support* are statistically significant in all specifications. It is important to here mention that the most benefited kinds of supports have been *wage subsidy* and *fiscal exemptions* as provided in Section 4.3 and the least benefited one has been the category of *other kinds of support*. The category of *other kinds of support* is followed by a verbal explanation part in the survey for the firm to describe the government support that is benefited and therefore changes from firm to firm. In the regression results, we see that the positive effect of *wage subsidy* is not robust in all specifications. On the other hand, the employment impact of *other kinds of support* seems to be negative and its statistical significance is robust in all specifications which is a surprising result since we see that no matter which type is some kind of government support may lead to a negative outcome for labor demand at the firm level. In interpreting the results, however, we should keep in mind that this category constitutes only around 5 percent of the supports benefited; therefore, this outcome may indicate to some kind of outlier effect which may exist in the sample. Moreover, those firms which have been granted *other kinds of support* may have already problems more severely exacerbated by the Pandemic than the general deteriorating business conditions due to the Pandemic which may indicate to a kind of endogeneity problem. Another fact that should be kept in mind regarding government supports is that multiple kind of supports can be granted to businesses and this outcome may stem from the collinearity among the types of government support. However, we do not have a significant sign for multicollinearity according to the values of variance inflating factors. Lastly, firms might have obtained government support at the very beginning of the Pandemic if they are eligible no matter thinking about the usefulness or specific needs of the business they conduct. Although the country and industry dummies are sufficient to control for supply side heterogeneity of government

policies in different countries and sectors, they are not enough to account for the demand side endogeneity at the firm level in this sense¹⁶. Table 4.5 in Section 4.3 gives the distribution of various kinds of government supports and it can be seen from that table the ratios do not add up to 100 percent due to the existence of multiple kind of grants for one single firm.

4.5.3. Robustness Checks

With the concern that the results may not be robust under different specifications of the model, we try a different sectoral classification than the one used in the estimations above. The sectoral classification that we have used in the results so far has three broad categories as manufacturing sector, retail services and other services aligned with three sectoral levels used in the stratification methodology of the survey. Now we use the sectoral groups that we used in the Chapter 3 which has six categories and reported in Appendix A. In addition, the baseline survey years are different for the countries in the sample. Although the COVID-19 first round follow up surveys have been conducted during the period beginning from June 2020 and completed for all countries on May 2021 at latest, the baseline enterprise survey years were completed in different years; namely, 2016, 2017, 2018 and 2019. Generally, European and Central Asian countries in the sample have 2018 or 2019 as the baseline survey year whereas some of the African countries and most of the Central American countries have 2016 or 2017 as baseline survey years. Therefore, we control for the baseline survey years with dummy variables since the employment change between the two periods and also the employment impact of the innovation concerned may not possess the same dynamic due to the different time elapse between the baseline survey year and first round follow-up year.

Table 4.10 shows the re-estimation regressions of the Table 4.9 above. Although we have re-estimated the regressions of Table 4.6 and Table 4.8, it is not necessary to

¹⁶ Chundakkadan et al. (2022) analyzes the role of government support to alleviate the financial constraints for SMEs during the Pandemic with the WBES and COVID Follow-up Surveys for 34 countries. The paper uses the variable whether the firm has obtained an overdraft facility in the banking system in the pre-Pandemic period as a valid IV to control for the demand side endogeneity of government supports. By following the same path, we have tried the overdraft facility as an IV for government support but the variable did not pass the validity tests for IV in our sample and therefore we did not report the results here.

report those here for the sake of avoiding unnecessary repetition. The alternative sectoral decomposition reveals that there is an evidence for an extra employment shock for the hotels and restaurant sectors (which are not reported on the Table 4.10) since its coefficient is negative (almost around 20 percent) and statistically significant for all specifications whereas the other sectors do not differ from each other. Moreover, year dummies are significant and in those specifications, we see the positive effect of *wage subsidy* has become more persistent among all the regressions whereas the category of *other kinds of supports* has weakened in terms of its statistical significance although it preserves the negative employment outcome as in the previous section. The results still reveal that product innovation helps firms to persist their employment level during economic shocks and the magnitude of this positive effect has not changed considerably. In conclusion, the results of the robustness check show that our findings are robust to minor alterations of the model specification.

4.6. Conclusion

With the motivation to answer the question that whether a technological innovation that occurred before an economic shock has an employment impact during that shock, we have conducted an empirical analysis for 37 countries by using the data set which is consisted of the latest ES conducted before the COVID-19 Pandemic and their first round COVID follow-up surveys.

Since the universal sample is not obtainable with the onset of the Pandemic, there are lots of observation loss in the dependent variable. We have corrected this selection bias problem by using the selection bias correction based on multinomial logit model. Although the OLS estimations have not given a strong signal for employment impact of product or process innovation, after correcting for the selection bias, we see a significant improvement in the estimation results especially for the product innovation. we see that the employment impact of technological innovation before the Pandemic has helped to sustain employment level during the early period of the economic shock. This may be due to the fact that the increased demand for firms' products or services due to product innovation may help to smooth out the adverse

demand shock brought by the Pandemic. The results are persistent even if we control for the government supports which indicates that government supports have not any masking effect of the product innovation during the economic shock. The results are resistant to robustness checks. On the other hand, process innovation which emerged before the Pandemic does not have any effect on employment level during the early period of the Pandemic.

The results reveal that labor-enhancing effect of product innovation seems robust in various countries or during economic shocks. However, consistent with the previous literature, this is not the case for the process innovation. For the further research, the employment impact of technological innovation during an economic shock, or COVID-19 period specifically, may be studied under different classifications of the labor such as male-female or skilled-unskilled.

Table 4. 8. Effects of pre-COVID innovation on employment during COVID period, government supports are controlled

Dependent variable: Log of COVID-Round 1 Employment

	Standard OLS	Selection Bias Correction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of pre-COV employment	0.817*** (0.012)	0.815*** (0.014)	0.809*** (0.015)	0.802*** (0.022)	0.818*** (0.013)	0.818*** (0.013)	0.816*** (0.013)	0.815*** (0.014)
Log of pre-COV wage level	0.068*** (0.008)	0.084*** (0.008)	0.089*** (0.009)	0.09*** (0.01)	0.083*** (0.008)	0.083*** (0.008)	0.084*** (0.008)	0.086*** (0.008)
Product Innovation (Dummy variable)	0.031* (0.16)	0.077*** (0.024)	0.097*** (0.027)	0.099*** (0.033)	0.075*** (0.023)	0.073*** (0.023)	0.079*** (0.023)	0.086*** (0.026)
Process Innovation (Dummy Variable)	0.008 (0.019)	0.025 (0.022)	0.034 (0.023)	0.037 (0.028)	0.022 (0.022)	0.022 (0.022)	0.025 (0.022)	0.027 (0.023)
Any kind of government support	0.039** (0.016)	0.043** (0.017)	0.043** (0.017)	0.043** (0.017)	0.043** (0.017)	0.043** (0.017)	0.043** (0.017)	0.043** (0.017)
_m1		1.461*** (0.406)	1.07*** (0.42)	1.283*** (0.445)	1.191*** (0.388)	1.357*** (0.398)	1.278*** (0.394)	1.037** (0.412)
_m2		1.124 (0.78)	0.221 (0.902)	0.251 (1.276)	0.952 (0.696)	1.171 (0.696)	0.914 (0.725)	0.533 (0.832)
_m3		-0.332 (0.461)	-0.85* (0.489)	-0.645 (0.509)	-0.508 (0.441)	-0.362 (0.448)	-0.499 (0.452)	-0.762 (0.468)
Constant	-0.249*** (0.088)	-1.225*** (0.392)	-2.057*** (0.552)	-2.116*** (0.754)	-1.196*** (0.356)	-1.146*** (0.372)	-1.266*** (0.371)	-1.806*** (0.507)
N	11,689	11,686	11,687	11,687	11,686	11,686	11,686	11,687
R ²	0.7275	0.7282	0.7282	0.7282	0.7281	0.7282	0.7282	0.7281

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors.

Selection Bias Correction: Estimation results through the columns of (2) to (8).

(2) "Response reliability" in the baseline ES is the only exogenous variable used in the first step.

(3) "Calculation reliability" in the baseline ES is the only exogenous variable used in the first step.

(4) "Survey Completion" in the baseline ES is the only exogenous variable used in the first step.

(5) All three exogenous variables used in (2), (3) and (4) are used together in the first step.

(6) "Response reliability" and "Survey completion" are used as exogenous variables in the first step.

(7) "Calculation reliability" and "Survey Completion" are used as exogenous variables in the first step.

(8) "Response reliability" and "Calculation reliability" are used as exogenous variables in the first step.

Table 4. 9. Effects of pre-COVID innovation on employment during COVID period, government supports are controlled according to their types*Dependent variable: Log of COVID-Round 1 Employment*

	Standard OLS	Selection Bias Correction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of pre-COV employment	0.816*** (0.012)	0.81*** (0.014)	0.806*** (0.015)	0.800*** (0.022)	0.813*** (0.012)	0.814*** (0.014)	0.810*** (0.013)	0.812*** (0.014)
Log of pre-COV wage level	0.07*** (0.008)	0.082*** (0.008)	0.085*** (0.009)	0.088*** (0.01)	0.081*** (0.008)	0.081*** (0.008)	0.082*** (0.008)	0.082*** (0.008)
Product Innovation (Dummy variable)	0.034** (0.016)	0.068*** (0.024)	0.082*** (0.027)	0.086** (0.033)	0.064*** (0.033)	0.063*** (0.023)	0.069*** (0.023)	0.071*** (0.026)
Process Innovation (Dummy Variable)	0.008 (0.019)	0.022 (0.019)	0.029 (0.023)	0.033 (0.027)	0.019 (0.021)	0.018 (0.021)	0.022 (0.021)	0.022 (0.022)
Government Support								
Cash transfers	-0.036 (0.025)	-0.032 (0.029)	-0.031 (0.029)	-0.032 (0.029)	-0.032 (0.029)	-0.032 (0.029)	-0.031 (0.029)	-0.031 (0.029)
Deferral/Rollover of payments	-0.029 (0.028)	-0.024 (0.03)	-0.026 (0.03)	-0.025 (0.03)	-0.025 (0.03)	-0.024 (0.03)	-0.025 (0.03)	-0.026 (0.03)
New credit access	0.031 (0.034)	0.029 (0.038)	0.028 (0.038)	0.029 (0.038)	0.029 (0.038)	0.029 (0.038)	0.029 (0.038)	0.029 (0.038)
Fiscal exemption	-0.005 (0.025)	-0.004 (0.029)	-0.003 (0.029)	-0.004 (0.029)	-0.004 (0.029)	-0.004 (0.029)	-0.004 (0.029)	-0.004 (0.029)
Wage subsidy	0.032* (0.018)	0.031* (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.032 (0.021)	0.031 (0.021)	0.032 (0.021)
Other kinds of support	-0.140** (0.058)	-0.136** (0.064)	-0.132** (0.064)	-0.132** (0.064)	-0.135** (0.064)	-0.136** (0.064)	-0.135** (0.064)	-0.134** (0.064)
_m1	-	1.351*** (0.404)	0.902** (0.418)	1.115** (0.439)	1.039** (0.384)	1.250*** (0.395)	1.121*** (0.392)	0.869** (0.409)
_m2	-	1.041 (0.775)	0.182 (0.895)	0.217 (1.266)	0.800 (0.691)	1.089 (0.736)	0.759 (0.720)	0.468 (0.824)
_m3	-	-0.004 (0.460)	-0.463 (0.491)	-0.333 (0.509)	-0.150 (0.440)	-0.022 (0.448)	-0.152 (0.453)	-0.372 (0.469)

Table 4.9. (Cont'd) Effects of pre-COVID innovation on employment during COVID period, government supports are controlled according to their types

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.282*** (0.088)	-1.455*** (0.406)	-1.722*** (0.480)	-1.826*** (0.656)	-1.391*** (0.373)	-1.358*** (0.387)	-1.476*** (0.389)	-1.511*** (0.441)
N	11,308	11,308	11,308	11,308	11,308	11,308	11,308	11,308
R ²	0.7366	0.7371	0.7370	0.7371	0.7370	0.7371	0.7371	0.7370

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors.

Selection Bias Correction: Estimation results through the columns of (2) to (8).

- (2) "Response reliability" in the baseline ES is the only exogenous variable used in the first step.
(3) "Calculation reliability" in the baseline ES is the only exogenous variable used in the first step.
(4) "Survey Completion" in the baseline ES is the only exogenous variable used in the first step.
(5) All three exogenous variables used in (2), (3) and (4) are used together in the first step.
(6) "Response reliability" and "Survey completion" are used as exogenous variables in the first step.
(7) "Calculation reliability" and "Survey Completion" are used as exogenous variables in the first step.
(8) "Response reliability" and "Calculation reliability" are used as exogenous variables in the first step.

Table 4. 10. Effects of pre-COVID innovation on employment during COVID period, government supports are controlled according to their types and with survey year dummies and different sectoral classification

Dependent variable: Log of COVID-Round 1 Employment

	Standard OLS	Selection Bias Correction						
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of pre-COV employment	0.819*** (0.013)	0.817*** (0.015)	0.810*** (0.017)	0.815*** (0.024)	0.817*** (0.013)	0.820*** (0.014)	0.814*** (0.013)	0.816*** (0.015)
Log of pre-COV wage level	0.068*** (0.008)	0.081*** (0.008)	0.085*** (0.01)	0.084*** (0.011)	0.081*** (0.008)	0.08*** (0.008)	0.082*** (0.008)	0.083*** (0.009)
Product Innovation (Dummy variable)	0.037** (0.016)	0.073*** (0.023)	0.088*** (0.026)	0.081** (0.033)	0.072*** (0.022)	0.070*** (0.023)	0.076*** (0.023)	0.079*** (0.025)
Process Innovation (Dummy Variable)	0.007 (0.019)	0.018 (0.022)	0.025 (0.023)	0.021 (0.026)	0.018 (0.021)	0.015 (0.021)	0.020 (0.021)	0.021 (0.022)
Government Support								
Cash transfers	-0.033 (0.025)	-0.029 (0.029)	-0.027 (0.029)	-0.032 (0.029)	-0.029 (0.029)	-0.028 (0.03)	-0.029 (0.029)	-0.028 (0.029)
Deferral/Rollover of payments	-0.026 (0.029)	-0.021 (0.03)	-0.022 (0.03)	-0.028 (0.03)	-0.022 (0.03)	-0.02 (0.03)	-0.021 (0.03)	-0.021 (0.03)
New credit access	0.032 (0.034)	0.03 (0.038)	0.03 (0.038)	0.03 (0.038)	0.03 (0.038)	0.03 (0.038)	0.030 (0.038)	0.03 (0.038)
Fiscal exemption	-0.003 (0.026)	-0.003 (0.03)	-0.003 (0.03)	-0.003 (0.03)	-0.003 (0.03)	-0.003 (0.029)	-0.002 (0.029)	-0.003 (0.03)
Wage subsidy	0.037** (0.018)	0.037* (0.021)	0.037* (0.021)	0.037* (0.021)	0.038* (0.021)	0.037* (0.021)	0.037* (0.021)	0.037* (0.021)
Other kinds of support	-0.131** (0.058)	-0.126** (0.065)	-0.123* (0.064)	-0.123* (0.065)	-0.126* (0.064)	-0.126 (0.064)	-0.126** (0.064)	-0.124* (0.064)
YEAR2019	0.607*** (0.201)	1.234*** (0.321)	1.401*** (0.388)	1.293** (0.575)	1.167*** (0.285)	1.135*** (0.305)	1.255*** (0.298)	1.221*** (0.354)
YEAR2018	0.164 (0.210)	0.662*** (0.188)	0.642*** (0.199)	0.651*** (0.246)	0.586*** (0.181)	0.610*** (0.186)	0.630*** (0.182)	0.575*** (0.193)
YEAR2017	0.555*** (0.203)	1.014*** (0.164)	0.998*** (0.172)	1.013*** (0.197)	0.951*** (0.160)	0.975*** (0.163)	0.984*** (0.162)	0.947*** (0.168)

Table 4. 10. (Cont'd) Effects of pre-COVID innovation on employment during COVID period, government supports are controlled according to their types and with survey year dummies and different sectoral classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
YEAR2016	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
_m1	-	1.443*** (0.376)	1.068*** (0.388)	1.281*** (0.405)	1.167*** (0.360)	1.348*** (0.369)	1.244*** (0.367)	1.035** (0.379)
_m2	-	1.322* (0.746)	0.486 (0.870)	1.004 (1.215)	1.012 (0.669)	1.347* (0.708)	0.980 (0.698)	0.735 (0.799)
_m3	-	-0.152 (0.446)	-0.545 (0.475)	-0.410 (0.495)	-0.283 (0.427)	-0.193 (0.434)	-0.266 (0.438)	-0.483 (0.454)
Constant	-0.789*** (0.258)	-1.232*** (0.378)	-1.511*** (0.452)	-1.359** (0.625)	-1.229*** (0.345)	-1.159*** (0.360)	-1.298*** (0.360)	-1.334*** (0.414)
N	11,308	11,308	11,308	11,308	11,308	11,308	11,308	11,308
R ²	0.7369	0.7377	0.7376	0.7376	0.7376	0.7376	0.7376	0.7375

Note: ***, **, * denote 1%, 5% and 10% significance levels for coefficients and standard errors robust to heteroscedasticity. The values in parentheses are standard errors.

Selection Bias Correction: Estimation results through the columns of (2) to (8).

- (2) "Response reliability" in the baseline ES is the only exogenous variable used in the first step.
- (3) "Calculation reliability" in the baseline ES is the only exogenous variable used in the first step.
- (4) "Survey Completion" in the baseline ES is the only exogenous variable used in the first step.
- (5) All three exogenous variables used in (2), (3) and (4) are used together in the first step.
- (6) "Response reliability" and "Survey completion" are used as exogenous variables in the first step.
- (7) "Calculation reliability" and "Survey Completion" are used as exogenous variables in the first step.
- (8) "Response reliability" and "Calculation reliability" are used as exogenous variables in the first step.

CHAPTER 5

CONCLUSION

5.1. Main Findings

The employment impact of technological innovation has been debated throughout the modern economic history especially with the advent of the First Industrial Revolution. Although the fear of mass unemployment stemming from technical improvement arises from time to time, the technical change has been seen the most important condition of the economic growth and development of the societies. With this longstanding debate, we have tried to answer the same old question “Does technological innovation have an impact on employment at the firm level?” in two different essays having two different contexts. The data sets used in the empirical analyses of this Thesis belong to developing countries, so the question directs itself naturally to the dynamics existing in developing countries.

The broad review of the literature shows that it is important to put forth the definitions regarding innovation, its difference from invention and its categorization to understand and interpret the literature in a correct and meaningful manner. In Chapter 2, first of all, the concept of labor demand and the concepts related to technological innovation used in the literature are explained. Secondly, the theoretical and empirical literature on the relationship between technological innovation and labor demand is discussed in detail.

After those preliminary chapters, in the first essay, we have used a unique and comprehensive data set for 53 developing countries based on WBES and its linked Innovation modules conducted during the years 2013 and 2014 and applied HJMP model proposed in the paper Harrison et al. (2014). The results have revealed that

process innovation has a labor-saving impact only in Africa and the pooled sample where in other regions it has no significant impact whereas the product innovation contributes to job creation in all specifications. The relative efficiency of producing new products compared to old products vary on regional base. New products are produced more efficiently in all regions except MENA. Lastly, an efficiency increase for non-innovators also exists for the pooled sample, Africa and South Asia. Based on our main motivation for this essay, which is the hypothesis that business environments are important for firm performance from various aspects and therefore they naturally may have an effect on labor demand at the firm level, we include the perceived business obstacles provided by WBES into our estimations of HJMP model. Starting with no a priori theoretical approach for the selection of business obstacles among categories existing, we have conducted an exploratory factor analysis to determine the number of factors and the most representative obstacle category both for the pooled sample and four different regions we have in the data set. Our estimation results have especially confirmed that some categories of business obstacles have an effect on firms' employment decisions. For the overall sample, regulatory environment has an effect on labor demand (i.e. labor regulations and customs and trade regulations) although the dominant obstacles in each factor may vary according to different regions. It is important to note that the magnitudes and signs of coefficients of business obstacles diverge from economic theoretical expectations occasionally which may indicate to some sort of endogeneity problem naturally existing in perceived business obstacles and other variables in the estimation models. All in all, our findings provided evidence to some extent that dissociating the employment impact of *perceived business obstacles* improves the statistical significance of process innovation on regional base. Our results are compatible with the significant part of the literature showing that product innovation has a robust and labor enhancing effect on employment and therefore it may construct a compensation mechanism for the labor saving impact of process innovation if exist any aligned with the Schumpeterian approach explained in Chapter 2 and Chapter 3. However, the labor saving or enhancing outcome of process innovation is not so easily visible and more vulnerable to different model specification.

The second essay has aimed to investigate whether a technological innovation that occurred before an economic shock has an influence on employment during that shock. To answer that question, we have used a data set belonging to a special period of economic shock, namely, COVID-19 Pandemic. The empirical analysis is conducted for 37 countries by using the data set constructed by merging the latest pre-Pandemic ES and the first round COVID follow-up surveys based on the same sample. However, since the universal sample of baseline ES is not obtainable during the first round of Pandemic, there has been a significant information loss in the dependent variable which leads to a selection bias problem. To correct for this selection bias problem, we have followed the estimating strategy of the selection bias correction based on multinomial logit model. Although the OLS estimations have provided a weak signal for employment impact of product innovation and no signal for process innovation; after correcting for the selection bias, we see a significant improvement in the estimation results for the impact of product innovation. The product innovation has relatively led to less labor loss, approximately over 4 percent for the firms which have made product innovation, with respect to the ones which made no product innovation. This finding may be the result of the indirect effect of the increased demand for firms' products or services due to product innovation. The demand increase before the Pandemic may have helped to smooth out the adverse effects of COVID-19 shock on firm employment levels. The results are persistent even if we control for the government supports which indicates that government supports have not any masking effect of the product innovation during the economic shock. The results are resistant to robustness checks. On the other hand, process innovation which emerged before the Pandemic does not have any effect on employment level during the early period of the Pandemic.

Overall, this Thesis contributes to the ongoing debate on employment impact of technological innovation in different contexts. Being aligned with the previous literature, the job creating effect of product innovation seems valid in different geographical regions, during the economic shocks or downturns and robust to alternative specifications. On the other hand, the employment impact of process innovation, whether being in normal times or economic shock periods, is mixed and more complicated to estimate in a robust manner relative to the one of product

innovation. In developing countries, the employment impact of process innovation needs to be investigated further by taking into account the factors that may have an effect on labor demand in general and mask the real outcome of process innovation concurrently. However, endogeneity problem which may arise in those cases should be treated cautiously.

Future research can extend these insights by examining the impact of innovation on different labor categories, such as gender or skill levels, and exploring long-term employment trends in developing economies. As long as the limitations of the available data sources allow, the methods that have been used in this Thesis can be applied by controlling other various factors such as being an exporter, having a foreign ownership of the firm, the skill composition of the firm before the emergence of especially process innovation, or the degree of integration into the global value chain may be important factors in the divergence of the results of employment impact of technological innovation. In terms of the employment impact of technological innovation, the skill composition after the occurrence of technological innovation is also worth to investigation.

5.2. Main Limitations

For the first essay of the Thesis, first of all, the HJMP model does not provide an opportunity to make a dynamic analysis in its theoretical terms. On the other hand, the data set we have in hand does not also provide an opportunity to make dynamic estimation to compare the short run results that HJMP model provides. Particularly in terms of the influence of process innovation on labor demand, the dynamic estimation techniques may provide more promising results as many previous studies have demonstrated in the empirical literature.

Secondly, although the national innovation surveys have spread to all around the world and started to be conducted repeatedly for the last decades, comparable data sets like WBES and their linked Innovation Modules are not so much available. It would be very beneficial to produce such kind of data sets continually especially by internationally recognized institutions like WB. National innovation surveys

covering three-year period as in CIS or WBES should better include the exact time of innovations, especially process innovation within that three-year time period to open a way to make more robust estimations for employment impact of innovations. This would also add some kind of dynamic aspect to the short run estimations.

Also, since the data set used in the first essay of this Thesis does not include the pre-innovation labor and skill composition of the businesses, we are not able to decompose the employment outcomes in terms of gender, skill levels or on temporary and permanent employment basis. A general problem in both data sets used in two essays is that there are lots of missing values in each variable and this causes to significant observation and information loss in all estimations.

For the first essay, another issue is the potential endogeneity problem which may exist in perceived business obstacles. Although perceived business obstacles provide valuable information, solution alternatives should be considered in future research.

For the second essay, although selection bias correction has been conducted with multinomial logistic model in the first step regressions, there is still serious missing value problem in most of the variables in the data set. In general, data quality problem embedded in the two datasets that we have used forms a limitation for the Thesis. Another problem for the second essay is that demand side endogeneity of the variables of government supports has been remained unsolved due to the inexistence of appropriate instrumental variables.

5.3. Policy Implications

As mentioned in previous chapters, technological innovation has been seen the main engine for economic growth and development since the beginning of the modern economy. Many developing countries especially have been struggling to upgrade themselves in the innovation and technological advancements in global arena and produce high value-added in global value chains. For this aim, they construct various technology policies and labor market policies simultaneously. The main findings of this Thesis reveal that technological innovation may interact labor demand in various

ways. Therefore, those two streams of policies, which are technology and labor market policies, should be aligned continually with monitoring the evolution of the economy. Public or private policymakers may pay attention to those two streams of policies support each other. Moreover, policies should also target the non-innovative firms to become innovative. As we see from our results, innovative firms seem more resilient during economic shocks and are more successful in protecting their employment levels or lose relatively less labor during downturns. Another important point to keep in mind that policymaking on sectoral, gender and various vulnerable groups of labor markets should be paid attention. The proper and high-quality data production on micro-, meso- and macro-level in this area is a significant policy by itself.

Another policy line that should be paid attention is related to improving business environments. As WB and many other important institutions or academic researchers have mentioned in the beginning of the new millennium, improving business environments is one of the key development strategies. Our main findings also reveal that business obstacles affect firm behavior in terms of their employment decisions. Those obstacles may also interact with the innovation decisions of the firms. This area should be focused both in terms of future research for researchers and improving appropriate policies and strategies for policymakers.

5.4. Future Research

Future research may focus on more diversified aspects of innovation employment nexus. At the firm level analysis, taking into account the export status of the firms, market power or competitiveness of the environment, foreign vs. domestic ownership of firms and many other economic factors may be included to estimate various extensions of HJMP models or the models may be re-estimated in business cycles or under different macroeconomic conditions. Many of those kinds of studies already exist in the literature; however, those diversifications are still being examined with new, more comprehensive and more granular data sets become available.

On the other hand, complementarity or substitutability of technology with skills can be studied if there is prior skill information of the firms. With repeated surveys, there

may be an opportunity to handle this issue with the model specifications used in this Thesis.

One other important problem encountered in the analyses of this Thesis is finding appropriate instrumental variables for various types of endogeneity problems. The demand for government support during COVID-19 period and perception of business obstacles are two examples that have been mentioned above. Future research may focus on finding appropriate instrumental variables to tackle this problem.

Lastly, focusing on dynamic estimations to determine the compensation mechanisms that are intact is another important research area since some compensation mechanisms reveal themselves with a time lag according to some researches in the literature. COVID-19 period and its ongoing effects on labor demand or labor markets in general may also be studied with panel data sets if available.

REFERENCES

- Aboal, D., Garda, P., Lanzilotta, B., & Perera, M. (2015). Innovation, firm size, technology intensity, and employment generation: Evidence from the Uruguayan manufacturing sector. *Emerging Markets Finance and Trade*, 51(1), 3-26.
- Acemoglu, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings.
- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6), 1488-1542.
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of economic perspectives*, 33(2), 3-30.
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy*, 128(6), 2188-2244.
- Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public economics*, 189, 104245.
- Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2), 323-351.
- Agrawal, S., Cojocaru, A., Montalva, V., Narayan, A., Bundervoet, T., & Ten, A. (2021). COVID-19 and inequality: how unequal was the recovery from the initial shock?.
- Albanesi, S., & Kim, J. (2021). Effects of the COVID-19 recession on the US labor market: Occupation, family, and gender. *Journal of Economic Perspectives*, 35(3), 3-24.

- Allen, R.G.D. (1938). *Mathematical Analysis for Economists*. London: Macmillan.
- Antonucci, T., & Pianta, M. (2002). Employment effects of product and process innovation in Europe. *International Review of Applied Economics*, 16(3), 295-307.
- Apedo-Amah, M. C., Avdiu, B., Cirera, X., Cruz, M., Davies, E., Grover, A., ... & Tran, T. T. (2020). Unmasking the Impact of COVID-19 on Businesses. *Policy research working paper*, 9434(6).
- Arenas Díaz, G., Barge-Gil, A., Heijs, J., & Marzucchi, A. (2025). The effect of external innovation on firm employment. *Economics of Innovation and New Technology*, 34(1), 44-69.
- Arenas Díaz, G., Guerrero, A. J., & Heijs, J. (2024). The effects of product and process innovation on employment: a meta-regression analysis. *Eurasian Business Review*, 14(1), 35-68.
- Barrachina, M. E. R., & Moreno, J. A. R. (2023). The role of innovation in employment growth, skill demand, and wages: Evidence from Ecuador. *Latin American Economic Review*, 32, 1-30.
- Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *How are small businesses adjusting to COVID-19? Early evidence from a survey* (No. w26989). National Bureau of Economic Research.
- Benavente, J. M., & Lauterbach, R. (2008). Technological innovation and employment: complements or substitutes?. *The European Journal of Development Research*, 20, 318-329.
- Béland, L. P., Brodeur, A., & Wright, T. (2023). The short-term economic consequences of Covid-19: exposure to disease, remote work and government response. *Plos one*, 18(3), e0270341.
- Bogliacino, F., & Pianta, M. (2010). Innovation and employment: a reinvestigation using revised Pavitt classes. *Research policy*, 39(6), 799-809.

- Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European microdata. *Economics Letters*, 116(1), 56-59.
- Bogliacino, F., Piva, M., & Vivarelli, M. (2014). Technology and employment: the job creation effect of business R&D. *Rivista internazionale di scienze sociali*: 3, 2014, 239-264.
- Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers*, 51(2), 96-113.
- Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic surveys*, 21(1), 174-205.
- Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., & TuYe, H. Y. (2020). *COVID-19 and remote work: An early look at US data* (No. w27344). National Bureau of Economic Research.
- Bundervoet, T., Dávalos, M. E., & Garcia, N. (2022). The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys. *World development*, 153, 105844.
- Calvino, F., & Virgillito, M. E. (2018). The innovation-employment nexus: a critical survey of theory and empirics. *Journal of Economic surveys*, 32(1), 83-117.
- Campa, R. (2017). Technological unemployment: A brief history of an idea.
- Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & The Opportunity Insights Team. (2020). *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data* (Vol. 91, pp. 1689-1699). Cambridge, MA: National Bureau of Economic Research.

- Chundakkadan, R., Natarajan, R. R., & Sasidharan, S. (2022). Small firms amidst COVID-19: Financial constraints and role of government support. *Economic Notes*, 51(3), e12206.
- Cirera, X., & Sabetti, L. (2019). The effects of innovation on employment in developing countries: evidence from enterprise surveys. *Industrial and Corporate Change*, 28(1), 161-176.
- Cochran, W. G. (1977). *Sampling techniques*. John Wiley & Sons.
- Couch, K. A., Fairlie, R. W., & Xu, H. (2020). Early evidence of the impacts of COVID-19 on minority unemployment. *Journal of public economics*, 192, 104287.
- Cortes, G. M., & Forsythe, E. (2023). Heterogeneous labor market impacts of the COVID-19 pandemic. *ILR Review*, 76(1), 30-55.
- Crespi, G., & Tacsir, E. (2012). Effects of Innovation on Employment in Latin America.
- Crespi, G., Tacsir, E., & Pereira, M. (2019). Effects of innovation on employment in Latin America. *Industrial and Corporate Change*, 28(1), 139-159.
- Crossley, T. F., Fisher, P., & Low, H. (2021). The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of public economics*, 193, 104334.
- Dachs, B., & Peters, B. (2014). Innovation, employment growth, and foreign ownership of firms: A European perspective. *Research Policy*, 43(1), 214-232.
- Dachs, B., Hud, M., Koehler, C., & Peters, B. (2017a). Innovation, creative destruction and structural change: firm-level evidence from European countries. *Industry and Innovation*, 24(4), 346-381.

- Dachs, B., Hud, M., Koehler, C., & Peters, B. (2017b). Employment effects of innovations over the business cycle: firm-level evidence from European countries.
- Dahl, G. B. (2002). Mobility and the return to education: Testing a Roy model with multiple markets. *Econometrica*, 70(6), 2367-2420.
- Data, I. I. (2005). Oslo manual. *Paris and Luxembourg: OECD/Euro-stat*.
- De Elejalde, R., Giuliadori, D., & Stucchi, R. (2015). Employment and innovation: Firm-level evidence from Argentina. *Emerging Markets Finance and Trade*, 51(1), 27-47.
- Devinney, T. M. (1993). How well do patents measure new product activity?. *Economics Letters*, 41(4), 447-450.
- Diaconu, M. (2011). Technological Innovation: Concept, Process, Typology and Implications in the Economy. *Theoretical & Applied Economics*, 18(10).
- Díaz, G. A., Barge-Gil, A., & Heijs, J. (2020). The effect of innovation on skilled and unskilled workers during bad times. *Structural Change and Economic Dynamics*, 52, 141-158.
- Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research policy*, 11(3), 147-162.
- Dosi, G., & Nelson, R. R. (2013). The evolution of technologies: an assessment of the state-of-the-art. *Eurasian business review*, 3, 3-46.
- Dosi, G., Piva, M., Virgillito, M. E., & Vivarelli, M. (2021). Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction. *Research Policy*, 50(4), 104199.
- Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica: Journal of the Econometric Society*, 345-362.

- Duysters, G., & Hagedoorn, J. (2001). Do company strategies and structures converge in global markets? Evidence from the computer industry. *Journal of International Business Studies*, 32, 347-356.
- Evangelista, R., & Vezzani, A. (2012). The impact of technological and organizational innovations on employment in European firms. *Industrial and Corporate Change*, 21(4), 871-899.
- Farnes, N. (1993). Modes of production: Fordism and distance education. *Open Learning: The Journal of Open, Distance and e-Learning*, 8(1), 10-20.
- Foronda, C., & Beverinotti, J. (2021). *Effects of innovation on employment: An analysis at the firm level in Bolivia* (No. IDB-WP-01244). IDB Working Paper Series.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological forecasting and social change*, 114, 254-280.
- Gaskin, C. J., & Happell, B. (2014). On exploratory factor analysis: A review of recent evidence, an assessment of current practice, and recommendations for future use. *International journal of nursing studies*, 51(3), 511-521.
- Greenan, N., & Guellec, D. (2000). Technological innovation and employment reallocation. *Labour*, 14(4), 547-590.
- Hagedoorn, J. (1989). *The dynamic analysis of innovation and diffusion: a study in process control*. Pinter, London.
- Hagedoorn, J., & Cloudt, M. (2003). Measuring innovative performance: is there an advantage in using multiple indicators?. *Research policy*, 32(8), 1365-1379.
- Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. *Industrial and corporate change*, 17(4), 813-839.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2005). Does innovation stimulate employment? A firm-level analysis using comparable micro data on four European countries.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2008). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35, 29-43.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.

Henderson, R., & Cockburn, I. (1994). Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic management journal*, 15(S1), 63-84.

Herstad, S. J., & Sandven, T. (2015). *Innovation and corporate employment growth revisited* (No. 2015/3). Lund University, CIRCLE-Centre for Innovation Research.

Hou, J., Huang, C., Licht, G., Mairesse, J., Mohnen, P., Mulkay, B., ... & Zhen, F. (2019). Does innovation stimulate employment? Evidence from China, France, Germany, and the Netherlands. *Industrial and Corporate Change*, 28(1), 109-121.

Howard, M. C. (2016). A review of exploratory factor analysis decisions and overview of current practices: What we are doing and how can we improve?. *International journal of human-computer interaction*, 32(1), 51-62.

Jaumandreu, J. (2003). Does innovation spur employment? A firm-level analysis using Spanish CIS data. *Universidad Carlos III de Madrid*, 17(4), 813-839.

- Khan, S. U. (2023). The firm-level employment impact of COVID-19: International evidence from World Bank Group's Enterprise Surveys. *Eastern European Economics*, 61(5), 457-490.
- Keynes, J. M. (1930). Economic possibilities for our grandchildren. In *Essays in persuasion* (pp. 321-332). London: Palgrave Macmillan UK.
- Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International journal of industrial organization*, 29(2), 210-220.
- Layard, R., & Nickell, S. (1985). The Causes of British Unemployment. *National Institute Economic Review*, 111, 62-85.
- Lazonick, W. (2015). Reforming the financialized business corporation. *EPRN*.
- Lee, L. F. (1982). Some approaches to the correction of selectivity bias. *The Review of Economic Studies*, 49(3), 355-372.
- Leitner, S. M., Pöschl, J., & Stehrer, R. (2011). *Change Begets Change: Employment Effects of Technological and Non-Technological Innovations-a Comparison across Countries* (No. 72). WIIW Working Paper.
- Lohr, S. L. (1999). Sampling: design and analysis [CD].
- Mastrostefano, V., & Pianta, M. (2009). Technology and jobs. *Economics of innovation and new technology*, 18(8), 729-741.
- Malerba, F., & Orsenigo, L. (1997). Technological regimes and sectoral patterns of innovative activities. *Industrial and corporate change*, 6(1), 83-118.
- Mahler, D. G., Yonzan, N., & Lakner, C. (2022). The impact of COVID-19 on global inequality and poverty.

- Medina, L., & Schneider, F. (2019). *Shedding Light on the Shadow Economy: A Global Database and the Interaction with the Official One* (No. 7981). CESifo Working Paper.
- Naidoo, K., Bengoa, M., Kraemer-Mbula, E., & Tregenna, F. (2023). Firm innovation and employment in South Africa: Examining the role of export participation and innovation novelty. *Emerging Markets Finance and Trade*, 59(2), 589-604.
- Norris, M., & Lecavalier, L. (2010). Evaluating the use of exploratory factor analysis in developmental disability psychological research. *Journal of autism and developmental disorders*, 40, 8-20.
- Özşuca, E. A. (2023). Firm survival in times of crisis: Do innovation and financing constraints matter? Insights from the COVID-19 pandemic. *Eastern European Economics*, 61(5), 421-456.
- Pavitt, K. (1987). The objectives of technology policy. *Science and public policy*, 14(4), 182-188.
- Pellegrino, G., Piva, M., & Vivarelli, M. (2019). Beyond R&D: the role of embodied technological change in affecting employment. *Journal of Evolutionary Economics*, 29(4), 1151-1171.
- Peters, B. (2004). *Employment Effects of Different Innovation Activities: Microeconometric Evidence* (No. 04-73). ZEW Discussion Papers.
- Peters, B. (2005). *Employment effects of different innovation activities: Microeconometric evidence* (No. 04-73 [rev.]). ZEW Discussion Papers.
- Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of economics*, 86, 65-83.
- Prisecaru, P. (2016). Challenges of the fourth industrial revolution. *Knowledge Horizons. Economics*, 8(1), 57.

Rabe-Hesketh, S., & Skrondal, A. (2008). Multilevel and longitudinal modeling. *Using Stata*, 2.

Reichelt, M., Makovi, K., & Sargsyan, A. (2021). The impact of COVID-19 on gender inequality in the labor market and gender-role attitudes. *European Societies*, 23(S1), S228-S245.

Ricardo, D. (1891). *Principles of political economy and taxation*, ed. by ECK Gonnner.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of political economy*, 94(5), 1002-1037.

Rosenberg, N. (1976). *Perspectives on technology*. Cambridge: Cambridge University Press.

Say, J. B. (1836). *A treatise on political economy: or the production, distribution, and consumption of wealth*. Grigg & Elliot.

Scheaffer, R. L., Mendenhall, W., Ott, L., & Gerow, K. (1990). *Elementary survey sampling* (Vol. 501). California: Duxbury Press.

Schmookler, J. (1966). *Invention and Economic Growth*. Harvard University Press

Schumpeter, J. (2013). *The Theory of Economic Development*. Harvard University Press

Schwab, K. (2017). *The fourth industrial revolution*. Crown Currency.

Sinclair, P. J. (1981). When will technical progress destroy jobs?. *Oxford Economic Papers*, 33(1), 1-18.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3), 312-320.

- Stern, N., & Stern, N. H. (2002). *A strategy for development*. World Bank Publications.
- Triguero, A., Córcoles, D., & Cuerva, M. C. (2014). Persistence of innovation and firm's growth: evidence from a panel of SME and large Spanish manufacturing firms. *Small business economics*, 43, 787-804.
- Van Reenen, J. (1997). Employment and technological innovation: evidence from UK manufacturing firms. *Journal of labor economics*, 15(2), 255-284.
- Van Roy, V., Vértesy, D., & Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research policy*, 47(9), 1762-1776.
- Vivarelli, M. (1995). The economics of technology and employment: Theory and empirical evidence. In *The Economics of Technology and Employment*. Edward Elgar Publishing.
- Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in the Italian manufacturing industry. *Research policy*, 25(7), 1013-1026.
- Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, 48(1), 123-154.
- World Bank. (2004). *A Better Investment Climate for Everyone: World Development Report 2005*.
- World Bank Group, *World Development Report 2022: Finance for an Equitable Recovery*. Washington, DC: World Bank Group, 2022.
- Xu, L. C. (2011). The effects of business environments on development: Surveying new firm-level evidence. *The World Bank Research Observer*, 26(2), 310-340.

APPENDICES

A. SECTORAL DECOMPOSITION

INDUSTRY GROUPS ACCORDING TO FIRST TWO DIGIT OF ISIC REV3.1

Group 1. Section D: Manufacturing (15-37)

Group 2. Section F: Construction (45)

Group 3. Section G: Retail and Wholesale (50-52)

Group 4. Section H: Hotels and Restaurants (55)

Group 5. Section I: Transport (60-64)

Group 6. Section K: Real Estate, renting and business activities (70-74)

B. COUNTRY LIST FOR WBES 2013-2014 DATA

- | | |
|----------------------------|------------------------|
| 1. Congo, Dem. Rep. | 28. Kosovo |
| 2. Ghana | 29. Kyrgyzstan |
| 3. Kenya | 30. Latvia |
| 4. Namibia | 31. Lithuania |
| 5. Nigeria | 32. Macedonia |
| 6. South Sudan | 33. Moldova |
| 7. Sudan | 34. Mongolia |
| 8. Tanzania | 35. Montenegro |
| 9. Uganda | 36. Poland |
| 10. Zambia | 37. Romania |
| 11. Malawi | 38. Russia |
| 12. Bangladesh | 39. Serbia |
| 13. India | 40. Slovakia |
| 14. Nepal | 41. Slovenia |
| 15. Pakistan | 42. Tajikistan |
| 16. Albania | 43. Türkiye |
| 17. Armenia | 44. Ukraine |
| 18. Azerbaijan | 45. Uzbekistan |
| 19. Belarus | 46. Egypt |
| 20. Bosnia and Herzegovina | 47. Israel |
| 21. Bulgaria | 48. Jordan |
| 22. Croatia | 49. Lebanon |
| 23. Czech Republic | 50. Morocco |
| 24. Estonia | 51. Tunisia |
| 25. Georgia | 52. West Bank and Gaza |
| 26. Hungary | 53. Yemen |
| 27. Kazakhstan | |

**C. COUNTRY LIST FOR WBES 2016-2019 DATA AND COVID FOLLOW-
UP SURVEYS**

Table C.1

Number	Country	ES Year	Round 1	Round 2	Round 3	Round 4
1	Albania	2019	June 2020	-	-	-
2	Armenia	2020	June 2020	March-Apr. 2021	Oct.-Nov. 2021	March- Apr. 2022
3	Azerbaijan	2019	May 2021	-	-	-
4	Belarus	2018	August 2020	-	-	-
5	Bulgaria	2019	June-Sept. 2020	Nov.-Dec. 2020	Apr.-May 2021	-
6	Croatia	2019	Sept. 2020	Jan. 2021	May-June 2021	-
7	Czechia	2019	Sept.-Oct. 2020	Jan.-Feb. 2021	May-June 2021	-
8	Estonia	2019	Oct. 2020	Feb. 2021	July-Aug. 2021	-
9	Georgia	2019	June 2020	Oct.-Nov. 2020	Sept.-Oct. 2021	-
10	Hungary	2019	Sept. 2020	Jan.-Feb. 2021	May-June 2021	-
11	Kazakhstan	2019	Feb.- March 2021	June-July 2022	-	-
12	Latvia	2019	Oct.-Nov. 2020	Feb. 2021	July-Aug. 2021	-
13	Lithuania	2019	Oct. 2020	Feb. 2021	July-Aug. 2021	-
14	Moldova	2019	May 2020	Oct.-Nov. 2020	May-June 2021	-

Table C.1 (Cont'd)

Number	Country	ES Year	Round 1	Round 2	Round 3	Round 4
15	Mongolia	2019	Aug. 2020	Feb. 2021	-	-
16	Montenegro	2019	Feb. 2021	-	-	-
17	Poland	2019	Aug. 2020	Nov.-Dec. 2020	May-June 2021	-
18	Romania	2019	Aug.-Sep. 2020	Nov.-Dec. 2020	May-June 2021	-
19	Russia	2019	June 2020	Feb.-March 2022	-	-
20	Serbia	2019	Feb. 2021	-	-	-
21	Slovakia	2019	Sep.-Oct. 2020	Jan.-Feb. 2021	May-June 2021	-
22	Slovenia	2019	July-Aug. 2020	Nov.- Dec.2020	May-June 2021	-
23	Cyprus	2019	June 2020	Nov.-Dec. 2020	Apr. 2021	-
24	Greece	2018	June 2020	Nov. 2020	Apr.-May 2021	-
25	Italy	2019	May-June 2020	Nov. 2020	Apr.-May 2021	-
26	Malta	2019	Sept.-Oct. 2020	Jan. 2021	May 2021	-
27	Portugal	2019	Sept.-Oct. 2020	Jan.-Feb. 2021	May-June 2021	-

Table C.1 (Cont'd)

Number	Country	ES Year	Round 1	Round 2	Round 3	Round 4
28	Turkish Cypriot Community	2019	June 2020	Nov.-Dec. 2020	Apr. 2021	-
29	Jordan	2019	July-Aug. 2020	Dec. 2020-Jan. 2021	June-July 2021	Dec. 2021
30	Lebanon	2019	Nov.-Dec. 2020	May-June 2021	Oct. 2021	-
31	Morocco	2019	July-Aug. 2020	Feb. 2021	May-June 2021	-
32	Chad	2018	June 2020	-	-	-
33	Guinea	2016	June 2020	-	-	-
34	Mozambique	2018	Sep.-Dec. 2020	June-Nov. 2021	-	-
35	Niger	2017	June 2020	-	-	-
36	Togo	2016	June 2020	-	-	-
37	Zambia	2019	June-July 2020	Dec. 2020-Jan. 2021	July-Aug. 2021	-
38	Zimbabwe	2016	June-July 2020	March-May 2021	June-Aug. 2022	-
39	El Salvador	2016	June-Aug. 2020	-	-	-
40	Guatemala	2017	June-Aug. 2020	Dec. 2020-Jan. 2021	-	-
41	Honduras	2016	June-Aug. 2020	Dec. 2020-Jan. 2021	-	-
42	Nicaragua	2016	June-Aug. 2020	Dec. 2020-Jan. 2021	-	-
43	Turkish Cypriot Community	2019	June 2020	Nov.-Dec. 2020	Apr. 2021	-

D. EFA RESULTS FOR THE POOLED SAMPLE

	Factor Loadings						Uniqueness
	1	2	3	4	5	6	
Electricity		0.512					0.603
Telecommunication		0.714					0.497
Informality				0.303			0.792
Transportation		0.467					0.540
Customs and trade						0.330	0.586
Access to land				0.543			0.610
Crime							0.632
Access to finance				0.589			0.609
Tax rates			0.774				0.419
Tax administration			0.708				0.360
Business licensing							0.587
Political instability	0.678						0.537
Corruption	0.743						0.388
Courts							0.639
Labor Regulations					0.650		0.528
Education					0.537		0.645

Note. 'Principal axis factoring' extraction method was used in combination with a 'oblimin' rotation [3]

Factor Statistics

Summary

Factor	SS Loadings	% of Variance	Cumulative %
1	1.490	9.31	9.31
2	1.376	8.60	17.92
3	1.332	8.32	26.24
4	1.194	7.46	33.70
5	1.173	7.33	41.03
6	0.462	2.89	43.92

Inter-Factor Correlations

	1	2	3	4	5	6
1	—	0.398	0.478	0.495	0.536	0.234
2		—	0.344	0.543	0.494	0.159
3			—	0.436	0.536	0.241
4				—	0.565	0.299
5					—	0.353
6						—

Model Fit

Model Fit Measures

RMSEA	RMSEA 90% CI		TLI	BIC	Model Test		
	Lower	Upper			χ^2	df	p
0.0313	0.0296	0.0330	0.972	579	974	39	<.001

Assumption Checks

Bartlett's Test of Sphericity

χ^2	df	p
103981	120	<.001

KMO Measure of Sampling Adequacy

MSA

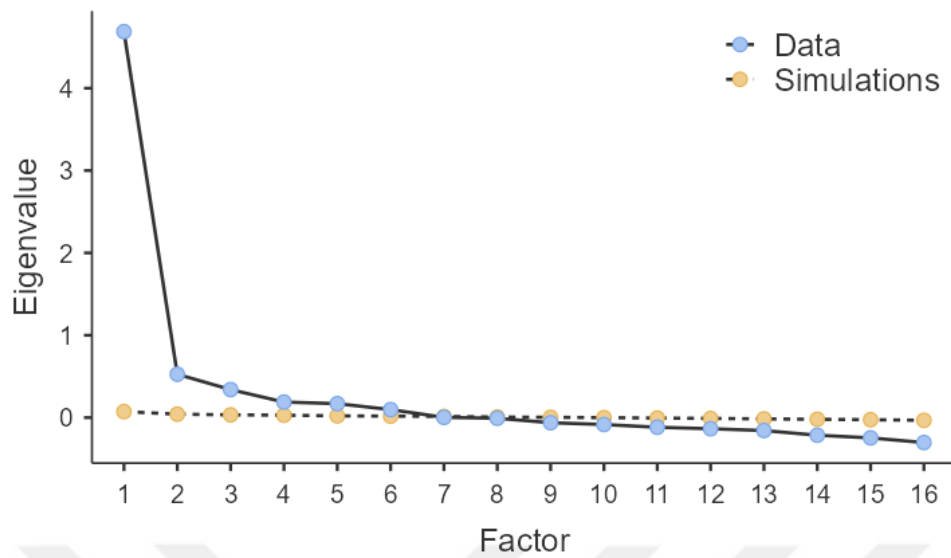
Overall	0.912
Electricity	0.911
Telecommunication	0.886
Informality	0.952
Transportation	0.917
Customs and trade	0.936
Access to land	0.931
Crime	0.946
Access to finance	0.935
Tax rates	0.836
Tax administration	0.860
Business licensing	0.947
Political instability	0.875
Corruption	0.889
Courts	0.939
Labor Regulations	0.932
Education	0.934

Eigenvalues

Initial Eigenvalues

Factor	Eigenvalue
1	4.68707
2	0.52656
3	0.34028
4	0.18898
5	0.16973
6	0.09742
7	0.00304
8	-0.00813
9	-0.06205
10	-0.08385
11	-0.11706
12	-0.13513
13	-0.15706
14	-0.21369
15	-0.24625
16	-0.30273

Scree Plot



References

- [1] The jamovi project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from <https://www.jamovi.org>.
- [2] R Core Team (2024). *R: A Language and environment for statistical computing*. (Version 4.4) [Computer software]. Retrieved from <https://cran.r-project.org>. (R packages retrieved from CRAN snapshot 2024-08-07).
- [3] Revelle, W. (2023). *psych: Procedures for Psychological, Psychometric, and Personality Research*. [R package]. Retrieved from <https://cran.r-project.org/package=psych>.

E. CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: CEBİR BENLİ, Bilgen

Nationality:

Date and Place of Birth:

Phone:

Email:

EDUCATION

Degree	Institution	Subject	Year of Graduation
PhD	Middle East Technical University	Economics	2025
MA	Sabancı University	Economics	2012
BSc	Middle East Technical University	Economics	2010

WORK EXPERIENCE

Year	Place	Enrollment
Oct. 2024-Present	Ministry of Treasury and Finance	Head of Department
July 2018-Oct. 2024	Ministry of Treasury and Finance	Expert
March 2013-July 2018	Turkish Treasury	Treasury Expert

INTEREST AREAS

Applied Microeconomics, Microeconometrics and Labor Economics.

SKILLS

Microsoft Offices, Stata and E-views

FOREIGN LANGUAGES

Advanced English

F. TURKISH SUMMARY / TRKE ZET

Ekonomik teoninin nemli bir kısmı, teknik deęiřimi ekonomik bymenin vazgeilmez bir parası ve nedeni olarak deęerlendirir. Neo-klasik byme modeli ve Solow'un (1957) nl makalesi, retim fonksiyonunun yukarıya doęru kaymasının yalnızca teknik deęiřimin varlıęıyla mmkn olduęu teorik bir model sunarak, teknolojik deęiřimi ekonomik bymenin tek itici gc olarak ortaya koymuřtur. te yandan Schumpeter [1934] (2013), yenilięi, eski retim ve rn yollarının ařamalı olarak ortadan kalkmasına neden olan yeni retime, rnlere ve kurumsal yapıya yol aan bir "yaratıcı yıkım sreci" olarak tanımlamıřtır. Bu nedenle, yeni byme teorisi, inovasyon ve bilgi birikiminin ekonomik byme srecinde merkezi bir role sahip olduęu ana fikriyle Romer (1982) ve Aghion ve Howitt'in (1992) alıřmalarında kendini gstermiřtir.

Birinci Sanayi Devrimi'nin bařlangıcından itibaren dnya ekonomisi eřitli teknolojik deęiřimlere tanık olmuřtur. Daha yakın zamanda eřitli alıřmalar, zellikle Klaus Schwab'ın 2017'de yayınlanan popler kitabı "Drdnc Sanayi Devrimi" ile birlikte yeni bir yaklařan sanayi devrimini tanımlamaya alıřmıřtır. Bu yeni devrim Drdnc Sanayi Devrimi'nin yanı sıra "Endstri 4.0" olarak da isimlendirilmektedir.

Schwab (2017) ve Priscearu (2016) tarafından belirtildięi ve birok alıřmada da anlatıldıęı zere dnya ekonomisi modern zamana kadar her biri kendi iinde farklı zelliklere sahip  sanayi devrimi yařamıřtır.

Birinci Sanayi Devrimi; Schwab'a (2017) gre 1760'tan 1840'lara, Priscearu'ya (2016) gre ise 1900'lere kadar 100 yıldan fazla bir sreyi kapsamıřtır. retim srecindeki en byk deęiřim, buhar gcnn icat edilmesiyle ve onu retmek iin enerji kaynaęı olarak kmrn kullanılmasıyla gerekleřmiřtir. retim srecinde buhar gcnn kullanılmasıyla, retim sreci, insan gcnn temel retim girdisi

olduğu emek yoğun olan yapıdan, makine gücünün eşlik ettiği mekanik olan bir yapıya dönüşmeye başlamıştır.

19. yüzyılın sonlarında başlayıp 20. yüzyılın başlarından 1960'lara kadar devam eden İkinci Sanayi Devrimi, temel enerji kaynağı olarak petrol ve elektriği kullanmış ve “montaj hattı” (Prisecaru, 2016, s. 57; Schwab, 2017, s. 11) ile seri üretimi mümkün kılmıştır. Bu üretim biçimi aynı zamanda Henry Ford'un adını taşıyan Fordist üretim biçimi olarak da adlandırılmıştır (Farnes, 1993).

1960-2000 yılları arasındaki dönemi kapsayan Üçüncü Sanayi Devrimi; 1960'lara kadar yarı iletkenler ve anabilgisayarların, 1980'lere kadar kişisel bilgisayarların ve 1990'lara kadar internetin ortaya çıktığı (Schwab, 2017, s. 11) ve nükleer enerji ile doğal gazın yeni enerji kaynakları olarak kabul görmesiyle karakterize edilmektedir (Prisecaru, 2016, s. 57).

Son olarak, yeni milenyum ile birlikte başlayan Dördüncü Sanayi Devrimi; dijital devrim üzerine kurulu, daha yaygın ve mobil internet, daha ucuza üretilebilen daha küçük ve daha güçlü sensörler, yapay zekâ (YZ), nesnelerin interneti (IoT) ve makine öğrenmesi (ML) ile temsil edilen çok daha karmaşık bir olgu olarak ortaya çıkmıştır ve henüz yeni bir sanayi devrimi olarak oluşumunu sürdürmektedir (Schwab, 2017, s. 12; Prisecaru, 2016).

Tüm endüstriyel devrimler işgücü piyasası üzerinde derin bir etki yaratmıştır. Toplumlar yeni teknolojilerin ortaya çıkmasıyla daha fazla ekonomik ve sosyal refah beklerken; diğer yandan ekonomideki her teknolojik dönüşüm teknolojik işsizlik konusunda yeni bir korku yaratmıştır.

Literatürde teknolojik değişime bağlı olarak ortaya çıkacak “kitlel işsizlik” öngörüsünün en çok bilinen örneklerinden biri David Ricardo'ya aittir. Ricardo, 1891 yılında yayımlanan “Politik Ekonomi ve Vergilendirme İlkeleri” adlı kitabında teknolojik işsizliği bir kavram olarak vurgulamıştır. Ricardo'nun kavramsallaştırmasından Keynes'e kadar teknolojik işsizlik, iktisat biliminin farklı düşünürleri tarafından ele alınmış olup Keynes de özellikle kısa vadede ekonominin

teknolojik deęiřimden doęan aşırı istihdamı absorbe edecek kadar zamana sahip olamayacağı durumlarda teknolojik işsizlięin gerçeklięinden bahsetmiş; ancak uzun vadede ekonomik sistemlerin bu sorunu çözölmeyeceęini ileri sürmüřtür (Keynes, 1930; Campa, 2017, s. 8).

Birinci Sanayi Devrimi'nden bu yana kitlesel işsizlik korkusu her zaman var olmasına rağmen, řu ana kadar teknolojik deęiřim nedeniyle kitlesel işsizlięe dair net bir işaret olmamıştır (Vivarelli, 2014). Bununla birlikte, teknolojik işsizlik konusundaki tartışma Dördüncü Sanayi Devrimi'nin ortaya çıkışıyla birlikte tazelenmiştir. Birçok araştırma ve ekonomist, Dördüncü Devrim döneminin bilgisayarlaşma, dijitalleşme ve otomasyonun ayırt edici özellikleri nedeniyle üretim sürecinde işlerin ve görevlerin radikal bir şekilde dönüşme olasılıęına dikkat çekmiştir. Bu alandaki en yankı uyandıran çalışmalardan biri Frey ve Osborne'dur (2017). Frey ve Osborne (2017), mevcut işlerin son teknolojik gelişmeler nedeniyle yok olma riskine olan duyarlılıęını sınıflandırmaya ve hesaplamaya çalışır ve toplam ABD istihdamının yaklaşık %47'sinin otomasyon nedeniyle son on yıllarda kaybedilme riskinin yüksek olduęunu ortaya koyan şaşırtıcı bir sonuca varmıştır. Ancak bazı dięer çalışmalar, otomasyonun işgücü piyasasındaki etkisini analiz ederken odak noktasının işin tamamından ziyade görev içerięinin olması gerektięini vurgulamışlardır (Acemoglu, 2011; Acemoglu ve Restrepo, 2018; Acemoglu ve Restrepo, 2019; Acemoglu ve Resrepo, 2020).

Teknolojik yenilięin olumsuz istihdam etkisine ilişkin řüpheler zaman içinde tartışılmış olsa da; klasik iktisatçılardan başlayarak birçok iktisatçı, teknolojik yenilięin olumsuz etkisini hafifleten “telafi mekanizmalarının” varlıęından bahsetmiştir. Literatürde çeşitli telafi mekanizmaları teorik olarak “Klasik-Neoklasik Yaklaşım” ve “Keynesçi-Schumpeterci Yaklaşım” olmak üzere iki ana bakış açısıyla incelenmektedir (Calvino ve Virgillito, 2018). Ampirik literatürde çeşitli çalışmalar bu telafi mekanizmalarının geçerlilięini makro veya mikro düzeyde test etmeye çalışmıştır.

řimdiye kadar özetlenen bu arka plana dayanarak, bu Tez esas olarak yukarıda tarihsel geçmiři kısaca açıklanan aynı eski soruyu yanıtlamayı amaçlayan iki farklı

makaleden oluşmaktadır: "Teknolojik yenilik işgücü talebini nasıl etkiler?". Ancak, bu iki makale bu soruyu farklı bağlamlarda yanıtlamayı amaçlamaktadır. Her iki makale de 2000'lerin başından beri dünyanın dört bir yanındaki gelişmekte olan ve yükselen ülkelerde yürütülen Dünya Bankası İşletme Anketleri (WBES) tarafından sağlanan şirket düzeyindeki verileri kullanarak bu soruyu cevaplamayı hedeflemektedir.

2000'li yılların başından itibaren birçok politika yapıcı veya Dünya Bankası (DB) gibi uluslararası kuruluşlar, iş ortamlarını iyileştirmenin temel kalkınma stratejilerinden biri olarak önemini vurgulamıştır (Stern, 2002; WB, 2005; Xu, 2011). Kalkınma sorununa bu yaklaşımla DB, yatırım ortamı hakkında karşılaştırılabilir veriler toplamak için dünya çapında firma düzeyinde anketler yapmaya başlamıştır. Xu (2011), bu alandaki önceki literatüre dayanarak çeşitli iş ortamı kategorilerinin firma performansı üzerindeki etkilerini tartışmaktadır. Xu (2011) tarafından yürütülen inceleme çalışması bazı önemli gerçekleri ortaya koymaktadır. Her şeyden önce, iş ortamının bazı unsurlarının firma düzeyindeki ekonomik performansla güçlü bir ilişkisi olduğu ortaya çıkmaktadır. Örneğin, mülkiyet haklarının temel düzeyde korunması, işgücü esnekliği, düşük giriş maliyetleri, verimli hukuk sistemleri veya mahkemeler ve iyi altyapı gibi unsurlar firma büyümesini artırıcı etkiye sahip faktörlerdir. Öte yandan, örneğin yolsuzluk, firma büyümesi veya pazara yeni firma girişi için ağır bir yük oluşturmaktadır. İkinci olarak, iş ortamının çeşitli unsurlarının etkilerinde eşlik eden tamamlayıcı kurumlara, iş ortamının başlangıç koşullarına ve farklı endüstrilere göre heterojenlik olduğu görülmektedir. Örneğin, finans veya mahkemelere erişim gibi sözleşme kuruluşlarının ekonomi olgunlaştıkça etkileri daha görünür hale gelmektedir veya altyapı çok yoksul olan gelişmekte olan ülkeler için daha büyük önem taşımaktadır. Öte yandan, giriş maliyetleri özellikle yeni fikirlere bağımlı olan veya teknoloji yoğun endüstriler için önem taşımaktadır. İş ortamlarının rolü ve firma düzeyindeki artan önemi, teknolojik yeniliğin istihdam sonucunu ölçerken iş ortamlarının firma performansı veya firma davranışı üzerindeki rolünü hesaba katma ihtiyacıyla karşı karşıya kalmamız noktasına getiriyor. Bu motivasyonu akılda tutarak, ilk makale, kullandığımız verilerin fırsatlarından yararlanarak algılanan iş engellerinin potansiyel istihdam etkisini kontrol ederek

"teknolojik yenilik geliřmekte olan lkelerdeki iřgc talebini nasıl etkiler?" sorusunu yanıtlamaya alıřmaktadır.

Literatrde iř dngs veya kriz dnemlerinde rn veya sre inovasyonunun istihdam zerindeki etkisini inceleyen eřitli alıřmalar bulunmaktadır (rneėin bkz. Dachs vd., 2017b; Arenas Diaz vd., 2020). Bu alıřmalardan biroėu, inovasyonun kriz veya kř dnemlerinde yeniliki olmayanlara kıyasla firmaların istihdam dzeylerinin dayanıklılıėını artırdıėı bulgusunu ortaya koymaktadır. Literatrden elde edilen bu arka plan bilgileriyle, ikinci makale, zellikle COVID-19 dnemine zel bir atıfla, bir ekonomik řoktan nce ve bu ekonomik řok sırasında meydana gelen teknolojik inovasyonun firma dzeyindeki istihdam etkisine odaklanmaya motive olmuřtur. COVID-19, dnya apında bir ekonomik řok sırasında farklı ekonomileri karřılařtırarak ve zıtlařtırarak inovasyon ve iřgc talebi arasındaki iliřkinin dinamiklerini incelemek iin benzersiz bir fırsat sunmaktadır.

Tez beř blmden oluřmaktadır. İkinci blm,  alt kısımdan oluřan kapsamlı bir kavramsal ve literatr blmdr. Birinci alt kısımda, teknolojik inovasyon ve onun trleri zerinde zel bir vurgu yaparak inovasyon kavramı ele alınmaktadır. zellikle, mikro veri retmek iin tm dnyada yrtlen ulusal inovasyon anketlerinde kullanıldıėı řekliyle inovasyon tanımı ele alınmaktadır. İnovasyona ve trlerine iliřkin tanımları ortaya koymak, inovasyon ve iřgc talebi kavramlarını birleřtiren literatrn daha doėru anlařılmasına yardımcı olacaktır. Bu blmn ikinci kısmı, inovasyon ve iřgc talebi arasındaki iliřkinin hem teorik hem de ampirik ynlerini ele alan kapsamlı bir literatr incelemesidir. Bu kısımda inovasyonun, zellikle teknolojik inovasyonun istihdam ıktılarına iliřkin teorik yaklařımlar ve teknolojik ilerlemenin potansiyel emek tasarrufu etkisini hafifletmede dengeleyici rol oynayabilecek farklı iktisat dřnce bilimcileri tarafından ortaya atılan olası telafi mekanizmaları ele alınmaktadır. Bu blmn nc kısmında ise, inovasyonun istihdam etkisine ve olabilecek potansiyel telafi mekanizmalarına ynelik kanıt saėlamaya alıřan ampirik literatr tanıtılmakta ve tartıřılmaktadır.

İkinci blmde ele alınan kavramlara kısaca deėinecek olursak, burada ilk nce “icat” kavramı ile inovasyon kavramı arasındaki farka deėinilmiřtir. Malerba (1997),

icadı yeni bir fikir, bilimsel teori veya henüz uygulanmamış teknolojik bir inovasyon olarak tanımlar; inovasyonu ise bu icadın somut bir ürüne, hizmete veya sürece dönüşmesi ve ticari olarak uygulanabilir hale gelmesi olarak nitelendirir. Diaconu (2011), icat ile inovasyon arasında net bir ayrım yapmanın her zaman mümkün olmadığını belirtir; teknolojik inovasyonda, bir icadın inovasyona dönüşmesi için uzun bir zaman dilimi gerekebilir ve bu süre; ekonomik, sosyal ve teknik koşulların uygunluğuna bağlı olarak değişmektedir. Teknolojinin doğasına yönelik tartışmalarda ise Pavitt (1987), teknolojinin patentler, planlar veya kullanım kılavuzlarıyla sınırlı olduğu ve bu nedenle de üretilmesinin dağıtılması ve yaygınlaşmasından daha zor olduğunu savunan fikre karşı çıkararak teknolojinin spesifik, karmaşık, genellikle örtük (açıkça ifade edilemeyen, deneyimle öğrenilen) ve birikimli bir doğaya sahip olduğunu ileri sürmektedir. Pavitt'e (1987) göre, teknoloji, bir firmanın veya toplumun bilgi birikimiyle şekillenir ve bu birikim, yeniliklerin uygulanabilirliğini belirlemektedir. Diaconu (2011), inovasyonun firmaların kendi faaliyetlerinden doğduğunu ve icadın inovasyona dönüşmesi için bilgi, insan kaynakları, finansal sermaye ve maddi altyapının etkin bir şekilde birleştirilmesi gerektiğini vurgulayarak bu görüşü geliştirmiştir.

Schumpeter (1934), inovasyonu beş kategoriye ayırmaktadır ve bu sınıflandırma, modern inovasyon anket çalışmalarının da temelini oluşturmuştur. Schumpeter (1934) tarafından yapılan sınıflandırmada inovasyon; yeni ürünler, yeni üretim yöntemleri, yeni pazarların keşfi, ürünlerin yeni sunum yolları ve iş organizasyonunda yeni yöntemler olmak üzere beş kategori altında toplanmaktadır. Schmookler (1966), “teknolojik ürün” (ürünlerin yaratılması veya iyileştirilmesi) ve “teknolojik üretim” (üretim süreçlerinin geliştirilmesi) arasında bir ayrım yapar; bu ayrım, inovasyonun hem çıktı hem de süreç boyutlarını kapsadığını göstermektedir. Pavitt (1987), teknolojik inovasyonu ürün ve süreç inovasyonu ile sınırlandırmaktadır; pazarlama ve organizasyonel inovasyonlarını ise “teknolojik olmayan inovasyon” kategorisine yerleştirmektedir. Oslo Kılavuzu (OECD, 2005) inovasyonu, firma düzeyinde “yeni veya önemli ölçüde geliştirilmiş bir ürün (mal veya hizmet), süreç, pazarlama yöntemi veya iş uygulamaları, işyeri organizasyonu ya da dış ilişkilerde yeni bir organizasyonel yöntem” olarak tanımlamaktadır. Schumpeter (1934) sınıflandırmasına benzer şekilde bu kılavuz, inovasyonu dört türe

ayırmaktadır: (1) ürün inovasyonu (yeni veya geliştirilmiş mal/hizmetin piyasaya sunulması), (2) süreç inovasyonu (yeni üretim veya teslimat yöntemlerinin uygulanması), (3) pazarlama inovasyonu (yeni pazarlama stratejileri veya ambalajlama yöntemleri) ve (4) organizasyonel inovasyon (yeni yönetim yapıları veya iş süreçleri). Oslo Kılavuzu, teknolojik inovasyonu ürün ve süreç inovasyonu ile sınırlandırmaktadır; bu Tezde de bu yaklaşım esas alınmaktadır. Ürün inovasyonu, “özellikleri veya kullanım amaçları açısından yeni veya önemli ölçüde geliştirilmiş bir mal veya hizmetin piyasaya sunulması” olarak; süreç inovasyonu ise “üretim veya teslimat yöntemlerinde yeni veya önemli ölçüde geliştirilmiş bir uygulamanın hayata geçirilmesi” olarak tanımlanmaktadır.

Tanımlar kısmından sonra İkinci Bölümde ele alınan teorik yaklaşımlara kısaca değinecek olursak; teknolojik inovasyonun istihdam üzerindeki etkisi, iktisadi ekonomik düşüncede iki ana yaklaşımla ele alınmaktadır: Klasik/Neo-klasik ve Keynesçi/Schumpeterci yaklaşım. Calvino ve Virgillito (2018), bu yaklaşımları “denge” (Klasik/Neo-klasik) ve “dengesizlik” (Keynesçi/Schumpeterci) perspektifler olarak da ayırmaktadır. İlk görüş, inovasyonun verimliliği artırarak ekonomik büyümeyi ve dolayısıyla istihdamı teşvik ettiğini savunmaktadır; bu süreçte piyasa mekanizmaları, işgücü talebini otomatik olarak piyasa mekanizmasıyla dengeye getirmektedir. Keynesçi-Schumpeterci yaklaşım ise inovasyonun karmaşık yapısı nedeniyle istihdam etkisinin doğrudan öngörülemez olduğunu öne sürmektedir. Bu iki akımda toplamda inovasyonla birlikte işlemesi muhtemel olan toplam altı telafi mekanizması teorik olarak tanımlanmaktadır:

- 1) Yeni Makineler: Teknolojik yenilik, işgücünü makinelerle değiştirir; ancak makine üreten sektörler, yerinden edilen işçileri absorbe edebilir (Say, 1836).
- 2) Fiyat Düşüşü: Teknoloji, üretim maliyetlerini düşürür, bu da rekabetçi piyasalarda fiyatların azalmasına yol açar. Düşük fiyatlar talebi artırır ve firmalar daha fazla işçi istihdam eder. Bu mekanizmanın işleyebilmesi için yüksek fiyat elastikiyeti ve rekabetçi piyasa koşullarının olması gerekmektedir.
- 3) Ücret Düşüşü: Teknolojik inovasyon istihdamı ikame eder ve bu nedenle açığa çıkan fazla işgücü nedeniyle işgücü arzı artar. İşgücü arzı fazlası ücretleri düşürerek firmaların daha fazla işçi almasını sağlar. Ancak Keynes’e

göre, ücret düşüşü tüketim talebini azaltabilir; bu da firmaların gelecek beklentilerini olumsuz etkileyerek istihdamı düşürebilir. Öte yandan, Dosi'ye (1988) göre, teknolojinin “zamanla geri döndürülemez” olduğunu belirtir; yani firmalar, ücretler düşse bile teknoloji ile işgücünü yeniden ikame edemeyebilir ve işgücünü artırmayı tercih etmeyebilir.

- 4) Yeni Yatırımlar: Teknoloji, birim maliyetleri düşürerek kar marjını artırır; bu kar, yeni yatırımlara yönelir ve işgücü talebi artar. Say yasasına dayanan bu mekanizma, yatırımların işgücü tasarrufu sağlayan makinelere yönelmesi durumunda başarısız olabilir. Lazonick (2015), modern ekonomilerde yatırımların finansal spekülasyona veya menkul kıymet yatırımlarına kaydığını belirterek bu mekanizmanın istihdam artışını sınırlayabileceğini belirtmektedir.
- 5) Gelir Artışı: İşçiler, teknolojiden kaynaklanan verimlilik artışından pay alırsa tüketimleri artar; bu, talebi ve dolayısıyla istihdamı yükseltir (Keynesçi yaklaşım). Ancak bu mekanizma, sendikaların pazarlık gücüne ve gelir dağılımı politikalarına bağlı olarak değişebilmektedir; günümüz rekabetçi piyasalarında bu etki zayıflamıştır.
- 6) Yeni Ürünler: Schumpeterci yaklaşıma göre ürün inovasyonu yeni talepler yaratarak istihdamı artırmaktadır; süreç inovasyonu ise verimliliği artırarak işgücünü azaltmaktadır. Öte yandan, ürün inovasyonu ile birlikte ortaya çıkan yeni ürünler, eski ürünlerin yerini alabilir (kannibalizasyon), rakip firmaların pazar payını çalabilir (iş çalma etkisi) veya süreç inovasyonu ile birleşirse verimlilik artışı işgücünü daha da düşürebilir.

Yukarıda tanımlanan altı telafi mekanizması, bazı piyasa dürtülerinin teknolojik inovasyonun başlangıçtaki emek tasarrufu etkisini dengelemesi için önemli bir olasılık olduğunu ortaya koymaktadır. Ancak, diğer taraftan, bu altı telafi mekanizmasının etkinliği veya baskınlığı, mekanizmaların birçoğunun birbirleriyle etkileşime girmesi veya bu karmaşıklık nedeniyle bazen çalışmayabileceği gerçeği nedeniyle önceden tahmin edilmesi zordur.

Teknolojik inovasyonun türlerine göre istihdam etkisi ve yukarıda özetlediğimiz telafi mekanizmalarının işleyip işlemediğini ölçmek için literatürde makro, sektörel

ve mikro düzeyde birçok ampirik çalışma yürütülmüştür. Vivarelli (2014), inovasyon ölçümünde üç temel sorun tanımlar: (1) yeniliğin ölçülmesi, (2) inovasyonun nihai etkisinin ölçülmesi ve (3) yeniliğin istihdam etkisinin diğer etkenlerden ayrıştırılması. İnovasyonun ölçülmesi için literatürde yaygın olarak kullanılan göstergeler arasında Ar-Ge (R&D) harcamaları, patent sayıları, patent atıfları ve yeni ürün duyuruları gibi göstergeler yer almaktadır (Hagedoorn ve Cloodt, 2003). Hagedoorn ve Cloodt (2003), bu göstergelerin tek başına eksik olabileceğini ve bu nedenle birleşik bir ölçümün daha güvenilir olduğunu savunan makalesinde bu göstergelerin avantaj ve dezavantajlarına yer vermiştir. Buna göre; Ar-Ge harcamaları, yenilik kapasitesini yansıtsa da firmanın geçmiş başarılarına da dayanabilir ve firmanın güncel inovasyon girdisini göstermeyebilir; patentler, tüm yenilikleri kapsamayabilir ve sektörel farklılıklar gösterebilir; patent atıfları kaliteyi ölçse de yine de patentlere dayandığı için patentlenemeyen inovasyonları kapsayamamaktadır; yeni ürün duyuruları ise yalnızca ürün inovasyonunu kapsar ve süreç inovasyonunu göz ardı eder.

İnovasyonun ölçümü sorunundan sonra Vivarelli (2014) tarafından ampirik çalışmaların karşılaştığı diğer iki ölçüm sorununu sırasıyla, inovasyonun nihai etkisini ölçmek ve inovasyonun istihdam üzerindeki nihai etkisini diğer faktörlerden ayırmak oluşturmaktadır. Nihai etki, farklı kurumsal mekanizmalarla güçlü bir şekilde ilişkilidir ve bunlar mikro, mezo ve makro düzeyde ve farklı sektörlerde veya ülkelerde farklı etkilere sahip olabilmektedir (Vivarelli, 2014, s.132). Bu nedenle, istihdam sonucu bu mekanizmalara bağlı olarak farklı olacaktır. Öte yandan, üçüncü sorun, makroekonomik ve döngüsel koşullar, işgücü piyasası dinamikleri vb. gibi birçok diğer ekonomik koşulla ilgilidir (Vivarelli, 2014, s. 132).

Makro düzeyde yapılan çalışmalar arasında Sinclair (1981), Layard ve Nickell (1985) ve Vivarelli (1995) çalışmaları incelenmiştir. Bu çalışmaların ışığında ortaya çıkan en önemli noktalardan birisi, makro analizlerde işgücü talebi esnekliğinin teknolojik inovasyonun istihdama olumlu yönde etki edebilmesi için en önemli belirleyicilerden birisi olduğudur. İşgücü talebinin belirli bir esneklik düzeyinde olması durumunda inovasyonun istihdama olumlu etkisi görülebilmekte; telafi

mekanizmalarının etkinliđi ele alınan dönemin ve ekonominin özelliklerine göre deđişmektedir.

Sektörel analizler, inovasyonun istihdama etkisindeki sektörel farklılıkların yanı sıra özellikle teknolojik deđişime bađlı sektörel kaymaların anlaşılmasına da yardımcı olabilmektedir. Bu başlık altında; Vivarelli vd. (1996), Antonucci ve Pianta (2002), Mastrostefano ve Pianta (2009), Bogliacino ve Pianta (2010) ile Bogliacino ve Vivarelli (2012) çalışmaları ele alınmaktadır. İncelenen çalışmalar, ana sektörel ayrıştırmanın genellikle imalat ve hizmet sektörü arasında yapıldığını ancak yüksek teknoloji ile düşük teknoloji veya bilgi yoğun veya bilgi yoğun olmayan gibi farklı sektörel özelliklere bađlı olarak daha ayrıntılı bir farklılaştırmanın da teknolojik yeniliğin istihdam etkisini daha iyi anlamak açısından yararlı olabileceğini göstermektedir. Sektörel kanıtlar, ürün ve süreç yeniliğinin farklı sektörel sınıflandırmalar altında farklı istihdam sonuçlarına sahip olabileceğine işaret etmektedir.

Mikro veri ile yapılan çalışmalar 2000’li yıllardan itibaren ulusal inovasyon anketlerinin yaygınlaşmaya başlamasıyla birlikte son on yıllarda literatürde ağırlık kazanmaya başlamıştır. Bu Tezin ikinci bölümünde ele alınan mikro veri çalışmaları Van Reenen (1997), Greenan ve Guellec (2000), Piva ve Vivarelli (2005), Harrison vd. (2008, 2014), Lachenmeier ve Rottman (2011), Triguero vd. (2014), Herstad ve Sandven (2015), Evangelista ve Vezzani (2012) ve Roy vd. (2018) çalışmalarıdır. Farklı yaklaşımlarla, inovasyon ölçümü için farklı deđişkenler kullanılarak veya farklı ülkeler için uygulanan bu çalışmalarda genel olarak ortaya çıkan ana fikir ürün inovasyonunun istihdam kolaylaştırıcı etkisinin daha belirgin olduđu, süreç yeniliğinin ise istihdam kolaylaştırıcı ya da istihdam tasarrufu etkisinin analizlere ve yaklaşımlara göre farklılık gösterdiğidir.

Üçüncü bölüm Tezin ilk makalesini oluşturmaktadır. Örneğimizde yer alan 53 ülke için 2013-2014 yılları arasında gerçekleştirilen Dünya Bankası İşletme Anketleri (WBES) ve buna bađlı İnovasyon Modülleri ile üretilen mikro veriler kullanılmaktadır. Bu 53 ülke dört ayrı grup altında toplanmaktadır: Afrika (Sahra-altı Afrika), Güney Asya, Avrupa ve Orta Asya (ECA) ile son olarak Orta Dođu ve

Kuzey Afrika (MENA) bölgeleri. Bu veri seti kullanılarak, gelişmekte olan ülkelerde teknolojik yeniliğin istihdam sonucunu ölçmek için Harrison vd. (2014) tarafından önerilen yapısal model ile bu modele dayanarak Cirera ve Sabetti (2019) makalesinin ampirik yaklaşımları takip edilmektedir. Harrison vd. (2014), ürün ve süreç inovasyonunun istihdam üzerindeki etkilerini ayrıştırarak tahmin edilmesini sağlayan ampirik bir model önermektedir. Model, yeni ürün veya hizmet üretimi nedeniyle oluşan istihdam büyümesinin, süreç inovasyonu ile üretim sürecinde meydana gelen verimlilik artışının getirdiği eski ürünlerin üretiminin artması nedeniyle oluşan istihdam büyümesinden farklılaştırılmasını sağlamaktadır. Ayrıca bu model, ürün inovasyonunun süreç inovasyonunun işgücü talebi azaltıcı etkisini hafifleten tek telafi mekanizması olduğunu iddia eden Schumpeterci yaklaşımı test etme fırsatı sunmaktadır. Harrison vd. (2014) önerilen modellerini dört Avrupa ülkesi için CIS verilerini kullanarak tahmin etmektedir. Öte yandan Cirera ve Sabetti (2019), bu Tezdeki durumda olduğu gibi, aynı modeli yukarıdaki paragrafta da bahsetmiş olduğumuz 2013-2014 yılları arasında 53 gelişmekte olan ülke için yürütülen Dünya Bankası Anket verileri ve ona bağlı İnovasyon Modüllerinden oluşan veri setine uygulamakta ve tahminlerinde işgücü talebi üzerinde de etkisi olabilecek organizasyonel inovasyonu dâhil ederek ve ülke-endüstri heterojenliğini hesaba katarak modeli iki temel ekseninde genişletmektedir. Cirera ve Sabetti (2019), temel model ve kendi genişletilmiş modellerinde de süreç yeniliğinin istihdam üzerinde anlamlı bir etkisi olmadığını, öte yandan ürün yeniliğinin istihdam kolaylaştırıcı etkisinin daha açık bir şekilde tüm model tanımlamalarında kendini ortaya koyduğunu göstermektedir.

Bu iki makalenin yaklaşımı üzerine inşa edilen modelimizde temelde Cirera ve Sabetti (2019) yöntemi takip edilerek, ana farklılaştırma unsuru olarak iş engelleri temel modele dâhil edilmektedir. Firmaların iş ortamına ilişkin algılarının firma düzeyindeki işgücü talebi üzerinde bir etkisi olabileceği hipotezinden yola çıkılarak bu etkinin hesaba katılmasının tahmin sonuçlarını iyileştirmede yardımcı olabileceği değerlendirilmektedir. Cirera ve Sabetti'nin (2019) süreç inovasyonunun firma düzeyindeki istihdam üzerinde önemli bir etkisi olmadığını ortaya koyan ana bulgusuna dayanarak, algılanan iş engellerini kontrol etmenin Harrison vd. (2014) modelinin sonucunu bu ülke grubu için bir dereceye kadar değiştirebileceği hipotezi

bu makalenin ana hipotezini oluşturmaktadır. Anket verileri, dereceleri “hiç engel değil” kategorisinden “çok ciddi engel” kategorisine kadar değişen on altı kategorideki iş engelleri için sıralı değişkenler içermektedir. Anket ayrıca on beş kategori arasında hangisi kategorinin en büyük engel olduğunu sormaktadır (“en büyük engel” sorusunda kategorik değişkenlerden “telekomünikasyon” kategorisi hariç tutulmaktadır). İş engelleri arasında teorik bir ilişki varsayımıyla başlamadığımız için; öncelikle modelimizde firmalar tarafından algılanan “en büyük engeller” kontrol edilmektedir ve ardından yukarıda belirtilen sıralı yapıya sahip on altı ayrı iş engeli kategorisiyle devam edilmektedir. Sıralı değişkenler için keşifsel bir faktör analizi (EFA) yaparak, öncelikle hem birleştirilmiş örneklem hem de bölgesel ayrıştırma için faktör sayısını ve her faktör için en temsili iş engeli kategorileri belirlenmektedir. İkinci aşamada ise, her faktör için en temsili engelleri modele dâhil ederek sonuçlar ortaya çıkarılmaktadır.

Harrison vd. (2014) ve Cirera ve Sabetti (2019) makalelerinde de belirtildiği üzere firma düzeyinde fiyat bilgisinin olmaması ürün inovasyonundan kaynaklanan toplam satış artışının fiyat etkisinden arındırılmamasına neden olmaktadır. Bu nedenle Harrison vd. (2014) tarafından ortaya konulan yaklaşımda bu sorunun giderilebilmesi için geçerli bir araç değişken veya değişkenlerin kullanılmasının yerinde olacağı ya da firma düzeyi fiyat yerine endüstri düzeyi fiyat verisi ile ürün inovasyonundan kaynaklanan toplam satış artışı değişkeninin fiyat etkisinden arındırılmasının yöntem olarak kullanılabileceği belirtilmiştir. Bu içsellik sorununun çözümü için Cirera ve Sabetti (2019) makalesinde kullanılan araç değişkenler kullanılarak tahminler İki Aşamalı En Küçük Kareler Yöntemi (2SLS) ile yürütülmektedir. Kullanılan araç değişkenler, yeni ürün veya hizmetin firma için de tamamen yeni olup olmadığı ile firmanın Ar-Ge harcaması yapıp yapmadığı değişkenleridir. Başlangıçta, içsellik sorunu çözülmeden Sıradan En Küçük Kareler Yöntemi (OLS) ile tahminler yürütülüp daha sonra 2SLS yöntemi ile yapılan tahmin sonuçlarıyla karşılaştırılarak başlangıçta var olan içsellik sorununun ne kadar büyük olup olmadığı da test edilmektedir.

Tablo 3.1, hem birleştirilmiş veriler hem de yukarıda belirtilen dört bölge için örneklem hakkında ayrıntılı bilgi sağlamaktadır. Tablo, örneklemdeki toplam

gözlemlere göre modelde kullandığımız firmaların yaş, büyüklük ve endüstri gruplarına göre dağılımını göstermektedir. Örneklemdeki gözlem sayısı 53 ülke için 33.000'in üzerindedir; ancak model tahmininde kullanılmak üzere tanımlanan her değişkende bulunan eksik değerler nedeniyle tahminlerde önemli miktarda gözlem kaybı vardır. Firmaların büyüklüklerine göre dağılımı, genel örneklemdeki firmaların neredeyse yarısının küçük (çalışan sayısı 19'a kadar) ve yalnızca %15,17'sinin büyük firmalardan (çalışan sayısı 100'ü aşan) oluştuğunu ortaya koymaktadır. Bölgesel bazda, Afrika ve ECA, yarıdan fazla küçük ölçekli firmaya sahip iki bölgedir. Yaş yapısı açısından, genel örneklem nispeten daha yaşlı firmaları temsil etmektedir; 5 yıldan eski firmalar örneklemin neredeyse %85'ini oluşturmaktadır ve bölgesel bazda Güney Asya, örnekleminde genç firmaların (5 yıldan genç) en küçük paya sahip olduğu bölgedir. Endüstriyel dağılım, genel örneklemde imalat ve hizmet sektörünün dengeli bir temsile sahip olduğunu ortaya koymaktadır; ancak, bölgesel dağılım yine değişmektedir. Örneğin; Güney Asya, ikinci sırada MENA bölgesi tarafından takip edilen imalat firmaları tarafından yoğun bir şekilde temsil edilirken, ECA bölgesinde perakende ve toptan hizmet sektörünün payının imalat sektörünün payına neredeyse eşit olduğu görülmekte; diğer hizmet sektörleriyle birlikte toplam hizmet sektörünün ise imalat sanayiini aştığı (yaklaşık %60 oranla) görülmektedir. Öte yandan, Afrika'da imalat sektöründen daha ağır basan hizmet sektörü bulunmaktadır.

Örneklem yenilikçilik açısından incelendiğinde, yenilikçi olmama oranı genel örneklemde %55'in üzerindedir. Bölgesel bazda bakıldığında ise en yüksek yenilikçilik oranının Güney Asya'da olduğu, en düşük yenilikçilik oranının ise MENA'da bulunduğu görülmektedir. Ürün ve süreç inovasyon oranları birbirine yakın olmakla birlikte, ürün inovasyonu genel örneklemde süreç inovasyonunu biraz aşarken; süreç inovasyonu Afrika'da ürün inovasyonunu ciddi oranda aşmaktadır. Diğer tüm bölgelerde ürün inovasyonu süreç inovasyonunu 2 ila 4 yüzde puanı aşmaktadır.

Tablo 3.2, imalat sektörü için istihdam ve satış büyüme oranlarının örneklem ortalamalarını göstermektedir. İmalat sektöründeki istihdam büyümesi açısından, yenilikçi olsun veya olmasın tüm firmalar, bu 3 yıllık dönemde genel örneklemde ve MENA hariç bölgesel olarak bir istihdam büyümesine tanık olurken, MENA

bölgesinde yenilikçi olmayan firmalarda istihdam düşüşü görülmektedir. ECA ve MENA bölgelerinde, ürün veya süreç yenilikçi firmaların istihdam seviyeleri açısından yenilikçi olmayanlara göre çok daha fazla büyüdüğünü görüyoruz. Öte yandan, Güney Asya'daki istihdam büyüme oranları açısından yenilikçiler ve yenilikçi olmayanlar arasında çok anlamlı bir farklılık bulunmamaktadır. Afrika'da ise şaşırtıcı bir şekilde, yenilikçi olmayanların istihdam büyümesinin yenilikçileri epey aştığı gözlemlenmektedir.

Tablo 3.2'de gösterilen istatistikler satış büyümesi açısından incelendiğinde, yenilikçilerin satış büyümesinin yenilikçi olmayanlardan önemli ölçüde daha yüksek oranda olduğu görülmektedir. Ürün inovasyonu açısından bakıldığında ise, ürün inovasyonu olduğunda, eski ürünlerden kaynaklanan satış büyümesinin negatif hale geldiğini ve ürün inovasyonu tüm bölgelerde mevcut olduğundan, aynı eğilimin tüm bölgeler için gözlemlendiği görülmektedir.

Hizmet sektöründe; diğer yandan, Tablo 3.3'te görülebileceği gibi, hem istihdam büyümesi hem de satış büyümesi yenilikçiler ve yenilikçi olmayanlar arasında daha eşit bir büyüme ayrışması göstermektedir. Ancak, Tablo 3.2 ve Tablo 3.3'te de satış büyümesinin nominal terimlerle olduğunu ve şirket düzeyinde fiyat etkisini içerdiğini akılda tutmak önemlidir. Nominal satış büyümesi açısından, MENA tüm kalemlerde negatif büyüme oranına tanık olan tek bölgedir.

Verinin temel özellikleri sunulduktan sonra tahmin sonuçlarına geçilmektedir. Tablo 3.4, bir referans tahmin yöntemi ve içsellik sorununun ne denli ciddi olup olmadığı açısından da bir kontrol mekanizması sağlaması açısından OLS tahminlerini sunmaktadır. Tablo 3.4'te görüldüğü üzere, hem genel örneklem hem de bölgesel bazda yapılan OLS tahminleri ürün inovasyonunun istihdam kolaylaştırıcı etkisini Afrika hariç genel örneklem ve diğer üç ülkede istatistiksel açıdan anlamlı bir bizimde gözlemlediğimizi ortaya koyarken, süreç inovasyonunun genel örneklem ve MENA hariç diğer tüm bölgelerde ciddi oranda istihdam azaltıcı etkisi olduğunu göstermektedir. Ürün inovasyonu değişkeninin katsayıları arasında ciddi farklılık olduğu görülmektedir. Ancak, fiyat etkisinden kaynaklı içsellik sorunu kontrol

edilmediğinden yapılan bu OLS tahminleri sonucu katsayı büyüklüğü veya istatistiksel anlamlılık açısından sağlıklı bir biçimde yorumlanamamaktadır.

Tablo 3.5, bu içsellik sorunun çözümü için araç değişkenler (yeni ürün veya hizmetin firma için de tamamen yeni olup olmadığı ile firmanın Ar-Ge harcaması yapıp yapmadığı değişkenleri) kullanılarak yapılan 2SLS tahmin sonuçlarını vermektedir. Sonuçlar Harrison vd. (2014) makalesinde sunulan modelin ya da başka bir deyişle Tez içerisinde kullanılan kısaltma ile HJMP modelinin, teorik çıkarımlarıyla tutarlı hale gelmektedir. HJMP modelinin teorik çıkarımlarına göre sabit terim katsayısı yenilikçi olmayanların üretim sürecindeki verimlilik değişimini temsil eder; süreç inovasyonu kukla değişkeninin katsayısı eski ürünlerin üretim sürecindeki süreç inovasyonu ile birlikte gelen ek verimlilik etkisini temsil eder; ürün inovasyonu ile birlikte sunulan yeni ürünlerden kaynaklanan hasılat artışı değişkeninin katsayısı ise eski ve yeni ürünlerin üretiminin göreceli verimliliğinin etkisini yakalar, bu etkinin pozitif olması beklenir ve birden küçük bir değere sahipse bu, yeni ürünlerin daha verimli üretildiğini gösterir. Bu çıkarımları akılda tutarak, Tablo 3.5'teki sonuçlar şu şekilde yorumlanmaktadır:

Sütun (1), genel örneklem için tahmin sonuçlarını göstermektedir. Sabit terim, yenilikçi olmayanların üretim sürecinde genel bir verimlilik artışı olduğunu gösteren negatif ve istatistiksel olarak anlamlı bir katsayıya sahiptir. Süreç inovasyonuna ilişkin katsayısı da negatif ve %1 düzeyinde istatistiksel olarak anlamlıdır ve istihdam düzeyinde yaklaşık %9,8'lik bir azalmaya işaret etmektedir. Yeni ürünlerdeki satış büyümesi değişkeninin katsayısı ise, ürün inovasyonu için pozitif bir istihdam sonucuna işaret etmektedir. Ayrıca, katsayının büyüklüğü bakımından yeni ürünlerin üretiminde eski ürünlerin üretimine kıyasla biraz daha fazla bir verimliliğin varlığına işaret etmektedir. Genel olarak, genel örneklem tahmin sonuçları Schumpeterci büyüme teorisinin beklentileriyle tutarlılık göstermektedir.

Tablo 3.5'te , (2) ile (5) arasındaki sütunlarda yer alan bölgesel bazda tahmin sonuçlarına bakıldığında ise, ürün inovasyonunun istihdam kolaylaştırıcı etkisinin tüm bölgelerde de güçlü bir biçimde varlığını göstermesine karşın, süreç inovasyonunun istihdam etkisinin öyle olmadığı ortaya çıkmaktadır. Sadece Afrika

için yapılan tahminler, süreç inovasyonunun emek tasarrufuna neden olduğu sonucunu verirken; diğer bölgeler için yapılan tahminler süreç inovasyonunun firma düzeyinde emek talebi üzerinde anlamlı bir etkisi olmadığını ortaya koymaktadır. Öte yandan, ürün inovasyonu konusunda bölgesel bazda eski ürünlerin yeni ürünlere göre üretimindeki göreceli verimlilik açısından farklı sonuçlar ortaya çıkmaktadır. Afrika'da, yeni ürün üretmedeki göreceli verimlilik diğer bölgelere göre daha yüksektir; Güney Asya'da, yeni ürünlerdeki değişken satış büyümesinin katsayısının büyüklüğü, 1'e çok yakın olduğundan, eski ve yeni ürünlerin üretiminde neredeyse eşit verimliliğe işaret etmektedir; ECA'da, yeni ürün üretmedeki göreceli verimlilik de eski ürünlerdekinden çok fazla ayrılmamaktadır; ancak MENA bölgesinde yeni ürünlerdeki satış büyümesi değişkeni katsayısının büyüklüğü, eski ürünlerin yeni ürünlerden daha verimli üretildiği gerçeğine işaret etmektedir.

Bu makalenin ikinci kısmında ise firmalar tarafından algılanan iş engellerinin firma düzeyinde işgücü talebinin açıklayıcı bir değişkeni olabileceği hipoteziyle, bu etkenlerin kontrol edilmesinin tahmin sonuçlarını değiştirip değiştirmediğini görmek için bu değişkenler kontrol edilmektedir. İlk olarak tahminlere “en büyük engel” kategorisi dâhil ederek başlanmıştır. Toplamda on beş kategoriden oluşan “en büyük iş engeli” sorusuna verilen yanıtlar ışığında, bu on beş kategoriden korelasyonu en çok açıklayanların hangileri olduğunu görmek için Temel Bileşenler Analizi (PCA) yürütülmüştür. Ancak, PCA analizi bu on beş kategorinin kümülatif korelasyona neredeyse eşit şekilde katkıda bulunduğunu gösterdiğinden anlamlı bir sonuç vermemektedir. Bu nedenle, temel kategoriyi “iş lisansları ve izinleri” olarak seçilerek, Tablo 3.5'te bildirilen önceki tahminler yeniden yürütülüp yeni sonuçlar Tablo 3.7'te bildirilmektedir.

Tablo 3.7'te yer alan sonuçlara göre, yenilikçi olmayan firmaların üretim sürecindeki verimlilik değişimini temsil eden sabit terimin OLS tahmini de dâhil olmak üzere tüm model tanımlamalarında istatistiksel önemini kaybettiği görülmektedir. Bu nedenle, algılanan iş engellerini kontrol ettiğimizde, Schumpeterci büyüme teorisinin üretim verimliliğinde beklenen genel artışa kanıt ortadan kaybolmaktadır. Öte yandan, süreç inovasyonunun istihdam sonucunun istatistiksel önemi özellikle bölgesel bazda artarken, Tablo 3.5'te sağlanan sonuçlara göre hem istatistiksel önem

hem de büyüklük genel örneklem tahmininde düşmektedir. Öte yandan, süreç inovasyonunun emek tasarrufu sonucu Afrika'da hala belirgin bir biçimde görülmektedir ve ayrıca süreç inovasyonunun istihdam etkisi MENA ve Güney Asya'da istatistiksel açıdan önem kazanmaktadır. MENA bölgesinde, Schumpeterci büyüme teorisiyle çelişen bir sonuç olarak süreç inovasyonunun istihdam kolaylaştırıcı bir etkiye sahip olduğu görülmektedir. Güney Asya'da süreç inovasyonunun emek tasarrufu etkisi anlam kazanmaktadır. Ürün inovasyonunun istihdam etkisine gelince, genişletilmiş tahminlerde sonuçlar Afrika bölgesi hariç ürün inovasyonunun etkisinde çok fazla değişiklik olmadığını ortaya koymaktadır. Yeni ürünler üretmedeki göreceli verimlilik, büyüklüğü açısından Afrika'da önemli ölçüde artmıştır (katsayının değerinin 0,838'den 0,598'e düşmesi nedeniyle). Diğer bölgelerde ise, ürün inovasyonunun istihdam etkisinin Tablo 3.5'teki sonuçlardan çok farklılaşmadığı söylenebilir.

Tablo 3.7'te raporlanan tahmin sonuçları, algılanan iş engellerinin kontrol edilmesinin sonuçları iyileştirmeye yarayabileceği konusunda ipucu vermektedir. Bu kapsamda, genişletilmiş modelimizin ikinci aşamasında ankette sorulan her engel kategorisi için tanımlanan ordinal değişkenler kullanılarak iş engellerinin kontrol edildiği bir diğer tahmin süreci yürütülmüştür. Bu ordinal değişkenler Temel Bileşenler Analizi yürütme açısından uygun olmadığından, Keşfedici Faktör Analizi (EFA) kullanılarak anlamlı faktör sayısı ve her faktör içinde en temsili olan iş engeli kategorisi belirlenmektedir. Keşfedici Faktör Analizi'nin kullanılmasının iki temel nedeni, başlangıçta iş engellerinin altında yatabilecek gizli değişkenlere yönelik önsel bir teorik yaklaşımın bulunmaması ve algılanan iş engelleri arasında olması muhtemel olan çoklu doğrusallık sorununu da hafifletmeye yardımcı olmasıdır. Bu kapsamda yürütülen EFA sonucunda tüm örneklem ve bölgesel bazda yaklaşık yedi faktör ortaya çıkmış ve her faktör için temsili önemi en yüksek olan iş engelleri kategorileri aşağıda verilmiştir:

- **Genel Örneklem:** Yolsuzluk, telekomünikasyon, vergi oranları, finansmana erişim, işgücü piyasası düzenlemeleri, gümrük ve ticaret düzenlemeleri.
- **Afrika:** Vergi yönetimi, işgücü piyasası düzenlemeleri, finansmana erişim, siyasi istikrarsızlık, mahkemeler, gümrük ve ticaret düzenlemeleri, telekomünikasyon.

- **Güney Asya:** Vergi oranları, mahkemeler, yetersiz eğitim düzeyine sahip işgücü, işgücü piyasası düzenlemeleri, finansmana erişim, elektrik.
- **ECA:** Telekomünikasyon, siyasi istikrarsızlık, vergi yönetimi, işgücü piyasası düzenlemeleri, gümrük ve ticaret düzenlemeleri.
- **MENA:** Yolsuzluk, vergi yönetimi, telekomünikasyon, bina/arsaya erişim, gümrük ve ticaret düzenlemeleri.

Bu kapsamda, yukarıda belirlenen faktörler ve her faktörü temsil eden iş engeli kategorileri kontrol edilerek yapılan tahmin sonuçları Tablo 3.8’de raporlanmaktadır. Genel örneklem için tahmin sonuçları, yalnızca işgücü piyasası düzenlemeleri ile gümrük ve ticaret düzenlemelerinin işgücü talebi üzerinde önemli bir etkiye sahip olduğunu ortaya koymaktadır. Öte yandan, süreç inovasyonunun işgücü tasarrufu sonucu %1 düzeyinde istatistiksel olarak anlamlıdır, ürün inovasyonu hala işgücünü artışı destekleyen sonucunu korumaktadır ve yeni ürün üretmedeki verimliliğin önceki tahminlerdeki gibi eski ürünleri üretme verimliliğinden biraz daha yüksek olduğunu göstermektedir. Yenilikçi olmayanların üretim sürecindeki genel verimlilik artışı, negatif ve istatistiksel olarak anlamlı olan sabit terimde kendini göstermektedir. Süreç inovasyonu katsayısı ve sabit terim birlikte, tüm üretim süreçlerinde işgücü tasarrufu sağlayan bir sonuca yol açan genel bir verimlilik artışı göstermektedir. Tablo 3.8’deki (2) ila (5) arasındaki sütunlar sırasıyla Afrika, Güney Asya, ECA ve MENA için tahmin sonuçlarını göstermektedir. Afrika, süreç inovasyonunun işgücü tasarrufu sonucunu bir kez daha doğrulamıştır ve katsayının büyüklüğü, süreç inovasyonundan kaynaklanan %1 verimlilik artışının firma düzeyinde yaklaşık %30 oranında istihdam azalmasına yol açtığını göstermektedir. Ürün inovasyonu istatistiksel önemini %1 seviyesinde korurken kontrol edilen faktörlere göre katsayısı büyüklüğünün değişebileceği görülmektedir. Bu durumda, eski ürünlere göre yeni ürün üretmenin göreceli verimliliği Afrika için de, genel örneklem veya Güney Asya ve ECA tahmin sonuçlarıyla benzer bir sonuç göstermektedir. MENA bölgesinin hala – ne eski ürünler ne de yeni ürünler üretmede – herhangi bir verimlilik artışı göstermediği görülmektedir ve süreç inovasyonunun istihdam düzeyi üzerinde önemli bir etki göstermediği gözlemlenmektedir; yalnızca ürün inovasyonu istihdam artışına katkı sağlamaktadır. Önceki MENA sonuçlarında

olduğu gibi, ürün inovasyonu sonuçları da yeni ürünlerin yenilerinden daha az verimli üretilmesi anlamında farklılık göstermektedir. Son olarak, MENA bölgesi için, araziye erişim ve gümrük ve ticaret düzenlemeleri iş engelleri kategorileri işgücü talebi üzerinde anlamlı bir etki göstermektedir. Şaşırtıcı bir sonuç, en büyük iş engelleri kontrol edildiğinde ortaya çıkan Güney Asya'daki süreç inovasyonunun iş gücü tasarrufu sonucunun ortadan kalkmasıdır. Güney Asya'da, iş gücü talebi üzerinde anlamlı bir etkiye sahip olan tek iş engeli kategorisi, yetersiz eğitilmiş iş gücü engel kategorisidir. Güney Asya'daki ürün inovasyonu, önceki durumlarla tutarlı bir tahmin sonucu göstermektedir. ECA bölgesi için bir başka şaşırtıcı sonuç ortaya çıkmaktadır. EFA'ya göre seçilen iş engelleri kontrol edildikten sonra, süreç inovasyonunun iş gücü tasarrufu sonucunun yüzde 10 düzeyinde istatistiksel olarak anlamlı hale geldiği, ürün inovasyonu sonucunun ise önceki sonuçlarla hemen hemen aynı olduğu görülmektedir. ECA bölgesi için tek önemli engel iş gücü piyasası düzenlemeleridir.

Analizlerimiz önemli sonuçlar ortaya koymaktadır. Öncelikle, ampirik çalışmanın veya kontrol edilen faktörlerin odak noktası hangi konum olursa olsun, ürün inovasyonu firma düzeyinde emek yaratmaktadır. İkinci olarak, süreç inovasyonunun istihdam etkisi literatürdeki önceki bulguların çoğuyla uyumlu olacak şekilde model tanımlamalarına ve kontrol edilen faktörlere göre daha hassaslık göstermekte ve kesin yorum yapma açısından yeterince sağlam sonuçlar sunamamaktadır. Öte yandan, süreç inovasyonunun gelişmekte olan ülkelerde işgücü tasarrufu sağlayabileceğine dair bir dereceye kadar kanıt sunulabilmektedir ve bu ülkelerde firma işgücü talebi kararlarını etkileyen faktörleri tespit ederek kontrol etmenin önemi ortaya çıkmaktadır. Gelişmekte olan ülkelerde işgücü talebi üzerinde etkisi olan bazı faktörler, özellikle de süreç inovasyonunun firma işgücü talebi üzerine etkisini maskeleyebilir.

Dördüncü bölüm Tezin ikinci denemesini oluşturmaktadır. Daha önce de belirtildiği gibi, bu Tezin motivasyonlarından biri, ekonomik bir şoktan önce ve o ekonomik şok sırasında meydana gelen teknolojik yeniliğin firma düzeyindeki istihdam etkisini araştırmaktır. Yakın zamanda yaşanan ve dünya çapında bir sağlık, sosyal ve ekonomik kriz olan COVID-19 Pandemisi, bu soruyu incelemek için eşsiz bir fırsat

sunmaktadır. WBES Birimi, Pandemi ülkelerde görülmeye başladıktan hemen sonra son İşletme Anketlerinin devamı olarak Takip Anketleri yapmaya başlamıştır. Bu mikro verilerin faydalarını elde ederek, Pandemi öncesi dönem ile Pandeminin ilk turu arasındaki istihdam değişimine yönelik bir model tahmin edilmektedir. Bu modelde, firmanın pazardan çıkması durumu da dâhil olmak üzere, Pandemi öncesinde meydana gelen firmanın ücret düzeyi ve ürün ve süreç inovasyonu ana açıklayıcı değişkenler olarak kullanılmaktadır. Ancak, Takip Anketleri için örnekleme tekrar iletişime geçilmeye çalışıldığında, bazı firmalara ulaşılamaması, bazılarının pazardan çekildiklerini teyit etmeleri, bazılarının Takip Anketini toplam olarak yanıtlamayı reddetmeleri ve bazılarının da açık olduklarını teyit ederek Takip Anketini yanıtlamaları nedeniyle burada bir seçim yanlılığı sorunu ortaya çıktığına dikkat etmek önemlidir. Bu nedenle, başlangıç İşletme Anketine göre dört kategori firmayla karşılaşılmaktadır; “ulaşılamayan”, “faaliyeti durduran”, takip anketini yanıtlamayı “reddeden” ve “açık olduğu teyit edilen”. İlk üç kategorinin eksik verilerinden kaynaklanan seçilimsel tahmin yanlılığını düzeltmek için çok kategorili multinomial lojistik modeline dayalı seçim yanlılığı düzeltme yöntemi kullanılmaktadır. İki aşamadan oluşan bu yöntemde ilk aşama (seçim aşaması) “firma durumu” olarak adlandırılan çok kategorili bir bağımlı değişken ile seçilimsel tahmin yanlılığının düzeltilmesini amaçlamaktadır. İkinci aşama olan sonuç aşamasında ise, Pandeminin ilk turunda ürün ve süreç inovasyonunun istihdam üzerindeki etkisini ölçmeye çalışan işgücü talebi denklemi tahmin edilmektedir. Ayrıca, Pandeminin olumsuz ekonomik etkilerini hafifletmek için dünyadaki hemen hemen tüm hükümetler tarafından sağlanan çeşitli türden hükümet desteklerinin etkisi de kontrol edilmektedir.

Makalenin veri özelliklerine bakıldığında temel evrensel örneklem kümesine Pandeminin erken aşamalarında ulaşma çabalarına rağmen ulaşılamayan veya COVID Takip Anketini yanıtlamayı tamamıyla reddeden firmalar nedeniyle evrensel örneklem kümesinin yaklaşık %25’ine yakınının bilgi kaybına uğradığı görülmektedir. Bu seçim yanlılığını düzeltmek amacıyla uyguladığımız multinomial lojistik modeline dayalı seçim yanlılığı düzeltme yönteminin ilk aşamasında dışlama değişkenleri olarak Pandemi öncesi temel ankette yer alan sorulara dayanarak “yanıt güvenilirliği”, “hesaplama güvenilirliği” ve “anket

tamamlama süresi” değişkenleri kullanılmıştır. İlk değişken anketör tarafından belirlenen verilen yanıtların gerçeği ne kadar yansıttığına ilişkin üç kategorili bir ordinal değişkene dayanmaktadır. İkinci değişken de firma tarafından sağlanan sayısal verilerin ne denli somut hesap ve firma kayıtlarına dayanarak sunulduğu üzerine bir anketör sınıflandırmasına dayanmaktadır. Üçüncü değişken ise anketin tamamlanmasının firmaya kaç ziyarette veya kaç farklı kişi ile görüşülerek gerçekleştirildiği bilgisine dayanmaktadır. Tüm dışlama değişkenlerinin tek tek veya ikili ve üçlü kombinasyonlar şeklinde ilk aşama regresyona dâhil edilmesiyle yapılan seçim yanlılığı düzeltme sonuçları özellikle ilk iki dışlama değişkeninin seçim yanlılığını düzeltmede başarılı olduğunu ortaya koymaktadır.

Örnekleme, Birinci Tur COVID Takip Anketleri mevcut olan tüm ülkeler (toplam 40 ülke) dâhil edilse de, üç ülkede (Azerbaycan, Kıbrıs ve Mozambik) çok fazla eksik gözlem olması, yani eksik gözlemlerin sayısının gözlenen değerlerden fazla olması nedeniyle bu ülkelerde seçim yanlılığını düzelteren ilk aşama regresyon tahminlerinin yapılamaması nedeniyle 37 ülke ile model tahminlerine devam edilmiştir.

Tablo 4.6’da, Bölüm 4.4’te ayrıntılı bir şekilde açıklanan metodolojide belirtildiği gibi temel regresyonumuz olan (4.1) numaralı eşitlik için tahmin sonuçları sunulmaktadır. Tüm tahminler, bundan sonraki tüm regresyonların, verilerden gözlemlenmeyen ülke ve endüstri düzeyindeki heterojenliği kontrol etmek için ülke ve endüstri kukla değişkenleri içermekte; ancak bu değişkenlerin katsayıları sonuçlarda raporlanmamaktadır. İlk sütun, seçim yanlılığı düzeltmesinin tahmin sonuçlarını ne kadar ve hangi şekilde iyileştirdiğini kontrol etmek için bir kıyaslama analizi olarak standart OLS tahmin sonuçlarını vermektedir. (2) ila (8) arasındaki sütunlar, ilk adım seçim regresyonunda farklı dışlama değişkenlerinin kombinasyonlarıyla multinomial (çok terimli) lojistik modeline dayalı seçim yanlılığı düzeltmesinin tahmin sonuçlarını göstermektedir. İlk adım regresyonunun çok terimli bağımlı değişkeni, ordinal değere sahip olmayan ve üç kategoriden oluşan “firma durumu”dur. Bu kategorileri ankete CEVAP VEREN firmalar, ankete CEVAP VERMEYEN firmalar ve FAALİYETİ DURDURAN (ÇIKIŞ YAPAN) firmalar oluşturmaktadır.

Tablo 4.6'nın ilk sütunu, yani (4.1) numaralı eşitliğin OLS ile elde edilen tahmin sonuçları, COVID dönemi istihdam düzeyinin firma düzeyinde çoğunlukla COVID öncesi dönem istihdam düzeyi ile oldukça ilişkili olduğunu göstermektedir. COVID dönemi istihdam düzeyinin yaklaşık %82'si COVID öncesi istihdam düzeyiyle açıklanmaktadır. Öte yandan COVID öncesi işgücü maliyetine ilişkin sonuçlar teorik beklentinin tersine bir sonuç vermektedir; çünkü COVID öncesi işgücü maliyeti COVID dönemi istihdam düzeyi üzerinde pozitif ve istatistiksel olarak anlamlı bir düzeye sahiptir. İşgücü talebinin standart teorisine göre, bir üretim girdisine olan talep, çoğu ekonomi ders kitabında açıklandığı gibi girdinin fiyatı ile ters yönde ilişkilidir. Ancak tahmin sonuçlarına göre COVID öncesi dönemin işgücü maliyeti veya toplam ücret düzeyi, COVID döneminde işgücü talebini pozitif yönde etkilemektedir. Bu durum, yüksek ücret düzeyinin yüksek işgücü verimliliğini gösterebilmesinden veya daha yüksek işgücü verimliliğine sahip firmaların ekonomik şoklar sırasında istihdam düzeylerini daha kolay koruyabilmelerinden kaynaklanıyor olabilir. Ürün ve süreç inovasyonu açısından, OLS'nin tahmin sonuçları, istatistiksel kanıt çok güçlü olmasa bile COVID öncesi ürün inovasyonunun pozitif bir istihdam etkisine işaret ettiğini, COVID öncesi süreç inovasyonunun ise COVID dönemi istihdam seviyesi üzerinde anlamlı bir etkisinin olmadığını ortaya koymaktadır.

Seçim yanlılığının düzeltildiği tahminlere dönersek, tahmin sonuçlarının önemli ölçüde iyileştiği görülmektedir. Öncelikle, tüm regresyonlarda (OLS tahmininin ilk sütunu dâhil) sabit terimin negatif olduğunu ve COVID-19 dönemi istihdam seviyesi boyunca genel bir düşüş eğilimi gösterdiğini görüyoruz. İkincisi, COVID-19 öncesi istihdam seviyesinin istatistiksel önemi ve değeri çok fazla değişmezken, COVID-19 öncesi işgücü maliyeti katsayısının değeri yaklaşık %6,8'den %8'in üzerine çıkmaktadır. Üçüncüsü ve daha önemlisi, ürün inovasyonunun katsayısının değeri ve istatistiksel önemi seçim yanlılığı düzeltmesiyle birlikte önemli ölçüde artarken, süreç inovasyonunun durumu değişmemektedir. Temel sonuçlarımızın tahmini, ekonomik şoktan önce uygulanan ürün inovasyonunun, firmaların o ekonomik şok sırasında istihdamlarını sürdürmelerine yardımcı olduğunu göstermektedir. Bu sonuç, literatürde de daha önce benzer kanıtlar sunan çalışmalarla uyumlu olarak ürün inovasyonlarının, yeni ürünlerin (veya hizmetlerin) piyasaya sürülmesiyle elde

edilen ek gelir ve kâr yoluyla firmaların ürünlerine olan talebin dış şoklara karşı firmayı daha dayanıklı hale getirdiğine ilişkin temel bir gerçeğe işaret ediyor olabilir.

Bu tahminlere ek olarak ana modelimizin Pandemi ile mücadele için sağlanan devlet desteklerinin kontrol edilerek tahminlerin yenilendiği bulgular Tablo 4.8 ve Tablo 4.9'da sunulmaktadır. Devlet desteklerinin etkisini kontrol etmek önemlidir; çünkü COVID-19 sırasında sağlanan devlet destekleri, özellikle COVID-19 nedeniyle iş yavaşlamasına karşı daha savunmasız olan sektörler veya firmalar arasındaki dezavantajları hafifletmeyi amaçlamıştır. Bu, yalnızca Pandeminin getirdiği ekonomik şoktan kaynaklanan yan etkilerin hafifletici bir etkisine sahip olmakla kalmayıp, aynı zamanda Pandemiden önce var olan ve bu destekler sağlanmasaydı firmalar arasında ortaya çıkabilecek bazı farklı yapısal zayıflıklarını (veya tam tersi güçlü yönlerini) "maskeleme" etkisine de sahip olabilir. Bu olası gerçeği aklımızda tutarak, devlet desteklerinin firma düzeyindeki istihdam etkisi kontrol edilmektedir. Tablo 4.8, herhangi bir tür devlet desteğinin etkisinin kontrol edildiği sonuçları sunarken, Tablo 4.9, devlet desteklerinin alt kategorilerinin etkilerini ayrı ayrı kontrol ederek sonuçları raporlamaktadır.

Devlet desteklerinin kontrol edildiği Tablo 4.8 ve Tablo 4.9'daki sonuçları yorumladığımızda, şu bulgular ortaya çıkmaktadır: Hangi tür destek sağlanırsa sağlansın, devlet desteği COVID-19'un erken dönemlerinde olumlu bir istihdam etkisi yaratmıştır ve her model tanımlamasında %4,3'e yakın bir katsayı değeri ortaya koymaktadır (standart OLS tahmininde %3,9). Ancak, devlet desteğini kontrol etmek, diğer açıklayıcı değişkenlerin katsayılarının istatistiksel anlamlılığında veya büyüklüğünde ciddi bir fark yaratmamıştır. Başka bir deyişle, devlet desteğinin etkisini kontrol ettikten sonra bile Pandemi öncesi dönemde uygulanan ürün inovasyonunun olumlu istihdam etkisinin devam ettiği ve bu etkinin büyüklüğünün devlet desteklerinin etkisinden bağımsız olduğu sonucuna varılmaktadır. Öte yandan, devlet destekleri türlerine göre kontrol edildiğinde, ürün yeniliği katsayısının büyüklüğünün tahminlerde yaklaşık yüzde 1 veya 1,5 oranında düştüğü, istatistiksel açıdan önemliliğinin değişmediği görülmektedir. Devlet desteklerinin istihdam etkileri açısından, ücret sübvansiyonunun OLS tahmininde ve ikinci regresyonda istihdama pozitif etkisine ilişkin zayıf bir kanıt görülmekte; diğer model

tahminlerinde önemini yitirmektedir. Ücret sübvansiyonunun sağlamlık testinin yapıldığı ve sonuçlarının Tablo 4.10’da raporlandığı durumda istihdama olumlu katkısı daha belirgin hale gelmekte ancak ürün inovasyonu ya da süreç inovasyonu açısından sonuçların değişmediği görülmektedir. “Diğer destek türleri” kategorisi ise istihdam üzerinde negatif etkisiyle tüm regresyonlarda istatistiksel olarak önemlidir. Burada, en çok yararlanılan destek türlerinin “ücret sübvansiyonu” ve “mali muafiyetler” olduğunu ve en az yararlanılanın ise “diğer destek türleri” kategorisi (yararlanma oranı %5) olduğunu belirtmek önemlidir. “Diğer destek türleri” kategorisi, ankette firmanın yararlandığı hükümet desteğini tanımlaması için sözlü bir açıklama bölümüyle takip edilmekte ve bu nedenle firmadan firmaya değişiklik göstermektedir. “Diğer destek türleri” kategorisinin küçük bir oranda olması ve bir tür aykırı değer etkisine işaret edebilecek olması nedeniyle bu kategoriye ilişkin sonuca ihtiyatlı yaklaşmakta yarar görülmektedir. Dahası, diğer tür destekler verilen bu firmaların, Pandemi nedeniyle genel olarak kötüleşen iş koşullarından daha ciddi şekilde kötüleşen sorunları olabilir ve bu da bir tür içsellik sorununa işaret edebilir. Devlet destekleriyle ilgili olarak akılda tutulması gereken bir diğer gerçek, firmalara birden fazla türde destek verilebileceği ve bu sonucun devlet desteği türleri arasında çoklu doğrusallık olması ihtimalini ortaya çıkarmaktadır. Ancak, yapılan testlere göre çoklu doğrusallık için anlamlı bir işaret bulunamamıştır. Son olarak, firmalar, yürüttükleri işin yararlılığı veya özel ihtiyaçları düşünüldüğünde, koşulları sağladıkları sürece Pandeminin en başında devlet desteğinden ihtiyaçlarından bağımsız olarak yararlanmış olabilirler. Ülke ve endüstri kuklaları, farklı ülkelerde ve sektörlerde hükümet politikalarının arz tarafı heterojenliğini kontrol etmek için yeterli olsa da, bu anlamda firma düzeyinde talep tarafı içselliği hesaba katmak için yeterli değildir.

Sonuç olarak tezin beşinci ve son bölümünde ana bulgular özetlenerek, ana kısıtlar, politika çıkarımları ve gelecek çalışmalara ilişkin yorumlara yer verilmektedir. Kısaca özetlersek bu Tez; teknolojik yeniliğin istihdam etkisine ilişkin devam eden tartışmalara farklı bağlamlarda katkıda bulunmaktadır. Önceki literatürle uyumlu olarak, ürün yeniliğinin iş yaratma etkisi farklı coğrafi bölgelerde, ekonomik şoklar veya gerilemeler sırasında geçerli görünmektedir ve alternatif model tanımlamalarına karşı bulgular sağlamdır. Öte yandan, süreç yeniliğinin istihdam etkisi daha karmaşık

bir yapıya sahip olup, normal zamanlarda veya ekonomik şok dönemlerinden bağımsız olarak ürün yeniliğine kıyasla kontrol edilen faktörlere ve model tanımlamalarına göre daha kırılgan sonuçlar göstermektedir. Gelişmekte olan ülkelerde, süreç yeniliğinin istihdam etkisinin, genel olarak işgücü talebini etkileyebilecek ve süreç yeniliğinin gerçek sonucunu aynı anda maskeleyebilecek diğer faktörler tespit edilip kontrol edilerek fazla araştırılması gerekmektedir. Ancak, bu durumlarda ortaya çıkabilecek içsellik sorunu dikkatli bir şekilde ele alınmalıdır.



G. THESIS PERMISSION FORM / TEZ İZİN FORMU

(Please fill out this form on computer. Double click on the boxes to fill them)

ENSTİTÜ / INSTITUTE

- Fen Bilimleri Enstitüsü** / Graduate School of Natural and Applied Sciences ☐
- Sosyal Bilimler Enstitüsü** / Graduate School of Social Sciences ☒
- Uygulamalı Matematik Enstitüsü** / Graduate School of Applied Mathematics ☐
- Enformatik Enstitüsü** / Graduate School of Informatics ☐
- Deniz Bilimleri Enstitüsü** / Graduate School of Marine Sciences ☐

YAZARIN / AUTHOR

Soyadı / Surname : CEBİR BENLİ
Adı / Name : BİLGİN
Bölümü / Department : İktisat / Economics

TEZİN ADI / TITLE OF THE THESIS (İngilizce / English): ESSAYS ON THE EMPLOYMENT IMPACT OF TECHNOLOGICAL INNOVATION

TEZİN TÜRÜ / DEGREE: Yüksek Lisans / Master ☐ Doktora / PhD ☒

1. **Tezin tamamı dünya çapında erişime açılacaktır.** / Release the entire work immediately for access worldwide. ☒
2. **Tez iki yıl süreyle erişime kapalı olacaktır.** / Secure the entire work for patent and/or proprietary purposes for a period of **two years**. * ☐
3. **Tez altı ay süreyle erişime kapalı olacaktır.** / Secure the entire work for period of **six months**. * ☐

* Enstitü Yönetim Kurulu kararının basılı kopyası tezle birlikte kütüphaneye teslim edilecektir. / A copy of the decision of the Institute Administrative Committee will be delivered to the library together with the printed thesis.

Yazarın imzası / Signature

Tarih / Date

(Kütüphaneye teslim ettiğiniz tarih. Elle doldurulacaktır.)
(Library submission date. Please fill out by hand.)

Tezin son sayfasıdır. / This is the last page of the thesis/dissertation.