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ESSAYS ON INNOVATIONS, FIRM PRODUCTIVITY, AND EMPLOYMENT IN THE CONTEXT OF AFRICA

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Approval and Signature Sheet

This dissertation entitled "Essays on Innovations, Firm Productivity, and Employment in the Context of Africa" is submitted to Department of Economics, Addis Ababa University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics. We, board of examiners, have read and evaluated this dissertation, and examined the nominee. We recommend the dissertation be accepted as partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics.

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Dedication

This thesis is dedicated to my Mother, Zulfat Surur, and my wife, Fatuma Mohammed Ali. Both of them have paid unbearable costs while I was writing this thesis[1].

[1] I will strive to find myself where you put me in your mind.

Author’s Statement

I, **Mezid Nasir Keraga**, would like to declare that this dissertation entitled “Essays on Innovations, Firm Productivity, and Employment in the Context of Africa” is my original work and none of the essays has been submitted to any other institution elsewhere to award any degree. All sources of information, ideas and views used in this dissertation are dully acknowledged.

Candidate: Mezid Nasir Keraga
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Date: August 2023

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Acronyms

AU African Union. 74

BoP balance of payment. 12

CDM Crépon, Dugue and Mairessec. vi, 31–33, 47, 50, 59

CMP conditional mixed process. vi, 32, 35, 45–47, 50, 59

CSA Central Statistical Agency. 5–7, 14, 79

DID difference in difference. 16, 17

ES enterprise survey. xiv, 5, 7, 56, 79, 80

FE fixed effect. 21

GSEM general structural equation model. xiv, 30, 32, 45–47

ICT information and communication technology. xiv, 4–7, 49, 50, 56, 59, 91

IMF International Monetary Fund. 4, 69

LMSM large and medium scale manufacturing. 5, 7, 14, 17, 18

LP Levinsohn-Petrin. 19, 21

OLS ordinary least square. 10, 16, 17, 21

OP Olley-Pakes. 13, 21

RM Rivigatti-Mollisi. 21, 23

TFP total factor productivity. vi, 7, 23, 25, 37

WB World Bank. xiv, 5–7

WLRDG Wooldridge. 21

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[3]The author is responsible for all errors and omissions in this thesis. Supervisors and others who have contributed to this thesis are not responsible for any factual errors.

Abstract

Seemingly contentious views are mainstreamed in the literature regarding the most important sources for productivity changes in general. More precisely, it is reasonable to inquire why there are differences in productivity across countries, sectors, and businesses. This study mainly aims to investigate factors that could explain firms' heterogeneity in Ethiopia. In line with this main objective, it also intends to provide empirical evidence about the impact of innovations on firm-level productivity and to identify sources of firm-level innovations in the developing countries context. Moreover, this study attempts to answer two key research questions: Does devaluation have a long-term impact on the performance of an exporting firm? And, is there any trade-off between firm-level innovation and employment in the context of Africa? To meet those objectives and to address the research questions mentioned above, four independent but interrelated studies were compiled in this dissertation. For all papers, panel data-sets are utilized, which allow to capture firm-specific fixed effects and track the changes in productivity within a firm over time. Total factor productivity (TFP) was estimated using control function estimators. To disentangle the effect of devaluation on firms' productivity, four waves of a panel data-set of large and medium scale manufacturing (LMSM) firms of Ethiopia are used and a quasi-experimental technique with time-invariant exporters as a treatment group has been applied. To examine the interrelationship between research & development (R&D), information and communication technology (ICT), innovation, and productivity, we used two waves (2011 and 2015) of the World Bank (WB) enterprise survey (ES) data-set. The interrelationship between variables of interest were modelled as general structural equation model (GSEM) and were estimated using a fixed effect estimator. Finally, the impact of firm-level innovation and its spillover effects on employment was investigated using a panel data-set of the WB for six African countries. To establish the impact, a difference in difference (DID) estimator is applied in combination with matching. Results from the first paper indicated that devaluation does not have a strong long-term impact on exporting firms' performance, but exporting firms are more productive than import-intensive firms in the post-devaluation period. We also found that R&D, innovations, and firm productivity are linked and the linkage between firm-level innovations and productivity is strong and robust. Thus, innovation is key to enhance firm-level productivity. Furthermore, our findings indicate that ICT increase firm-level innovations, and it has also a direct positive impact on firm's productivity. Finally, we provide robust new evidence that innovations expand employment in the African context, and innovative firms have also positive intra-industry employment spillover effects. Policy implications of each paper's findings are presented and discussed at the end of each chapter.

Keywords: Innovations; Devaluation; Firm productivity; GSEM, ICT; Employment

Chapter 1

GENERAL INTRODUCTION

1.1 Background

It was in the late 18th century that scientific and organized economic thoughts started to explore the factors that influence the prosperity of a nation. In this regard, Smith's (2010) works can be taken as a benchmark for modern political and economic studies. From then on, productivity has been at the center of economic and political thoughts: labor productivity (Smith, 2010); land productivity (Malthus, 1872; Ricardo, 1951); productivity driven by technological progress via capital augmentation (Say, 1964; Solow, 1956); labor productivity embedded in physical capital (Romer, 1987), skills, and information (Lucas Jr, 1988); or drastic productivity changes due to innovations (Schumpeter, 1982). The path to make a country fabulous needs to intersect the productivity stream at multiple points since productivity is everything in the long run (Krugman, 1997). In our realm of common sense, economic growth has the purpose to provide goods to a nation. Considering this philosophical underpinning, we attempt to explore the stream that directs a nation towards improvement in public goods.

In analyses on a macro-economic level, productivity is the core factor to explain long-run economic growth (Solow, 1956), convergence via embodied technology (Romer, 1990b), and technology transfer (Barro and Sala-i Martin, 1992; Coe et al., 1997). At the micro-level, productivity improvement is critical for a firm to sustain and survive in the market (See Syverson, 2011). Furthermore, understanding firm- or industrial-level productivity is key to explain market structure and share (Schumpeter, 1982), firm's engagement in knowledge production, i.e. in-house research and development (R&D) (see Crépon et al., 1998; Griliches, 1957, 1979; Klette and Kortum, 2004), and the extent of adoption or diffusion of information and communication technology (Jorgenson et al., 2008, 2011; Hall et al., 2013). Indeed, seemingly contentious views are mainstreamed in the literature regarding the most important source for productivity changes in general. More precisely, researchers wonder why there are differences in productivity across countries, sectors, and businesses. Is it a matter of fortune? Or something more systematic that can be found in the process of transforming inputs into outputs? Having these questions in mind, in this paper we examine whether research and development, innovations, and information and communication technology are important factors and could explain firm-level productivity variation in the context of Africa.

For instance, in 1960, rich countries were 23 times more productive than poor countries, and then the figure increased to 37 times in 2017 (Calderon, 2021). Africa has experienced natural and man-made shocks which affect factors of production and total factor productivity. Low productivity of Africa could be related to mal-policies that redistributed resources from more-productive sectors to less-productive sectors. Over the past six decades, Sub-Saharan Africa (SSA) countries lost labor productivity compared to East Asian dragons which comprised Indonesia, South Korea, Malaysia, Singapore, and Thailand. In 1960, Sub-Saharan labors were 40-45 percent more productive than East Asian while in 2010s workers in East Asia were as much as three times more productive than Sub-Sahara African workers (Calderon, 2021). In comparison, the labor productivity of Ethiopia was 40 percent of the average Sub-Saharan Africa labor in 2018 (Hailu et al., 2020). What explain the sluggish or dismal productivity trends in SSA countries compared to initially comparable regions, like east Asian countries? (Calderon, 2021) identified that low capital per worker, low human capital formation and declining educational quality, inefficiency in production technology are causes of slow productivity growth in SSA. Furthermore, Calderon (2021) pointed out that resource mis-allocation and prevalence of policies and institutions that push production units from efficiency benchmarks are the main causes of low productivity level and growth in SSA countries.

In the context of Ethiopia, (Hailu et al., 2020) reported that labor productivity of Ethiopia has been increased by more than 100 percent within one and half decades. From 7,080 ETB in 2000 to 15,610 ETB in 2016. On average, labor productivity grew by 4.94 percent annually. Sectoral wise, the service sector is relatively recorded a high labor productivity compared to agriculture and industry sectors while industrial sector labor productivity grew faster between the period 2005 and 2016 compared to the rest. On the other hand, TFP growth has been declining starting from 2004 to 2014. While TFP growth was the main driver of labor productivity improvement in Ethiopia from 2000 to 2010 then replaced by capital deepening starting from 2011 on-wards. As a challenge, (Hailu et al., 2020) report identified that poor working culture and worker attitude in terms of high attrition and absenteeism, no sense of urgency about work, and low motivation to work overtime are the top bottleneck that affect labor productivity of the apparel sub-industry. To mention one, labor productivity in terms of number of pieces per worker per day is much lower than some bench-marked Asian countries. For instance, one worker in China has produced 18-35 polo-shirt per day while one worker in Ethiopia produced only 7-18 polo-shirt per day. Hence, on average, an Ethiopian worker is 50 percent of the average efficiency of a Chinese's worker.

Most of classical and neoclassical growth thoughts and theories aim to explain the importance of productivity improvement for economic growth. To mention some of the widely circulated literature, Ricardo (1951) hypothesize that factor productivity difference is a source of advantage compared to trading partners; Solow (1956) assert that exogenous technological progress raises total factor productivity and then shifts the production frontier or growth trajectory. Lucas Jr (1988) and Romer (1990b) argue that improvement in labor productivity, i.e. education and skills, is a source of economic growth. In trade theories, Melitz (2003) provide an analytical framework on how trade is influenced by firms' heterogeneous productivity. The central point of all growth theories and models–whether they are efficiency-centered (endogenous) or concentrate on technological changes (exogenous)–is how to change factor productivity substantially to become competitive in the local and international market. Various empirical evidence has been documented to explain the sources of firm-level productivity. This study might update readers on recent developments and relevant information on the issue. Beyond that, this paper gives new insights into the structural interrelationship between R&D, innovations, and productivity in the context of developing countries.

Productivity in one or another way is associated with innovations and employment. Firm-level innovations enhance labor productivity, and labor productivity in turn may change employment. However, the relationship between innovations, productivity and employment is complicated (See Edquist et al., 2001; Harrison et al., 2014; Pianta, 2009). For instance, product innovations improve productivity either through requiring less amount of input and/or transferring resources to the new product production with a higher value (Peters et al., 2014) Largely, the effect of innovations on productivity is positive but its effect on employment is contentious. Product innovation has a demand expansion effect that could translate into employment. New products provide a higher utility for the consumer, and it stimulates demand and employment (Peters et al., 2014). This higher demand either completely new or replacing the old one through cannibalization effect, and its effect on employment also depends on the relationship between the new and old products-whether they are complementary or substitute to each other. On the other hand, both product and process innovations have labor-saving effects that reduce employment via productivity effect. In most cases, process innovations increase productivity which leads to negative effects on employment, but it could have a positive effect on employment through reducing the price of the new products since most often process innovation reduces average cost.

This study extends the previous studies' measurements of productivity by applying control function estimators. For the details of evolving productivity measurements over a time horizon, see Syverson (2011). We investigate the important factors that might explain firm-level productivity in the context of Africa. First, we examine the impact of macroeconomic shocks on firm-level productivity in Ethiopia using a data-set on large and medium scale manufacturing (LMSM) firms. Given the low contribution of export to the GDP and the stagnant performance of the Ethiopian export sector for the last couple of decades, it is worthwhile to investigate empirically how policy changes, like devaluation, affect firm-level productivity in Ethiopia. Theoretically, devaluation makes export relatively cheaper and encourages domestic firms to export more. The assumption is that devaluation could affect productivity of exporting firms in the long term. On the other hand, devaluation rises the cost of importation and Ethiopian firms have been highly dependent on abroad markets for physical capital and raw materials. There is empirical evidence that import improves productivity of firms in Ethiopia (see Abreha, 2019) and in other developing economies (see Coe et al., 1997; Coe and Helpman, 1995). The effect of devaluation on export, however, is a short-term phenomenon while its long-term impact is not well established. In other words, we attempt to examine whether the short-term objective of devaluation, i.e., making exports cheaper, is complementing a long-term objective, i.e., to improve productivity. In the third chapter, we took a more detailed look at the source of productivity differences and discuss how R&D and innovations interact with firm performance in Ethiopia. This chapter addresses one key question: are innovative firms more productive than their non-innovative counterparts? In our effort to answer this question, we also investigate whether expenditure on R&D is an important driver of firm-level innovations in the African context. In general, in this chapter we discuss the linkage between R&D, innovations, and firm productivity. In doing so, this dissertation highlights and indicates the factors that enhance/impend firm-level innovations as well.

Furthermore, at the macro level, average expenditure on R&D as a ratio of GDP is very small with 0.3 percent in Africa (Hamid et al., 2021). Similarly, at the firm level, on average, less than 0.3 percent of resources are allocated for in-house R&D. Nonetheless, firms have been introducing new/improved products and services to the local market. For instance, Rwanda and Malawi are ranked 1st and 3rd, respectively, in the top three innovative countries in the low-income category in 2021 (WIPO, 2021). Thus, it appears that in the African context, something else than R&D influences the innovation behavior of firms and, consequently, their productivity. Correspondingly, Keller (2004) estimated that more than 90 percent of the improvement of productivity in developing countries originated abroad–i.e., through the application of foreign technology. Keeping this in mind, we are interested in looking at the impact of information and communication technology (ICT) on firm-level innovations and productivity in Ethiopia. There is ample theoretical and empirical literature that supports the argument that productivity difference between firms is due to the utilization intensity of ICT capital and its accumulation (see Brynjolfsson and Yang, 1996; Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2003; Jorgenson et al., 2008). In chapter 4, we discuss the linkage between ICT, innovations, and productivity using relevant and recent empirical evidence. Finally, we look at the interplay between innovation and labor market outcome, i.e., employment. This is an unresolved issue, which is starting to attract the attention of many scholars. For instance, Acemoglu (2021) in the International Monetary Fund (IMF) spring issue has made a remark that innovations like automation have a negative impact on employment. Thus, it has policy and practical relevance to investigate whether there is a trade-off between innovations and employment in developing countries.

To give a theoretical perspective, in the pre-industrial period the assumption was a complementary relationship between employment and innovations (Petit et al., 1993), where innovations do not have displacement effects. Contentious views have emerged in the classical or industrial period on whether innovation creates or destroys jobs. For instance, Say (1964) state that for every machine there is a hand associated with it. For Say (1964), technology is neutral to an employment effect. That said, Pigou (1962) argue that innovation has contributed to employment expansion, but Schumpeter (1982) strongly argue for the substitution effect of innovations. In general, it can be said that innovation has a job displacement effect via substitution of capital for labor and a compensation effect via the expansion of demand due to price reduction. Thus, it is a question of whether the compensation effect of innovations is larger than the displacement effect. We aim to examine the possible impact of innovations on the labor market, specifically, on employment in the context of Africa. Remarkably, this study identified spillover effects of firm-level innovations on employment. This enables us to shed light on the aggregate impact of innovations on local employment for a policy prescription.

1.2 Objectives of the Study

The aim of this study was to critically examine the potential determinants that explain productivity differences between businesses and disentangle the impact of innovations on labor market outcomes in Africa. That said, the paper has the following four specific objectives.

1.2.1 Specific objectives

- Establish the impact of devaluation on productivity using a firm-level data-set.
- Examine the linkage between R&D, innovations, and firm productivity in the African context.
- Empirically investigate the interrelationship between ICT, innovations, and firms' productivity.
- Identify the impact of firm-level innovations on employment in Africa.

1.3 Significance of the Study

This study has used the WB's ES data-set and the data-set of the Central Statistical Agency (CSA) of Ethiopia for large and medium scale manufacturing (LMSM) firms. This study primarily focuses on firm performance, i.e., productivity. Furthermore, it also discusses at least three important policy issues: innovations, devaluations, and employment, which have both academic and policy relevance. Therefore firstly, it contributes to the existing empirical evidence that critically evaluates firm-level productivity differences in various aspects in the context of developing countries. To the best of our knowledge, this study is one of the few empirical studies that document the impact of devaluation on firm productivity in the African context. Moreover, it could be considered as groundbreaking for future studies by identifying the spillover effect of firm-level innovations on employment. Secondly, employment and innovation are the two most important issues set on the top three Agenda-2063 goals of Africa. Click this link to overview African Agenda-2063. Thus, the findings of the study provide interpretative insights for policymakers of Africa in drafting innovation policy and strategy.

This paper also provides organized information for governments on how to improve competitiveness of domestic firms. This study is the first rigor empirical evidence that disentangles the impact of innovations on employment using a cross-country panel data-set. This provides an important policy perspective and has theoretical relevance because it reveals whether there is a trade-off between innovations and employment. It could motivate further investigation into the issue and can be used as a reference. The ICT sector in Africa is developing very fast and one of the possible areas where convergence could happen between advanced and developing economies. In this study, we provide some evidence regarding the potential role of ICT in inducing firm-level innovations and productivity in Africa using a robust methodological approach. Finally, this study could be considered a benchmark study in Africa in structuring the interrelationship between ICT, innovations, and firm heterogeneity. Furthermore, the findings of this study could be an important policy input to look at all dimensions of the ICT sector in the process of facilitating globalization and fast transactions of goods and services.

1.4 Scope of the Study

This study is limited spatially to Africa. Out of the four compiled papers in this dissertation, three of them are focused on Ethiopia, while the final paper broadens its geographical coverage to Africa. Conceptually, this paper follows the Oslo Manual (2005) definitions of innovations–inclined to incremental innovation–while there are competing alternative conceptualizations of innovations.[1] The data-set instrument is developed per definition of the Oslo Manual. In the ES data-set, firms were requested to report whether the innovated product and service are "new to the firm" or "new to the market". Accordingly, in this study innovation is referring new to the firm. Methodologically, the study used at least two rounds of a survey panel data-set irrespective of the issues compiled in this cohort of the study. Moreover, this study is bound to firm-level micro-analyses where the data is collected by the WB and the CSA. We used multi-factor productivity to measure firm-level productivity rather than single-factor labor productivity while underscoring that both have their own pros and cons. For the details about productivity measurement, interested readers can review Bartelsman and Doms's (2000)[2] and Syverson's (2011) rigorous literature survey on productivity. Tybout (2000) pointed out that applying multi-factor productivity as measurement for micro-enterprise analysis is conceptually appealing.

1.5 Limitations of the Study

As with most empirical studies, this study also has a number of limitations. The following are the major weaknesses of this study. It is an open secret that data constraint is one of the stumbling blocks to realizing an empirical analysis in developing economies, in Africa in particular. Likewise, most of the limitations of this study emanate from data availability. The confounding nature of one of our interest variables, i.e. devaluation, with other macroeconomic shock indicators makes it hard to disentangle the impact of devaluation from other macroeconomic policy-change indicator variables. To address this methodological concern partially, we created an interaction term, which is an interaction of the time trend indicator variable with policy change (devaluation) to see whether there is a change in the significance level of the policy-change effect. Besides that, we don't have a natural control group of firms that can be used in comparison to the treatment group. In other words, we would need to have firms that are not influenced by devaluation to establish and figure out the real impact of the policy change. And yet, we have firms–we call them local firms–that are neither importing nor exporting and can be considered as a control group. The assumption is devaluation has a direct impact on trading firms only. However, local firms do have some linkages with trading firms through different channels, either through the input or output market.

Moreover, to a certain extent we used a soft version of ICT as a measurement, nevertheless, it is more relevant in the context of Africa. In most previous empirical works, ICT is measured either through the amount of investment in ICT as well as related infrastructure and facilities or broadband internet

[1] For instance, Frascati Manual (2015) can be used as a standard to measure research and experimental development, and R&D is defined as "creative and systematic work undertaken in order to increase the stock of knowledge – including knowledge of humankind, culture and society – and to devise new applications of available knowledge....for an activity to be an R&D activity, it must satisfy five core criteria, novel, creative, uncertain, systematic, and transferable and/or reproducible". Furthermore, based on technology and markets, innovation can be categorized as radical or incremental. Radical innovation is a departure from the existing products and processes due to a technology breakthrough (Ettlie et al., 2018), while changes in products and processes with less novelty are considered as incremental innovations (Oslo Manual, 2005)

[2] To mention a few points raised by Bartelsman and Doms (2000), the choice between labor productivity and TFP measurement is an important decision. Labor productivity can be increased by increasing the capital-labor ratio without a change in technical progress, while TFP provides us with better information about changes in technology. On the other hand, labor productivity is an appropriate measurement for welfare comparisons.

usage per worker. In this thesis, we used the availability of a web-page for the firm as an indicator for ICT utilization/adoption. In the World Bank ES data-set, there is not much freedom to change the measurement of ICT. As a final limitation of this thesis, we used firms' self-reported innovations as dummy variable to measure innovation output. It would have been still more insightful to use the value of innovative products and services to provide numerical figures rather than probabilistic information to policymakers. We recommend future studies to address those limitations mentioned above.

1.6 Structure of the Study

This thesis is organized into six chapters. Each chapter is further structured by sections and subsections. Except Chapter 1 & 6, all the other chapters are organized into six sections: Introduction, Literature Review, Data and Estimation Strategy, Results and Discussion, Robustness Check, and Conclusion and Recommendation. In the following, the content of each chapter is presented briefly. Chapter 2 discusses the impact of devaluation on exporting firms' productivity. For this chapter only, we used LMSM data-set of Central Statistical Agency (CSA), while for the other three papers, we used the World Bank Enterprise Survey data-set. In this chapter, we reviewed and presented both theoretical and empirical literature that discusses the mechanism how devaluation affects firms' productivity. Considering the price change adjustment, the key variables–which include capital, labor, sales revenue, and value of export–are described. Furthermore, summary statistics of total factor productivity (TFP), where TFP is estimated using different control functions, are presented. The variation in productivity between exporters and less-exporters as well as other firm-specific characteristics are also discussed in this chapter. Finally, multiple regression specifications that aim to establish the impact of devaluation on export are estimated and the results are presented. In Chapter 3, the interrelationship between R&D, innovations, and firms productivity is presented. The rationale behind and relevance of R&D and innovations in the context of developing economies is discussed with support of empirical literature from advanced and developing economies. The relationship between the three variables of interest is modeled as general structural equation model (GSEM) and estimated accordingly. Estimation is conducted for product and process innovations both separately and jointly to see if there are changes in the impact of the two types of innovations. Finally, to check the robustness of the findings, Crépon et al.'s (1998) and Roodman's (2011) methods are applied, and the results are presented.

Chapter 4 presents the link between ICT, innovations, and productivity. This chapter provides evidence on the relationship between ICT and innovations as well as ICT and productivity using a Ethiopian firm-level panel data-set. Relevant and recent literature that examines the impact of ICT on innovations and firm performance is reviewed. Empirical evidence of the direct and indirect impact of ICT on firm productivity is presented and discussed with respect to the literature. Finally, possibilities for policy interventions to promote innovation and improve firm-level productivity is indicated at the end of this chapter. Chapter 5 discusses and analyzes the impact of innovations on employment as well as its spillover effects. This chapter begins with providing historical background information about the nexus between innovation and employment. This is followed by a review of theoretical literature that focuses on the relationship between technological innovations and employment. Next, we discuss the trends of innovation and employment in Africa using the WB's development indicator data-set. Then, this chapter analyzes the relationship of innovation and employment in six African countries using the data-set of the ES of the WB. Finally, this thesis presents a summary of conclusions and recommendations of each essay in Chapter 6. The conclusions and recommendations of each chapter are synthesized and presented.

Chapter 2

THE IMPACT OF DEVALUATION ON THE PRODUCTIVITY OF EXPORTING FIRMS[1][2]

Abstract

It is expected that devaluation makes domestic firms more competitive in international markets, thereby boosting export and productivity in the long run through spillover and learning-by-doing effects. However, devaluation of home currency affects the cost and price structures of trading firms simultaneously. This study is designed to empirically establish the impact of devaluation on firms' productivity. The data comes from four waves of the annual survey of Ethiopian large and medium Scale manufacturing firms (LMSM). We applied control function estimation methods for estimating the production function. The main findings of the study are, in the short-term, that there is no strong evidence that devaluation has a positive impact on total factor productivity (TFP) of exporting firms. However, the short-term estimation results indicate that less import-dependent but export-oriented firms improve their competitiveness in the post-devaluation period. We extended the panel dimension of the data-set by adding four more waves (2013-2016) of LMSM panel data into analysis to establish the long-term impact of devaluation on exporting firms productivity. The result reveals that devaluation significantly eroded the competitiveness of exporting firms. Thus, macroeconomic policy like devaluation is not the right policy for boosting exports and raising productivity of exporting firms in Ethiopia. To gain some dividend out of devaluation, the share of imports needs to be reduced.

Keywords: Firm productivity, Devaluation, Export, Control Function, Ethiopia

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2.1 Introduction

On September 01, 2010, the Ethiopian government devalued its currency by about 20 percent which was increased the price of a USD from 13.6824 Ethiopian Birr (ETB) to 16.3514 ETB. It is also relevant to note that ETB was devalued by 10 and 9.9 percent in the year 2008 and 2009, respectively. But September's 2010 devaluation can be considered as a big push or shock. The main objective of this policy measure was to increase export value and minimize the trade deficit gap- it was close to 30 percent of GDP at that time-through import substitution as well as increase the inflow of remittance. In the long run, it has the ambition to enhance the competitiveness of domestic firms. On the other hand, it is important to look at how this nominal exchange rate change could affect real effective exchange rate (REER). Unfortunately, IMF has changed the base year to estimate REER index for Ethiopia to 2010. Accordingly, the REER for 2011 and 2012 was 105.144 and 124.51, respectively. In 2012, the nominal value of ETB against the dollar was devalued by 4.77 percent. Thus, 2010 devaluation has an impact on REER on post devaluation periods.

It is expected that devaluation makes domestic firms more competitive in international markets, thereby boosting export and productivity in the long run through spillover and learning-by-doing effects. However, devaluation of home currency affects the cost and price structures of trading firms simultaneously. For instance, Mengistu et al. (2017) have found that depreciation of Ethiopian Birr by 10 percent leads to an increase of the price of import and export by 7.9 and 6.2 percent, respectively. Given the huge dependency of Ethiopian firms on imported raw materials and intermediate inputs, the volume of import might not be disrupted in a meaningful way due to devaluation of domestic currency. In this context, depreciation of Ethiopian Birr would create a competitive disadvantage for Ethiopian firms. On the other hand, the Balance of Payment (BoP) deficit has been increasing over time–from 521.4 USD million in 2014/15 it got to 941.6 USD in 2018/19 (Natinal Bank of Ethiopia, 2019). Moreover, Natinal Bank of Ethiopia's (2019) annual report shows that the share of export in GDP was 13.8 percent in 2009/10 but has declined to 7.9 percent in 2018/2019. Therefore, it is appropriate to ask why this macroeconomic indicator for Ethiopia has not improved for more than a decade though government has been introducing several monetary policy changes. However, monetary economists argue that monetary policy changes can be expected to have a real effect on the macroeconomic indicators of a country. Accordingly, I study the hypothesis that monetary policy change (devaluation) has an impact on the productivity of firms.

To the best of my knowledge, there are hardly any previous studies which have examined the impact of devaluation on firm productivity, particularly in Africa. The few existing empirical studies are limited to advanced economies. To mention a few, Baggs et al. (2009) for Canadian firms; Choi and Pyun (2020) for South Korea firms; Forbes (2002) for a cross-countries study. Yet, the impact of devaluation on firm productivity has not been studied in the context of Ethiopia. This policy change in the form of devaluation can be used as quasi-experiment to understand the impact of devaluation on domestic firm performance. The impact of devaluation at the micro level is not straightforward and hard to predict due to firms' heterogeneity in their response to shocks. As a result, devaluation has not only a direct effect but also a spillover effect on firms' performance. For instance, Baggs et al. (2009) have suggested that devaluation can slow down innovation by raising the price of investment goods.

From theories and findings of previous empirical studies, it becomes evident that devaluation increases the prices of imports, but decreases the prices of exports. As a result, the volume of imports is expected to be lower after devaluation compared to the pre-devaluation period. Therefore, productivity gains due to R&D spillover effects through importing (Coe et al., 1997; Coe and Helpman, 1995) cannot be exploited by domestic firms. As a result, exporting firms might be negatively impacted by devaluation, as the volume of their importing of intermediate inputs could be affected. In this regard, Abreha (2019) provides empirical evidence that there is a productivity gain from importing in the manufacturing firms of Ethiopia. On the other hand, it is well understood that devaluation incentivizes export, and exporter firms could have a productivity gain due to learning the behavior of foreign consumers. Therefore, knowing the impact of devaluation on firms' productivity helps us to better understand the impact of macroeconomic policies on micro-level outcomes in general.

The impact of devaluation on aggregate productivity is also linked to the constraint that is imposed on firms' access to foreign intermediate inputs due to rising import costs. However, Blaum et al. (2017) provides evidence that both the share of exports and imports increased after devaluation using micro-data for Mexican firms where the share of a firm's imports is expected to decline. Hence, the impact of large currency depreciation may not affect a firm's productivity negatively by restricting the firm's access to foreign inputs. Tybout et al. (1997) confirmed Blaum et al.'s (2017) findings when investigating firms' reactions to currency devaluation in terms of productivity and market orientation using a Cameroonian firm-level data-set for the period 1992-95. They found that the devaluation of the Cameroonian currency improved firms' productivity. They also found that export-oriented firms had a better performance compared to non-exporters. Similarly, McLeod and Mileva (2011) found that real currency depreciation increased TFP and GDP growth from panel data of 58 countries. However, Lu et al. (2013) found that depreciation of the Colombian currency by 26 percent led to a 32 percent drop in import value. According to them, devaluation can slow down import and lead to a larger TFP decline. Further, Vellianitis (1974) examined the impact of two US devaluations, (1971 and 1973) on agriculture exports using ordinary least square (OLS)regression in a cross-section design. They found that changes in the exchange rate did not have a significant impact on agricultural exports. Thus, previous findings regarding the impact of devaluation on exports and imports, which is the standard channel that affects firm-level productivity, are inconclusive.

Moreover, the manufacturing base of Ethiopia has remained narrow and its contribution to overall GDP stood at 4.4 percent in 2013/14 and is planned to increase to 8 percent in 2019/20. Thus, to meet the planned target, the government of Ethiopia needs to take into account the ramification of a monetary policy change for the manufacturing sector. Therefore, this study empirically identifies the impact of the 2010 Ethiopian Birr (ETB) devaluation on exporters and importers. This study provides evidence for policy makers about the behavior of firms in response to macroeconomic shocks in terms of exchange rates in a common context.

On the other hand, Ethiopia is a country where foreign hard currency is controlled by the government and rationed based on some criteria and principles (export status and sector). Thus, the impact of devaluation on firms' decision behavior is not easily predicted. The intensity of firms' engagement in foreign trade might be independent of firm productivity due to foreign hard currency constraints for the import of intermediate inputs. Previous studies also signaled this assertion: for instance, Gebreeyesus (2008) finds that large and incumbent firms are more likely to survive than to exit. Probably, this is due to the fact that the survival of incumbent and large firms is related to the access to foreign hard currency rather than merely exclusive to the firm's productivity level.

The remainder of this paper is organized as follows. Related literature is presented in section 2.2 followed by data and identification strategy in 2.3. The data-set is described in Section 2.4. Results and discussion of the findings are presented in Section 2.5 and robustness checks in Section 2.6. Finally, Section 2.7 provides conclusions and some policy remarks.

2.2 Related Literature Review

At the micro level, the impact of currency depreciation can be assumed to be comparable to that of tariff changes or trade liberalization (Feenstra, 1989). Considering this notion of Feenstra (1989), Melitz (2003) has modeled international trade given firms' heterogeneity. He shows that depreciation makes exporting less difficult for firms, as their products have become cheaper in foreign markets and due to entry and exit of firms that could also improve productivity.

At the macro level, however, there is a common consensus among international trade economists, at least in the long run, about the impact of currency depreciation on export performance of a country (Mundell, 1963; Fleming, 1962). The famous J curve of balance of payment (BoP) and the Marshall-Learner condition are the pioneers in framing the relationship between currency depreciation and BoP. This study hypothesizes that monetary policy has an impact on the real economy. Thus, the currency depreciation (devaluation) that has been undertaken by the Ethiopian government in 2010 is assumed to have had an impact on productivity of the manufacturing sector and would affect the behavior of exporter and importer firms. According to Mundell's (1963) and Fleming's (1962) models, monetary policy is effective when the Marshall-Learner (ML) condition is satisfied, i.e., the depreciation of currency will improve the balance of payment by improving export in an imperfect capital mobility and flexible exchange rate regime. However, Weeks (2013), has criticized the Mundell-Fleming model stating that the model ignores the impact of devaluation on the domestic price level, which undermines the validity of their prediction. Moreover, Weeks (2013) has suggested the effectiveness of monetary policy depends on the values of import share and the sum of trade elasticities as well as the degree of capital mobility. Thus, the impact of devaluation on firm productivity and export might not be as straightforward as forecast by the Mundell-Fleming model. This study, however, attempts to identify the impact of devaluation on micro-level economic outcomes, i.e. productivity, which is a not well-discussed topic in the theoretical and empirical literature. One of the reasons for limited empirical literature is related to the assumption that macroeconomic policies have a similar effect on firm behavior. But in the real world firms are heterogeneous and respond differently to macroeconomic policy shocks or changes.

Melitz (2003) shows that trade liberalization makes the least productive firms exit from international trade and industry while more productive firms self-select into export. Melitz (2003) mentions that there are two channels that force the least productive firms to exit from international trade, i.e., product market competition and factor market competition. However, Melitz (2003) considers the second channel, where firms are competing for the common factor of production (labor) and, in the process, the least productive firms exit from the industry. Consequently, the market share of more productive firms has increased. Finally, Melitz's (2003) model predicts that the reallocation of market share due to international trade provides a welfare gain to the economy, as exporting costs disrupt the distribution of gain from trade across firms. Hence, depreciation of domestic currency has a reallocation effect within the industry due to firms' heterogeneity, and, in the aggregate, it alters the distribution of productivity gain to the industry.

Moreover, Fung (2008) introduces a model of exchange rate and firm dynamics, which is built based on Krugman (1979)'s model of monopolistic competition. Fung's (2008) model predicts that appreciation of domestic currency intensifies competition and forces some firms to exit the international market. However, the model assumes that all firms are equally productive while, actually, firms are heterogeneous in terms of productivity. Hence, this study was inspired by the contradictions of macroeconomic theoretical literature and micro-level predictions. Thus, our study makes an empirical contribution that sheds light on the possible impact of macroeconomic policy shocks on micro-level outcomes.

Previous empirical studies in developing countries are mainly focused on the impact of trade liberalization (inputs) on productivity. To mention a few, for instance, Amiti and Konings (2007) have investigated this for Indonesian firms and Pavcnik (2002) for Chile. However, few studies have examined the impact of devaluation on firm productivity. For instance, Kumara Swamy (1967) assessed the impact of Rupee depreciation on productivity in India but without applying econometric regression. Sharma (2016) has systematically identified the effect of Rupee depreciation on firms' profit through the disaggregation of importers by ownership.

However, there is thoroughly studied empirical evidence for advanced economies regarding the impact of devaluation on firms' productivity. For instance, Baggs et al. (2009) finds that the depreciation of the Canadian Dollar improves sales and survival of Canadian firms. Forbes (2002) investigates the impact of 12 large depreciations of 42 different countries, of which 30 countries are in the control group using a sample of 13,500 firms. He summarizes the evidence and concludes that, after devaluation, export-oriented and small firms have performed better than firms with less exposure to export markets and large firms. Similarly, Choi and Pyun (2020) show that Real Exchange Rate (RER) depreciation can improve the productivity of exporting firms in Korea. The above findings support the hypothesis that the depreciation of currency improves the productivity of exporting firms.

So far, there is no evidence for Ethiopia either supporting or refuting this hypothesis. Our review of empirical literature from Ethiopia found that most of the previous firm-level studies are concentrated on the causality between export and productivity of firms of the manufacturing sector (Siba and Gebreeyesus, 2016; Bigsten and Gebreeyesus, 2009) and the connection between importing and firm productivity of large and medium scale manufacturing (LMSM) firms (Abreha, 2019). Moreover, previous studies regarding firm productivity in Ethiopia have some limitations in measuring firm-level productivity. For instance, Bigsten and Gebreeyesus (2009) use total factor productivity (TFP) and labor productivity as a measure of firm productivity while Esmaile (nd) use both TFP and efficiency scores by disaggregating productivity into three components to identify the sources of inefficiency using stochastic frontier estimation method. However, in the above mentioned studies, simultaneity between input choice and unobserved productivity shocks as well as the selection bias is not appropriately dealt with. This present study attempts to deal with the problem of sample selection and simultaneity by applying control function estimation methods. Accordingly, Olley and Pakes (1996), Levinsohn and Petrin (2003) with Ackerberg-Caves-Frazer correction as well as Wooldridge (2009) and Rovigatti and Mollisi (2018) estimators are used to estimate firm-level productivity. Investment is used as a proxy variable for unobservable firm productivity shocks in Olley-Pakes (OP) estimator while intermediate input (raw materials) is used in the remaining control function estimators. In addition to the above control function estimators, an OLS estimator is also used for comparison. The production function is specified as Cobb-Douglas production technology and assumes constant returns to scale.

2.3 Data and Identification Strategy

The data source of this study is a survey of large and medium scale manufacturing firms (LMSM) from the years 2009 to 2012. This is an annual census of all manufacturing firms in Ethiopia with 10 or more employees surveyed by the Central Statistical Agency (CSA). The LMSM data provides information about the formal manufacturing sector with firm-level data on output, intermediate inputs, labor, capital, imports, exports, and foreign ownership. The output and input data are adjusted for inflation. To determine the impact of devaluation on firm productivity and export, we assume that the firms use a Cobb-Douglas production function specified as follows:

$$Y_{it} = A_{it}(\rho) L_{it}^{\alpha l} K_{it}^{\beta k}, \tag{2.1}$$

where y_{it} denotes output of firm i at time t and is a function of labor and capital. However, we are interested in examining whether the productivity (technical changes) of a firm is a function of monetary policy (ρ), denoted by $A_{it}(\rho)$. To establish the impact of monetary policy on firm productivity, we followed a two-step estimation. In the first step, we estimate firm-level TFP. In the second step, we specified how productivity is affected by the devaluation of ETB. To estimate firm-level TFP, we can linearize equation (1) by taking the natural logarithm, and we get the following equation after adding a constant and an error term while log of $A_{it}(\rho)$ is lumping together with the error term:

$$Y_{it} = \beta_0 + \beta_l L_{it} + \beta_k k_{it} + \epsilon_{it}. \tag{2.2}$$

The dependent variable is total value of production of firm i in year t. Output, capital costs, and imported raw materials are adjusted by the GDP deflator collected from the National Bank of Ethiopia while the values of local raw materials adjusted by the producer price index were obtained from the CSA of Ethiopia. Labor is measured as the number of employees working in the firm. We apply three estimation methods of productivity to check for the robustness of Olley and Pakes (1996) of TFP estimates and to establish the impact of exchange rate policy on firm productivity. Accordingly, we applied the Levinsohn and Petrin (2003) (LP) estimator with Ackerberg-Caves-Frazer (ACF) correction, as well as Wooldridge (2009) and Rovigatti and Mollisi (2018) estimators to estimate equation (2.2).

OLS is not a suitable estimator when the exogeneity condition fails to hold. Most likely there could be a positive correlation between the amounts of inputs used and unobservable productivity shocks in the firm. In contrast, the OP estimation method takes into account the simultaneity between input choices and productivity shocks as well as sample selection bias (Amiti and Konings, 2007). Investment is used as a proxy to measure unobserved shocks of productivity. However, the OP estimator has some limitations. The unobserved-productivity-shock proxy (investment) needs substantial adjustment costs and is only valid for firms that have nonzero investment (Levinsohn and Petrin, 2003). This observation is important for our data-set since more than 46 percent of firms do not re-invest, which is a quite substantial figure. Firms current investment decision is most likely correlated with past year's productivity. However, zero investment is not parallel with the exit of firms from the industry since the OP estimator addresses this concern technically. To overcome the above limitation, Levinsohn and Petrin (2003) suggest that intermediate inputs are a good proxy for unobserved productivity shocks. They argue that intermediate inputs are adjusted less costly and might fully reflect and respond to productivity shocks, rather than investment, which has substantial adjustment costs.

However, Ackerberg et al. (2015) have come up with a correction of the LP estimator in the data-generating process. Levinsohn and Petrin (2003) assume that firms can adjust inputs instantly with no cost of adjustment when there is a productivity shock, but Bond and Söderbom (2005) have shown that the coefficient of a free variable is not identified if the variation in the free variable (labor) is dependent on the intermediate (proxy) input in the first stage estimation. Accordingly, Ackerberg et al. (2015) introduced a correction to the Levinsohn and Petrin (2003) estimator.

Both Olley and Pakes (1996) and Levinsohn and Petrin (2003) estimators follow two-step estimation procedures while the Wooldridge (2009) estimator replaces the two-step procedure in one-step and uses a Generalized Methods of Moment (GMM) estimator. The advantage of Wooldridge's (2009) estimation over the two-step estimation methods is that it addresses the criticism posed by ACF of the LP estimation procedure regarding the identification of the coefficient of free variables in the first stage. Moreover, in Wooldridge's (2009) estimation method, robust standard errors are easily obtained, which take into account the serial correlation and/or heteroscedasticity. However, Wooldridge (2009) uses previous lags as a valid instrument in the GMM estimation frameworks, which reduce the sample dimension and mean a possible loss of valuable information (Rovigatti and Mollisi, 2018). The latter authors propose an estimation method that modifies the Wooldridge (2009) estimator. They introduce dynamic panel data instruments within Wooldridge's (2009) framework. This method is appropriate when the panel has a large N with a small T. The basic framework of the control function estimation approach is presented as follows, where the production function is specified as Cobb-Douglas technology:

$$Y_{it} = \alpha + W_{it}\beta + X_{it}\gamma + \omega_{it} + \varepsilon_{it}. \tag{2.3}$$

And the unobserved productivity shock is given by the following equation:

$$\omega_{it} = f^{-1}(m_{it}), x_{it} = h(m_{it}, x_{it}), \tag{2.4}$$

where Y_{it} is the log gross output, W_{it} is a $1 \times J$ vector of log free variable (labor), and x_{it} is a $1 \times K$ vector of log state variable (capital). Further, ω_{it} is the unobservable productivity and ε_{it} is an idiosyncratic output shock distributed as white noise. Finally, m_{it} is denoting the intermediate inputs. Plugging Equation (2.4) in (2.3) and adding an intermediate variable to distinguish from the free variable, we obtain the following:

$$\begin{aligned} Y_{it} &= \alpha + W_{it}\beta + X_{it}\gamma + m_{it} + h(m_{it}, x_{it}) + \varepsilon_{it} \qquad (2.5)\\ &= W_{it}\beta + \Phi(m_{it}, x_{it}) + \varepsilon_{it}. \\ &Where : \varepsilon_{it} = \zeta_{it} + e_{it}. \end{aligned}$$

Rovigatti and Mollisi (2018) assumed the productivity shock follows the first-order Markov process. Then, we have the following:

$$\omega_{it} = E(\omega_{it}|\Omega_{it-1}) + \zeta_{it} = E(\omega_{it}|\omega_{it-1}) + \zeta_{it} = g(\omega_{it-1}) + \zeta_{it}, \tag{2.6}$$

where Ω_{it-1} is the information set at $t-1$ and ζ_{it} is the productivity shock, assumed to be uncorrelated with productivity ω_{it-1} and with state variables x_{it}. Following the LP approach, we can re-write Equation (2.6) in the following manner:

$$\omega_{it} = E(\omega_{it}|x_{it}, \omega_{it-1}, x_{it-1}, m_{it-1}, ..., \omega_{i1}, x_{i1}, m_{i1}) = E(\omega_{it}|\omega_{it-1} = f[h(x_{it-1}, m_{it-1})] \tag{2.7}$$

Based on Equation (2.6) and orthogonality assumptions between the random error term and unobserved productivity shock, we can formulate two key functions to identify the coefficient of free and state variables. Using the estimates of the production coefficients in Equation (2.2), TFP of firm (i) at time (t) is denoted as follows:

$$TFP_{it} = Y_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_k} K_{it}, \tag{2.8}$$

The estimated input coefficients are obtained from calculating Equation (2.2) using the four control function estimation methods, while OLS and Fixed Effect (FE) estimates are also presented for comparison. Finally, the impact of devaluation on a firm's productivity is specified as follows:

$$TFP_{it} = \beta_1(Postd)_{it} + \beta_2(Postd * Export)_{it} + \beta_3 import_{it} + \beta_4 Foreign_{it} + \gamma_i + \delta_t + \epsilon_{it}, \tag{2.9}$$

where $Export$ stands for export status of a firm. A firm is considered as exporter when at least 10 percent of its output is sold at the international market. $Postd$ is a dummy policy variable that reflects the year immediately after the devaluation and $import$ stands for the import status of a firm. In the same fashion, a firm that imports at least 10 percent of its intermediate inputs before devaluation is considered as importer. Ownership of firms is also considered as an important variable because devaluation might have less impact on foreign-owned firms due to access to international finance and, thus, foreign hard currency. It is denoted by $Foreign$ in the equation above. Finally, γ and δ stand for firm-specific unobserved heterogeneity and time dummy, respectively. While ϵ is the random error term with independent identically distributed (IID) $N \approx (0, \delta^2)$. Interaction of the policy variable with time-invariant export and time-variant import status of a firm is included in the model to identify the impact of devaluation on the productivity of exporting and importing firms, respectively. In the Equation (2.9) the coefficient β_2 indicates the impact of devaluation on exporting firms.

In a two-period setting, where $t = 0$ indicates before and $t = 1$ after program implementation, letting y_t^T and y_t^C be the respective outcomes for treated and control group units at time t, the difference in difference (DID) method can estimate the average impact of program or exogenous intervention and can be specified as follows:

$$E(Y_1^T - Y_0^T | T_1 = 1) - (Y_1^C - Y_0^C | T_1 = 0) \tag{2.10}$$

In Equation (2.10), $T_1 = 1$ denotes treated group at t= 0,1, and $T_1 = 0$ denotes the control group at t= 0,1. The treatment group is being exposed to devaluation and at the same time is an exporter. Thus, firms that are exporting at least 10 percent of total output before and post-devaluation are the treated group. On the other hand, the control group consists of firms that are not exporters but are exposed to devaluation. This group is also comprised of firms that are switching from exporting from the early survey year and exporting either in one or two survey years. In the DID specification, unobserved heterogeneity is time-invariant and uncorrelated to the treatment group, and it vanishes through the process of estimation. Here are the basic assumptions of the DID estimator;

$$Cov(\epsilon_{it}, T_1) = 0 \tag{2.11}$$

$$Cov(\epsilon_{it}, t) = 0 \tag{2.12}$$

$$Cov(\epsilon_{it}, T_1 t) = 0 \tag{2.13}$$

The most critical assumption of the difference in difference (DID) estimator is the parallel trend assumption (2.13). It states that unobserved characteristics of the unit under consideration do not vary over time with treatment status or intervention. However, agents' responses to exogenous shocks would have a persistent influence on individual behavior, such as risk-taking behavior. Since we do have two periods–the pre- and post-devaluation period, i.e.,t=0,1–the fixed effect estimator is the same as the DID estimator (Verbeek, 2008; Angrist and Pischke, 2009). Since we do not have a natural control group to control the counterfactual in the data-set, as a result our estimate is pre- and post-policy change. However, there are firms that are not directly exposed to devaluation. These firms are neither exporters nor importers and can be considered as a counterfactual. Yet, they are indirectly affected by the policy change through input and demand linkage to exporters and importers. Even in this latest scenario, we cannot establish the impact of devaluation on exporters but rather on trading firms. Of course, we have shown this in our robustness check section. Therefore, it is safer to estimate the average difference in productivity of firms before and after devaluation. Thus, the policy change is likely to be confounded with time trends. Moreover, unobserved characteristics of agents can be changed due to interventions. The two-period model can be generalized for multiple time periods; we call it the panel fixed-effects model.

$$Y_{it} = \phi T_{it} + \delta X_{it} + \gamma_i + \epsilon_{it}, \tag{2.14}$$

Differencing both the right- and left-hand side of the equation over time, we get the following differenced equation:

$$Y_{it} - Y_{it-1} = \phi(T_{it} - T_{it-1}) + \delta(x_{it} - x_{it-1}) + (\gamma_i - \gamma_i) + (\epsilon_{it} - \epsilon_{it-1}). \tag{2.15}$$

And then we have the following equation:

$$\Delta Y_{it} = \phi \Delta T_{it} + \delta \Delta x_{it} + \Delta \epsilon_{it}. \tag{2.16}$$

In this case, because the source of endogeneity (that is, the unobserved individual characteristics (γ_i)) is dropped from differencing out the equation, and ordinary least square (OLS) can be applied to Equation (2.16) to estimate the unbiased effect of the program (ϕ) with two time periods, (ϕ) is equivalent to the DID estimate in Equation (2.16) controlling for the same covariates x_{it}.

2.4 Data Description

Four waves (2009 to 2012) of a LMSM annual survey data-set with a total of unbalanced panel data of 7349 firms are used for this study. Accordingly, 1946, 1580, 1867, and 1956 firms are considered for the year 2009, 2010, 2011, and 2012, respectively. From the total of these firms, 3922 (53.4%) have made an investment within four years, while 46.6 percent have not made an investment. Before calculating the share of investment to the total output we dealt with outliers of one percent of the bottom and the top observation using winsor2 trim cuts option. As can be seen from Table 2.1, the share of investment has increased to 43.24 percent in the year 2010 from 20.2 percent in 2009. Similarly, firms' average investment has increased from 10.7 percent in 2011 to 18.9 percent in 2012. However, the share of firms' investment on fixed asset to total output has been fluctuating, and it ranges from less than 10.7 percent in 2011 to close to 43.24 percent in 2010.

However, one might ask why the share of firms' average investment jumped to such a high rate in the devaluation year compared to the pre- and post-devaluation years. A possible reason is that firms rationally expected that the policy change (devaluation) could rise the inflation rate. Therefore, they rushed to invest in fixed assets through borrowing from financial institutions to exploit the time advantage. Thus, policymakers should take into account the impact of uncertainty on investment. In the context of Ethiopia, the price of borrowing adjusts and responds very slowly to monetary policy changes compared to a good market price response.

Table 2.1: Firms investment over time

Investment decision	2009	2010	2011	2012	Total
Size re-investing firms	933	846	990	1153	3922
Size of not re-investing firms	1013	734	877	803	3427
Share investment to total sales	20.2	43.24	10.7	18.9	.
Total Observations	1946	1580	1867	1956	7349

Moreover, it is crucial to provide the trends of firm survival and turnover, which is closely intertwined with the decision of firms' re-investment. Indeed, we do not know exactly whether firms that did not respond a second-time survey dropped out for other reasons or because they became bankrupt. Table 2.2 presents firms' turnover. Overall, 3886 (52. 9%) of firms survived/responded for the two rounds of survey periods while the remaining 3463 (47.1%) firms either exited the market or did not respond for some other reason within the four year period. However, overall, 4213 (57.3%) firms dropped out of the survey immediately after the entry period. Hence, more than 57 percent of firms survived only one survey period, whereas the remaining 42.7 percent of firms survived for two or more rounds of survey years.

Table 2.2: Firms survival/exit over time

	year				
firms status	2009	2010	2011	2012	Total
Survived firms	605 (31.1)	667 (42.2)	658 (35.2)	1956 (100)	3886 (52.9)
Exited firms	1341 (68.9)	913 (57.8)	1209 (64.8)	...	3463 (47.1)
Total	1946	1580	1867	1956	7349

However, using the data available to us, there is no way to check whether the firms that are reported to have exited are registered as such due to non-response (panel attrition) or because they have actually left the industry. However, from the estimation results of Olley and Pakes (1996) we got evidence that there is self-selection. In other words, less productive firms were expelled from the market while the others keep operating in the business. Indeed, their self-selection finding might also be due to non-response, i.e. panel attrition. Thus, there is no mechanism to cross-check whether firms did not appear in the subsequent years of the survey period because of panel attrition or self-selection or both. However, the Ethiopian LMSM data-set is an annual survey since 1996 and the possibility of changing location of firms is less frequent while there is a small margin of non-response. In sum, we can expect both panel attrition and self-selection to contribute to the dichotomy of either survival or exit of firms.

Table 2.3 below presents the survival of firms by import, export, and ownership status. From the total sample of firms, 49.9 percent are considered as importers while 19.8 percent are exporters. On the other hand, firms that neither import nor export account for 41.2 percent but do not show in 2.3 below. In this paper, we characterize these firms as less-trader or local firms. In other words, more than 40 percent of firms either do not have any or only have negligible interaction with the rest of the world. Thus, the finding of this study is valid for both trading and non-trading firms. Hence, the composition of firms is valid to identify the impact of monetary policy (devaluation) on firms' productivity.

Table 2.3: Firms turnover by characteristics

Firm characteristics	Survived	Exited	Total
Less-importers	1921 (49.4)	1762 (50.9)	3683 (50.1)
Importers	1965 (50.6)	1701 (49.1)	3666 (49.1)
Less-exporters	2891 (74.4)	3004 (86.7)	5895 (80.2)
Exporters	995 (25.6)	459 (13.3)	1454 (19.8)
Domestic owned (90% and above share)	3956 (92.5)	3254 (94.0)	6850 (93.2)
Foreign owned (10 % and above share)	290 (7.5)	209 (6.0)	499 (6.8)
Total	3886 (100)	3463 (100)	7349 (100)

We have also compared exited firms from the industry by import, export, and ownership status. There is no significant difference between importer and non-importer firms in terms of which firm types exited the market early. However, a relatively high proportion of non-exporter firms has survived for a longer period in the market compared to exporter firms. As can be seen in Table 3 below, a large proportion of domestically owned firms (47.5%) exited the market earlier than foreign-owned firms though the number is low (7.5%). In general, 46.4 and 31.6 percent of importer and exporter firms, respectively, have exited the market earlier. The manufacturing sector of Ethiopia is largely dominated by domestic businesses. Close to 6.8 percent of manufacturing firms in Ethiopia have a foreign share of 10 percent and above in firms' capital. Table 2.4 below presents trading, partially trading, and investment-oriented firms with respect to factors of production.

Table 2.4: Summary statistics importing firms (in million ETB)

Firm characteristics	Inputs	Obs	Mean	Sd	Min	Max
Importer firms	Age[a]	3607	(19.7)	(13.7)	(7)	(111)
	Output	3603	22.8	95.1	0.0045	3000
	Capital	3617	14.4	286	0.000113	14300
	Investment	2178	2.54	19.9	0.000103	731
	Raw materials	3666	18.6	68.6	0.000598	1370
Less-importer firms	Age	3627	(18.1)	(13.4)	(7)	(97)
	Output	3578	9.33	62.6	0.001179	2000
	Capital	3637	7.61	165	0.000103	8020
	Investment	1741	1.42	18.2	0.000107	593
	Raw materials	3683	4.24	24.3	0	900

[a]Except the variable Age, all the remaining variables are measured in millions of ETB here and in the subsequent tables

Table 2.4 above shows that less-importing firms have channeled large amounts of resources to the capital category of input while importing firms to raw materials. Importing firms use a large amount of inputs and invested more compared to non-importing firms. Moreover, higher proportions of importing firms have made re-investments compared to less-importing firms. It could be due to self-selection that large firms engaged in importing. Thus, there is a real possibility of simultaneity between input utilization and productivity shocks. Interestingly, the age of both types of firms (importing and less-importing) is comparable in all descriptive statistics. Therefore, age might not be the source of productivity differences between firms.

In the following Table 2.5, we applied score matching to compare the production characteristics of exporters with less-exporting firms using firms' productivity in the year before the devaluation (2009) as an outcome variable. Labor is the only covariate variable we used in this estimation. In this case, we have used Levinsohn-Petrin (LP) productivity estimates. Before executing the matching firms' propensity score based on productivity, we generated time invariant export as treatment variable. Accordingly, 459 firms are considered as treated (exporters) and 1337 firms are in the control (less-exporting) group. Though exporting firms are fewer in number compared to the control group, on average, they use rela-

Table 2.5: Summary of statistics for exporting firms

Firm characteristics	Inputs	Obs	Mean	Sd	Min	Max
Exporter firms	Age	(453)	(22.7)	(15.42)	(8)	(91)
	Output	459	19.4	60.9	0.21	795
	Capital	459	54.4	723	0.000297	14300
	Investment	260	2.844	16	0.000427	235
	Raw materials	459	9.92	21.7	0.007257	192
Less-exporter firms	Age	1320	(17.65)	(12.73)	(8)	(95)
	Output	1337	4.44	20.3	0.006153	3000
	Capital	1336	2.26	11.4	0.000119	14300
	Investment	612	0.63	4.3	0.000149	731
	Raw materials	1337	2.80	10.1	0.001332	1370

tively large amounts of inputs and make intensive investments compared to less-exporting firms. Exporting (treated) firms survive for a longer time compared to less-exporting firms. Of course, exporter firms are relatively larger in terms of capital as well. Furthermore, on average, exporting firms produce more output (19.4 million ETB) compared to less-exporting firms (4.44 million ETB). This descriptive result provides information about the differences in terms of investment and production decisions. One can expect that exporting firms are more productive than less-exporting firms due to scale effects and early entry (experience) advantages, which confirms results from previous literature. However, whether more productive firms select themselves into exporting, i.e., self-selection or export leads to higher productivity is an empirical question and beyond the scope of this study.

We have presented the descriptive statistics for treated and control group of firms after matching. This provides us a pertinent information whether there is violation of conditional independence assumption of propensity score matching. Accordingly, there is no statistically significance difference between treated and control group of firms on main indicators of firms production characteristics after matching.

Table 2.6: Descriptive statistics after matching

Variables	Mean			t-test		V(T)/ V(C)
	Treated	Control	% bias	t	p>|t|	
Age	23.83	22.991	5.7	1.27	0.206	0.97
Import	0.57285	0.60336	-6.1	-1.59	0.113	.
Export	0.00458	0.00305	2.3	0.63	0.526	.
Ownership	0.04729	0.05568	-3.7	-0.97	0.331	.
Log output	14.925	15.048	-5.6	-1.43	0.152	0.99
Log capital	13.541	13.619	-2.9	-0.78	0.433	1.09
Log labor	3.7102	3.7429	-2.5	-0.61	0.541	0.92

Finally, based on the descriptive statistics in Table 2.7 below, we can say a few points related to firms exit and entry behavior. On average, a firm that exited the industry earlier can be characterized as investing less and using less amount of raw materials compared to surviving firms, while both types of firms are inclined toward capital intensive production techniques. Therefore, investment and raw materials are a good proxy to capture a firm's productivity shock. Younger firms exit from the market more frequently than older firms.

Table 2.7: Summary statistics for survived and exited firms

Firm characteristics	Inputs	Obs	Mean	Sd	Min	Max
	Age	(3819)	(19.9)	(14.5)	(7)	(111)
	Output	3802	17	67.5	0.0031	2000
Survived firms	Capital	3828	11.8	266	0.00016	14300
	Investment	2203	2.31	22.6	0.00016	731
	Raw materials	3886	13.5	57.4	0	1030
	Age	3415	(17.9)	(12.4)	(8)	(97)
	Output	3379	15.1	93.5	0.001179	3000
Exited firms	Capital	3426	10.1	190	0.000103	7340
	Investment	1716	1.71	13.6	0.000103	367
	Raw materials	3463	9.05	44.8	0	1370

2.5 Results and Discussion

As can be seen from Table 2.8 below, compared to control function estimators Olley-Pakes (OP), Levinsohn-Petrin (LP), Wooldridge (WLRDG), and Rivigatti-Mollisi (RM) the coefficients of variable input (labor) and fixed input (capital) are upward biased for the OLS estimator. Theoretically, the coefficient of fixed input (capital) is supposed to be downward biased (Yasar et al., 2008), but this is not the case in this data-set. However, the Fixed Effect (FE) estimate of capital is downward biased compared to the control function estimators. This result indicates that there is simultaneity and a sample-selection problem. If we had estimated the production by ordinary least square (OLS) and FE estimators only, then the estimated productivity would be quite inaccurate and might lead to a possibly deficient policy prescription in establishing the impact of devaluation on productivity. Both inputs (capital and labor) have a positive coefficient and are significant at less than one percent. Labor contributes more to output increment than capital in this production function. However, in measuring firm-level productivity, labor productivity has a lot of shortcomings in comparison to TFP. For instance, it does not consider the substitution of labor by capital while TFP is a multi-factor productivity measure, which takes into account both factors of production (labor and capital).

Table 2.8: Input elasticity of the Cobb-Douglas production function specification

	Downward biased	Upward biased		Control function estimators		
Input	OLS	FE	(OP)	(LP)	(WLRDG)	(RM)
Log labor	0.739***	0.672***	0.651***	0.733***	0.565***	0.399***
	(43.66)	(17.87)	(21.01)	(379.11)	(13.62)	(18.03
Log capital	0.309***	0.100***	0.237***	0.312***	0.216***	0.172***
	(37.04)	(2.97)	(3.57)	(24.69)	(9.56)	(4.84)
Year	0.181	0.414***	0.131***	0.170***	-1.577***	
	(11.55)	(10.77)	(7.91)	(27.47)	(-3.73)	
cons	-356.786***	-821.1***				
	(-11.30)	(-10.64)				
N	6823	6823	3862	6736	1426	6736

We did not the use Wooldridge estimator to estimate firm-level productivity because it considers a small sample size (1426) compared to other estimators and the year effect is contradicting to other estimator results. t- Statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001

The production function does exhibit constant returns to scale in the OP estimator with a p-value of 0.1547 but not in OLS, FE, and RM estimation methods. However, RM estimator coefficients are consistent with theory compared to OP and LP estimates. Moreover, Breusch and Pagan Lagrangian multiplier test is applied to check the existence of firm-specific unobserved heterogeneity, and the result confirms that there is firm-specific heterogeneity. As a result, the OLS estimator is inefficient. Hence, consistent estimates of TFP can be obtained through the fixed-effect estimator after testing the choice between random and fixed-effect estimators. To choose between the random and fixed effect estimators, we applied the Hausman test. The result confirms that there is a systematic difference in coefficients of the two estimators. Thus, unobserved firm-specific heterogeneity is correlated with the other input variables in the production function. The fixed-effect estimator is preferable over the random effect estimator.

Before establishing the impact of devaluation on the productivity of exporting firms, it makes sense to check whether devaluation has an impact on the volume of firms' export. To do so, we estimated the policy change as exogenous shock against a share of export and logarithm of export using the panel Tobit estimator[3]. Panel Tobit regression is applied to consider the zero values of firms' export since a significant proportion of firms do not generate revenue from exporting goods and services. As can be seen from Table 2.9 below, devaluation has a positive and significant impact on both volume and share of export. Hence, compared to the pre-devaluation period, the volume and share of export have increased in the post-devaluation period in the short-term. However, in the long-term there is no statistically significant difference in firm's share and volume of export in the post devaluation periods compared to pre-devaluation years.

Table 2.9: The impact of devaluation on share and volume of export

	Short-term effect		Longer-term effect	
Variable	Share of export	Log of export	Share of export	Volume of Export
Devaluation	0.000442**	0.235**	0.324	-371,039
	(2.98)	(2.92)	(1.01)	(-0.19)
2010	0.000125	-0.0515	0.00777	96,070
	(0.83)	(-0.63)	(0.02)	(0.04)
2011	0.000239	0.00693	-0.180	2.145e+07***
	(1.60)	(0.08)	(-0.55)	(11.01)
2012			0.214	2.983e+06
			(0.67)	(1.55)
2013			-0.0499	889,374
			(-0.16)	(0.49)
2014			-0.308	144,702
			(-1.01)	(0.08)
2015			-0.314	64,623
			(-1.07)	(0.04)
cons	0.000379***	0.432***	0.0166	518,946
	(3.61)	(7.58)	(0.247)	(1.477e+06)
sigma (u)	0.00199***	1.211***	0.313	4839609.4**
	(15.22)	(22.09)	(0.26)	(3.28)
sigma (e)	0.00420***	2.228***	10.78***	64983359.5***
	(64.68)	(70.75)	(159.13)	(179.89)
N	7276	7276	17,199	17,645

t- Statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001.

2.5.1 The impact of devaluation on firm productivity and export

Before executing the regression, outliers of the bottom and top one percent of estimated productivity are dealt with using the Winsor2 technique. Accordingly, the average productivity level ranges from close

[3]We did not include the change in the number of exporting firms after devaluation, i.e., the impact of devaluation at extensive margin in the analysis thinking that volume and value of export could provide similar/ more pertinent information to policy makers.

to 8 to 14 in different methods of estimation. On average, the productivity level of a firm is higher with Olley and Pakes's (1996) estimation method and lower with Levinsohn and Petrin's (2003) estimation method. Except in Levinsohn and Petrin's (2003) estimation method, export-oriented firms are more productive than less-export-oriented firms. Likewise, exiting firms are less productive than surviving firms in all methods except LP estimation method. This is in line with theoretical and most empirical literature that exiting firms are less productive than incumbent firms, but there are some exceptions due to macroeconomic shocks, like what happened in Argentina in the 1980s (see Tybout, 2000). Moreover, in all estimation methods, relatively, importer firms are more productive than less-import-oriented firms. In Table 2.10 below, we present the summary estimates of productivity in all estimation methods. Furthermore, a T-test is applied to check whether there is a statistically significant difference in productivity between exporter and less-export-oriented, importer and less-import-oriented, exiting and surviving firms.

Table 2.10: Summary of TFP

	Export intensity		Import intensity				
Methods	High	Low	High	Low	Exit	Survives	Average Prod.
OP	15.465***	14.045	14.361***	13.735	13.874	14.207***	14.051
	(29)	(6741)	(3423)	(3347)	(3158)	(3612)	(6770)
LP	8.001	7.926	8.111***	7.731	7.903	7.947	7.927
	(28)	(6574)	(3399)	(3203)	(3072)	(3530)	(6602)
WLDRG	10.576**	9.586	9.796***	9.379	9.524	9.648***	9.590
	(29)	(6658)	(3389)	(3298)	(3106)	(3581)	(6687)
RM	11.855***	10.623	10.886***	10.36	10.52	10.718***	10.626
	(29)	(6657)	(3384)	(3302)	(3103)	(3583)	(6686)

Observations are in parentheses, * $p<0.05$, ** $p<0.01$, *** $p<0.001$, where H0: no productivity difference.

A firm is considered as export intensive if at least 10 percent of its output is sold on the international market. In the same fashion, a firm that imports at least 10 percent of its intermediate inputs from abroad is categorized as import intensive, otherwise it is a less-importing firm. Furthermore, a firm is assumed to exit if that firm does not appear in the subsequent survey years after entering the market.

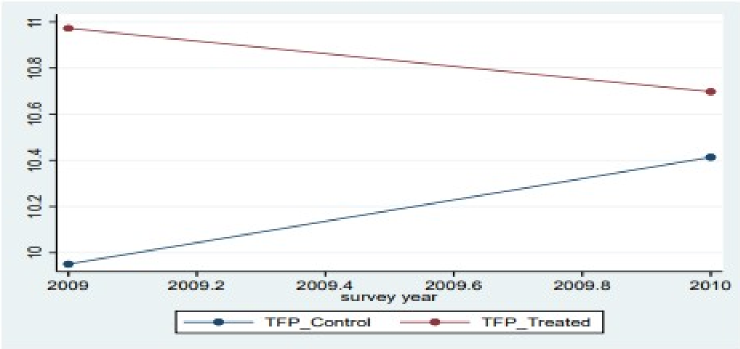
As we can see from Table 2.11 below, Wooldridge's and Rovigatti-Mollisi's productivity estimates are highly correlated with more than 98 percent. Hence, the exclusion of Wooldridge's productivity estimates could not affect the findings of this study. Of course, methodologically, both are the same while their difference shows when the data-set has a large N and small T. For this data-set, the Rivigatti-Mollisi estimator is preferable to the Wooldridge estimator. Similarly, the correlation between Levinsohn-Petrin's and Wooldridge's productivity estimates is more than 68 percent. On the other hand, Olley-Pake's productivity estimate is weakly correlated with Levinsohn-Petrin's, but relatively better associated with Rovigatti-Mollisi's productivity estimates.

Table 2.11: Correlations matrix of productivity estimates

Methods of productivity estimation	OP	LP	WLRDG	RM
(1) Olley-Pakes	1.000			
(2) Levinson-Petrin	0.072	1.000		
(3) Wooldridge	0.343	0.684	1.000	
(4) Rovigatti-Mollisi	0.498	0.643	0.985	1.000

From Table 2.11 above, it seems that the impact of policy change on productivity can be expected to

Figure 2.1: Test for parallel trend assumption



be comparable in magnitude in Levinson-Petrin, Wooldridge, and Rovigatti-Mollisi methods of estimation.

As we have mentioned earlier, one of the critical assumptions of DID is parallel trend between treated and control firms–unobserved characteristics of firms are independent of treatment and time. There is no formal test to check the violation of this assumption. But we can explore graphically what was look like before intervention. The figure below shows the productivity level trends of both type firms (treated and control) before and on the devaluation year. As we can see from the figure below, both lines don't look likes parallel but they are linear. Thus, productivity has some forms of relationship with time for both types firms. However, we have included time indicator in our DID estimation.

Table 2.12: Impact of devaluation on exporting firms' productivity

	Full Sample	Import intensity		Ownership		Export status	
		High	Low	Foreign	Domestic	Treated	Controlled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PD	0.0692	0.597	-0.158	-0.949	0.004	-0.341	0.254
	(0.36)	(1.12)	(-0.59)	(-0.41)	(0.02)	(-1.07)	(1.09)
PD*Export	0.0721	-0.0733	0.0957	0.101	0.103		
	(0.59)	(-0.36)	(0.50)	(0.11)	(0.82)		
Import	0.0555			0.0318	0.0532	-0.0270	0.181
	(0.71)			(0.06)	(0.67)	(-0.27)	(1.44)
Ownership	0.380	0.501	-0.0467			0.244	0.544
	(1.54)	(1.55)	(-0.10)			(0.78)	(1.39)
2010	-0.234***	-0.403***	0.115	-0.559	-0.198**	-0.256**	-0.211
	(-3.57)	(-3.99)	(1.05)	(-1.48)	(-2.96)	(-3.18)	(-1.95)
2011	0.746***	0.347	1.048***	1.189	0.792***	1.239***	0.567**
	(4.44)	(0.68)	(4.85)	(0.54)	(4.66)	(3.87)	(2.74)
Cons	10.40***	10.56***	10.16***	11.78***	10.39***	10.95***	10.15***
	(124.44)	(65.88)	(90.03)	(13.49)	(124.92)	(133.36)	(80.11)
N	6686	3384	3302	375	6311	1330	5356

t-statistics in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Ownership status of a firm is defined by the share of foreigners in the firm's total capital. Accordingly, if foreigners have at least 10 percent of the share then the firm is categorized as foreign-owned, otherwise it is a domestic-owned firm. We included year as a categorical variable in the estimation then we have 2011-year dummy and then a post-devaluation dummy. In this case, the variable PD (post-devaluation) represents 2012 since 2011 is directly controlled for. As result, we don't have a coefficient for year 2012.

In this case, the treated variable is export and is generated as time-invariant, as firms might not be an exporter in one of the periods in these four waves of the panel data. We used Rovigatti and Mollisi's (2018) productivity estimate since it is advantageous for large N but small T compared to the Wooldridge (2009) estimator. As can be seen from Table 2.12, except for the high importers sub-sample, the coefficient of the treatment variable is positive but statistically insignificant. Probably, devaluation has a marginal negative impact on total factor productivity (TFP) of import-dependent firms compared to less-importing firms. However, we do not have strong evidence to claim that devaluation has negatively impacted the productivity of importing firms. Theoretically, devaluation makes imports more expensive and imposes additional constraints on the production function of an importing firm. As a result, devaluation can be considered as a macro disincentive scheme for importing firms. To some degree, the result is in line with the theory. But, the coefficient is statistically insignificant. One of the possible justifications is that devaluation increases the general price level, and thus, importing firms probably continue importing more or less equivalent amounts like in the pre-devaluation period due to an increase in profit margin given a less competitive market structure. The other possible reason is that the output price changes parallel to the devaluation rate while the price of factors of production is not frequently adjusted due to market and institutional rigidity. Thus, firms engaged in exporting and with high import intensity will not gain from a policy shock. Furthermore, we find that there is no strong evidence that devaluation improves the productivity of exporter firms. Our finding is to some extent in line with Forbes's (2002) cross-country study. This result could be due to the lack of a natural control group that can be used as a counterfactual to the treatment group. However, we have domestic firms which are neither importing nor exporting that can be considered as a control group.

Moreover, there is no significant difference between domestic- and foreign-owned firms in terms of productivity. There are multiple advantages for foreign-owned firms compared to domestic firms, like easy access to foreign markets and technological transfer. Foreign-owned companies can pool competent labor force from the local labor market due to their competitive wage offer. Compared to the year 2009, the productivity of firms has been less in 2010 (devaluation period), as indicated in the Table 2.12 above, but has improved in 2011 (post-devaluation year). Consistent with the finding of Forbes (2002), when we sum up the two trends, devaluation has improved the productivity of firms after the period of policy change. It is important to note that devaluation is a macroeconomic phenomenon, and macroeconomic shocks are captured by time dummy in any panel specifications. But, it is worth looking into the details given that the year dummy is capturing many interacting macroeconomic variables. Certainly, devaluation is one of them, and its impact should be disentangled. Taking these empirical challenges into account, we have rather singled out each year's effect than considered years as time trends, even though our data is taken annually for four consecutive years (2009-2012).

In Table 2.12, Column 6 presents the impact of devaluation on sub-sample firms with time-invariant exporters using three estimation methods. The coefficient of the policy variable is negative but not statistically significant. Hence, contrary to the full-sample estimate result, this result indicates that devaluation could have a negative effect on the productivity of export-oriented firms. To identify the impact of any policy intervention, mechanically, we have to consider both treatment (exporters) and control group (non-exporters). Hence, the full-sample estimate result is more credible and consistent with theory. Interestingly, the year effect suspected to be co-founded with the policy change (devaluation) is positive for the post-devaluation year (2011) but negative in the devaluation year (2010) for treated firms. The productivity of firms in this sub-sample improved in the year 2011 compared to the year 2009. On the other hand, the results in Column 7 show the effect of devaluation on less export-oriented (control) firms of the sub-sample. The coefficient of the policy variable in the less-exporting sub-sample is positive but not statistically significant. The year effects are similar to that of export sub-sample results except for the devaluation year (2010), which is statistically insignificant. In general, this sub-sample estimate result contradicts the full-sample estimates. The effect of policy change has a higher magnitude (negative) in exporter firms compared to less-exporting (positive) sub-sample firms.

2.6 Robustness Check of the Findings

To check the robustness of our findings, an alternative specification is considered. The data-set is further split into sub-samples based on a positive share of export and interaction of export and import[4]; here, without imposing an export threshold and considering export as a continuous variable. We considered any positive level of export to test if there is any statistical difference due to the cutoff line (10 percentage points share). We are able to compare what happens to the productivity between exporters and non-exporters as well as between trading (exporter and importers) and less-trading (non-exporters and non-importers) firms after devaluation. We used the FE estimator to estimate these specifications. The result of each of the specifications is presented in the subsequent tables below.

Table 2.13: The impact of devaluation on exporting firms (the share of export)

	% export=0	% export>0	% import & exp>=10	% import & exp<10
	(1)	(2)	(3)	(4)
Post-Devaluation	0.0644	1.229	0.428	0.0245
	(0.36)	(1.73)	(0.61)	(0.08)
2010	-0.240***	0.581*	-0.348**	0.219
	(-3.53)	(2.05)	(-2.75)	(1.10)
2011	0.815***	-0.526	0.468	0.938***
	(4.74)	(-0.72)	(0.67)	(3.67)
Cons	10.37***	11.32***	11.05***	9.958***
	(158.00)	(42.83)	(132.42)	(59.85)
N	6362	324	754	2726

t-statistics in parentheses. * p<0.05, ** p<0.01, *** p<0.001

As an alternative specification, we have also considered the share of export (as a percentage of total output) to examine the effect of devaluation on export. The second column in Table 2.13 shows the impact of devaluation on firms that are exporting a positive amount of output. Contrary to the previous sub-sample estimate but consistent with the full-sample estimate, after the policy change the productivity of export firms has improved compared to the pre-policy-change period, though not statistically significant. This could be evidence that there is a potential of productivity gains due to devaluation for firms that are export-oriented. However, devaluation does not have a significant effect on either exporting or non-exporting firms, though coefficients are positive. Thus, there is no evidence to claim devaluation diminishes the productivity of firms that are less exposed to the export market.

Column 3 of Table 2.13 above presents the impact of devaluation on firms that are considered as importing and exporting, simultaneously. For sake of convenience, we call them trading firms. In this case, a firm's import status is not time-invariant like that of export. Accordingly, the results indicate that

[4] The sample split could be done by industry-level into export oriented and non-export oriented, however, devaluation does affect not only exporting firms but also importing firms too. So, we have made a sample split based on firm's international trade status. Firms which are neither exporting nor importing considered as control group in the robustness check exercise.

there is no significant change in the productivity of the trading firms after a policy change (devaluation). Similarly, column (4) shows the impact of devaluation on firms that are less exposed to foreign markets. Comparably, there is no significant difference in productivity between the pre- and post-devaluation period. Finally, the year effects are similar to previous full-sample estimation results. One can note that the year effect is consistent in all specifications irrespective of the type of sample. In sum, our baseline finding is consistent in all types of specifications.

In the above our main analysis, we considered four waves (2009-2012) of annual survey data to establish the impact devaluation on the productivity of exporting firms in Ethiopia. Now we have extended the analysis by adding four waves (2013-2016) of survey data of LMSM firms. In the latter case, the panel dimension is expanded. Thus, we used eight waves (2009-2016) of annual firm-level survey data to identify the long-term impact of 2010 devaluation on exporting firms performance of Ethiopia. This could be taken as a robustness check to our baseline analysis, and of course it gives us better information about the long-term impact of devaluation on firms competitiveness. Accordingly, we have estimated the production function using Wooldridge's (2009) estimator since we have sufficient time span to find appropriate instruments. The results below in Table 2.14 show that firms productivity has been improved in the post devaluation periods compared to pre-devaluation years, however, over time firm-level productivity is deteriorated significantly since 2009. Moreover, import dependent firms are more productive than less import dependant firms. Remarkably, in the long-term irrespective of firms import intensity, locally owned firms are productive than foreign owned. On the other hand, the result highlighted that devaluation does significantly eroded the competitiveness of exporting firms, particularly local owned firms. However, in the base line analysis of four wave data-set we couldn't find strong evidence that devaluation has a negative impact on exporting firms productivity.

Table 2.14: Long term impact of devaluation on exporting firms' productivity

	Full Sample	Import intensity		Ownership		Export status	
		High	Low	Foreign	Domestic	Treated	Controlled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PD	1.488***	1.637***	1.344***	1.794***	1.403***	0.810	1.487***
	(0.0470)	(0.0757)	(0.0731)	(0.183)	(0.0543)	(0.441)	(0.0471)
PD*Export	-0.877**	-0.649*	-0.649*	-0.446	-0.878**		
	(0.277)	(0.672)	(0.307)	(0.915)	(0.323)		
Import	0.130***			0.536***	0.0956**	0.161	0.130***
	(0.0318)			(0.114)	(0.0409)	(0.286)	(0.0320)
Ownership	-0.215***	-0.191***	-0.261***			-0.233	-0.215***
	(0.0285)	(0.0471)	(0.0375)			(0.302)	(0.0287)
Year	-0.328***	-0.337***	-0.328***	-0.434***	-0.295***	-0.378***	-0.328***
	(0.0110)	(0.0191)	(0.0145)	(0.0297)	(0.0139)	(0.0861)	(0.0110)
Cons	669.1***	686.8***	669.0***	881.4***	601.7***	771.0***	667.5***
	(22.03)	(38.34)	(29.09)	(59.72)	(28.04)	(173.0)	(22.22)
Observations	15,940	7,369	8,571	3,352	12,588	62	15,878

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2.7 Conclusions and Policy Remarks

This study mainly uses a data-set of four waves (2009-2012) of LMSM firms' annual census in Ethiopia; an unbalanced panel data-set of a total of 7349 firms. To estimate the TFP of firms, control function estimation methods are applied. Specifically, OP, LP, WLRDG, and RM estimators are employed. However, we did not present the WLRDG estimator result since the application of this estimator is better for large T-dimension panel samples. Moreover, WLRDG productivity estimates are more than 98 percent correlated with RM estimates. Therefore, we do not lose any important information due to dropping WLRDG estimates in the short-term analysis. But we have used WLRDG estimator to estimate the long-term impact devaluation on exporting firms performance in the robustness check section.

The production function estimation results provide evidence that there is self-selection (exit firms are less productive compared to surviving ones). Hence, there is some evidence of simultaneity between inputs and productivity shocks in the manufacturing sector of Ethiopia. Recently, Hailu et al. (2020) has reported that there is heterogeneity in productivity performance in the manufacturing sector of Ethiopia. Specifically, motor vehicles, basic metals, fabricated metal, and food & beverages have relatively higher labor productivity, while garment, wood, textiles, furniture, and leather & footwear have lower labor productivity. In general, economy wide, the TFP in Ethiopia has been declining from the year 2004 onward, whereas labor productivity grew at an annual average of 4.9% between the year 2000 and 2016. However, the trends of growth of labor productivity are highly fluctuating and inconsistent. For instance, a negative growth of labor productivity is registered in the years 2002 and 2003. While the report has shown that TFP of the manufacturing sector has grown an average of 2.11% per year over the period 1996 to 2016.

The short-term estimation results indicate that the devaluation of Birr against USD did not enhance the productivity of exporting firms significantly. However, we presented some evidence that devaluation has a negative impact on exporting firm productivity in the longer-term. Therefore, Currency devaluation in the least developed countries may not enhance domestic firms' competitiveness. The long-term impact of devaluation in terms of productivity gains is unlikely materialized. Moreover, there is no significant difference in the productivity of firms, which are simultaneously engaged in exporting and importing, due to this policy shock. In a country where domestic firms are highly dependent on foreign intermediate inputs, devaluation is a less effective policy instrument for enhancing the domestic firms' competitiveness. Hence, a macroeconomic policy like devaluation is not the right policy for boosting exports and raising firm-level productivity in Ethiopia. To gain some dividend out of devaluation, the share of imports needs to be reduced.

However, there are some limitations to this study. One is the confoundedness of devaluation with other macroeconomic shock indicators commonly captured through a year dummy in any panel model specification. Thus, it is hard to disentangle the impact of devaluation from other macroeconomic shock indicators. However, we have the time dummy interact with the policy change to check whether there is any change in the significance level of the policy change. The second weakness of this paper is that we don't have a control group that can be used in comparison to the treatment group to establish the real impact of the policy change. Yet, we have local firms that neither import nor export, which can be considered as a control group, while assuming devaluation has a direct impact on trading firms only. Of course, local firms have linkages with trading firms through different channels either through input or output.

We recommend that researchers should pursue a thorough investigation of the impact of devaluation on the productivity of firms and labor market outcomes, such as wages, employment, and income distribution. Furthermore, there are important issues that are not discussed deeply in this study but need further investigation. For instance, future research should analyze why local firms are negatively affected by devaluation and the mechanism through which this policy change affects the local firms compared to trading firms, as this is relevant for developing economies.

Chapter 3

R&D, INNOVATIONS, FIRM PRODUCTIVITY: EVIDENCE FROM ETHIOPIAN FIRM-LEVEL PANEL DATA-SET[1][2]

Abstract

Evidence of how research and development (R&D), innovation, and productivity are intertwined in African countries like Ethiopia is quite limited. This study provides empirical evidence on the relationship between R&D, innovations, and productivity for Ethiopian firms using two rounds of the World Bank's Enterprise Survey data-set of the years 2011 and 2015. We estimate firm-level productivity using a control function method. The link between R&D, innovations, and productivity is estimated using the general structural equation model (GSEM). The estimations were conducted for product and process innovations separately and jointly. The results show that innovations have a strong and positive impact on a firm's productivity in all estimation methods. Thus, innovative firms are more productive than their counterparts. However, the effect of R&D on innovations is positive and significant in GSEM estimation but not in other estimation methods. The findings also show that skilled labor and financial accessibility are key driving forces behind firms' engagement in R&D and innovative activities. Thus, there is a need to promote firms' engagement in knowledge production and to design appropriate policies to enhance firm-level innovation initiatives. This study contributes to developing countries' empirical literature in terms of modeling the relationship between R&D, innovations, and firm productivity.

Keywords: firm productivity, innovations, R&D, GSEM, Ethiopia

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3.1 Introduction

Understanding the link between innovation and performance at the firm level is an important and contemporary point of departure for policymakers in developing countries (DCs) in their quest for economic development and prosperity. Research and development (R&D) and innovation are considered a source of competitive advantage and an engine of long-run economic growth. R&D enhances productivity and economic growth via the infusion of innovation (Hammar and Belarbi, 2021; Romer, 1990a; Schumpeter, 1982; Solow, 1956). Such a relationship is well-established mainly in advanced economies at the macro-level and supported by micro-level empirical evidence: Baum et al. (2017) and Lööf and Heshmati (2006) for Sweden; Baumann and Kritikos (2016) for Germany; Hall and Mairesse (1995) for French companies; and Harrison et al. (2014) for several European countries. Interested readers can also look at a summary of empirical studies reviewed by Cardona et al. (2013) for advanced economies and Hall and Mairesse (2006) for European countries. Some empirical evidence from developing countries is also available. For instance, Álvarez et al. (2016) and Miguel Benavente (2006) for Chile; Tello (2014) for Peru; and Arza and López (2010) and Chudnovsky et al. (2006) for Argentinian firms.

Despite the enormous contribution of firm-level innovations to growth and development, innovative activities in Africa highly depend on R&D carried out abroad due to firms' limited investments in inhouse R&D (Keller, 2004). The social returns, i.e. the spillover effects, of R&D is higher than private returns. For instance, Comin (2004) estimated the post-World War II TFP growth of the USA, and found that the own return of R&D ranges between 0.2 to 0.5 points while R&D returns for users were between 0.4 to 0.8. He concluded the social return of R&D is between 70-100 percent. However, little is known about the impact of R&D and innovations on firms' performance. Africa has minimal empirical evidence regarding the nexus between R&D, innovations, and productivity. For example, Gebreeyesus (2011) assesses the relationship between innovations and a firm's performance (profitability) using cross-sectional data for the manufacturing sector in Ethiopia. Cirera and Sabetti (2019) also investigate the relationship between ICT, innovations, and labor productivity across countries using a cross-sectional data-set. Moreover, Hussen and Çokgezen (2022) investigate the relationship between R&D, innovations, and productivity in 15 African countries. Our study sheds light on the relationship between R&D, innovations, and productivity in the context of Africa with empirical evidence from Ethiopia. Unlike the previous studies, this study rigorously looks at the linkages between R&D, innovations, and productivity, following a more robust methodological approach to estimate productivity and establish a link between R&D, innovations, and productivity at the firm level using a panel data-set.

Here, we provide a brief description of the methodology we applied to this study. The link between innovation inputs, innovation outputs, and productivity surfaced in the empirical literature after Pakes and Griliches (1984) introduced a general model that framed the relationship among these three interdependent variables. Following this, Crépon et al. (1998) (CDM) introduced a model that follows a recursive procedure for addressing the problem of selection bias in innovations and simultaneity between innovations and productivity. In the CDM model, three equations are estimated step by step. However, Baum et al. (2017) noted the limitations of the Crépon, Dugue and Mairessec (CDM) model and provided an alternative estimation technique. A major shortcoming of the CDM model is that the feedback effect from productivity to knowledge production (innovation inputs) is not captured or cannot be incorporated into the model. Second, there is a cross-correlation between the disturbance terms in the CDM model's setup because they used the predicted values of endogenous variables in subsequent equations. Consequently, Baum et al. (2017) extended the CDM model to incorporate the time dimension and the feedback effects following the general structural equation model (GSEM) approach. In the GSEM estimation method, all three equations in the system are estimated at once recursively. Thus, this paper follows Baum et al.'s (2017) estimation approach for modeling the relationship between R&D, innovations, and productivity.

This study aims to provide empirical evidence on the relationship between R&D, innovations, and firm-level productivity in Ethiopia using two rounds (2011 and 2015) of Enterprise Survey data from the World Bank. Investigating the relationship between innovation input and firms' performance is important to understand the potential of knowledge production and the possible gains from R&D initiatives in Africa. It also considers the impact of process and product innovations on a firm's productivity separately and jointly. The results indicate that firm-level innovations (both of products and processes) are determined by the proportion of skilled labor and firm size. A firm's size is positively associated with its propensity to innovate, and skilled labor is also an important driving force behind firm-level innovations. GSEM estimation results provide evidence that there is a strong linkage between R&D, innovations, and productivity. However, the relationship between R&D, innovations, and productivity is not robust in conditional mixed process (CMP) and CDM estimation methods. All estimation methods confirm that innovations enhance firm-level productivity. This suggests that innovative firms are more productive than less-innovative ones.

The rest of the paper is organized as follows. The next section, 3.2, discusses relevant theoretical and empirical literature, followed by the presentation of the data source and the empirical strategy in Section 3.3. Then, Section 3.4 presents descriptive and estimated results. The penultimate section, 3.5, discusses the robustness checks. Conclusions and policy implications of the findings are presented in the final section, 3.6.

3.2 Theoretical and Empirical Literature Review

The theoretical foundation of innovations in economic growth and productivity dates back to Solow (1956). Innovations are considered technological progress, which shifts the production technology frontier. However, there are varying views on the origin of technological progress or innovation. The classical theory of the growth models considers technology to be exogenous and available to all countries simultaneously. For this reason, the classical growth model is commonly called exogenous growth theory and ignores the role efficient technological progress could play in smooth economic growth, mainly due to diminishing returns. Contrary to exogenous growth theory, endogenous growth theory argues that technological changes (innovations) are determined locally through knowledge spillover effects embodied in physical capital (Romer, 1987; Lucas Jr, 1988). This theory states that economic growth is determined through endogenous forces and not through exogenous ones. The approach contrasts with the neoclassical growth model, which claims that external factors, such as technological progress, are the primary sources of economic growth. However, there are varying views within the endogenous growth model as well. Romer (1990a)'s endogenous growth theory argues that economic growth is an endogenous outcome of the economic system, and technology is expressed as a function of R&D, while Lucas Jr (1988)'s model centers on human capital spillover effects that increase the level of innovations rather than physical capital. Barro and Sala-i Martin (1992) show that technology might differ from country to country, but it diffuses from high to low technological regions, and Romer (1994) states that innovations are a side effect of investment decisions. Romer's endogenous growth model is not only an aggregate level analysis, but it also elapses technology as a function of time.

There is an analytical contradiction in understanding the impact of technological changes in a macro- and micro-level analysis. For instance, for Romer (1986), technological change shares the same characteristics as public goods, that is, they are not rivals, while for Schumpeter (1982), technological changes (innovations) have a business stealing effect at micro-level analysis. Therefore, Schumpeter sees innovations as having characteristics that are the opposite of public goods; thus, Romer (1986)'s basic assumption about technological change is not appropriate for firm-level analysis.

Therefore, we switch to micro-level theoretical literature, which is in line with the central hypothesis of this study. At the micro-level, the importance of innovations for a firm's performance, such as growth, is highlighted in Griliches (1979). He specifies productivity as a function of technical knowledge, determined by the current and past levels of R&D expenditure. R&D investments indirectly affect productivity, as they affect a firm's knowledge capital. Klette and Kortum (2004) introduced alternative theoretical frameworks for a micro-level analysis of innovations, firm behavior, and performance.

Their model considers firms' heterogeneity and multiple products and provides an analytical perspective on the economy's general behavior. The authors assume that a firm's innovation rate depends on R&D investments and knowledge capital. Klette and Kortum (2004)'s model has four basic assumptions: (i) innovations are strictly increasing to knowledge's function, (ii) innovations are strictly concave to R&D, (iii) innovations are homogeneous of degree one in R&D, and (iv) knowledge production neutralizes the effects of firm size on innovations. Like Gibrat and Économiques's (1931)'s law, Klette and Kortum's (2004) model predicts that a firm's growth depends on its initial size. Of course, Griliches's (1957) and Klette and Kortum's (2004) theoretical models may not fully capture developing countries' innovative practices because in developing countries firms allocate little resources for formal in-house R&D activities.

Our primary interest is to identify the impact of these small investments on a firm's performance and innovative behavior. Crépon et al. (1998) are pioneers in structuring the relationship between research, innovations, and productivity (RIP). They considered the selection bias using a data-set of French manufacturing firms and found a positive relationship between innovations and labor productivity. Baum et al. (2017) established research, innovations, and productivity relationships using a data-set of Swedish manufacturing and service sector firms employing a more robust methodological design. Baum et al.'s (2017) methodological contribution emanates from overcoming a significant drawback of Crépon et al.'s (1998) CDM model.

Compared to developing countries, more evidence from developed countries has been documented. For example, Lööf and Heshmati (2006) found a positive association between innovations and a firm's performance heterogeneity (productivity) for Swedish firms; Hall and Mairesse (2006) for French manufacturing firms; and Hall et al. (2008) found similar evidence for Italian small and micro enterprises(SMES). Moreover, Stiel (2017) found that organizational innovations positively impacted firms' productivity in Germany's state-owned energy and water supply sectors. In closely related literature, Heshmati and Kim (2011) investigated the relationship between R&D investment and firm productivity using Korean firm panel data and found a bi-directional relationship between firm productivity and R&D investment.

Despite mixed results, empirical evidence from other emerging economies, such as Latin American countries, is well documented. Álvarez et al. (2016) investigated the impact of R&D investment on innovations and productivity in Chilean firms. He found a positive effect of R&D investment on innovations and productivity. Similarly, Arza and López (2010) examined the relationship between innovations and productivity in the Argentinian manufacturing sector. They found a positive relationship between innovations and firm productivity, while Miguel Benavente (2006) found no association between innovations and labor productivity using a data-set for Chilean firms during 1995–1998. Using a cross-sectional data-set, Tello (2014)'s findings show that the impact of innovations on labor productivity was not statistically significant for Peruvian firms. Hence, the relationship between innovations and productivity is less evident in the context of developing economies.

We have minimal empirical evidence from sub-Saharan African countries on the links between RIP. However, of course, this issue has been getting the attention of researchers and academicians recently. Hussen and Çokgezen (2022) established a link between R&D, innovations, and productivity in 15 African countries using the World Bank Enterprise Survey data-set. Morsy and El-Shal (2020) investigated the relationship between R&D, innovations, and labor productivity in developing economies. They found that, in Africa, product innovations do enhance firm-level productivity. However, both studies are designed as cross-sectional and did not deal with simultaneity in the production function. Moreover, Hussen and Çokgezen (2022) did not consider the feedback effect that moves from firm productivity to the innovation input equation because they estimated the structural equations following CDM's estimation approach.

On a related topic for sub-Saharan African countries, Bekana (2020) examined the nexus between innovations and governance quality and found a positive association between innovations and governance quality indicators for 37 sub-Saharan African countries. Similarly, Fu et al. (2018) investigated the nexus between innovations and firms' performance by sectoral (formal vs informal) segregation using 501 Ghanian manufacturing firms. They found that innovations have a positive impact on firms' labor productivity. On the other hand, Barasa et al. (2018), using the World Bank ES data-set of 418 firms from sub-Saharan African countries provide evidence that internal R&D harms a firm's technical efficiency. Kasongo et al. (2021) investigated the impact of innovations on labor productivity in the service sector firms in South Africa. They found that innovations positively impact labor productivity of service sector firms. Moreover, Mazorodze and Tewari (2018) identified the spillover effects of Asian innovation technologies on South African firms' productivity. The authors concluded that Asian R&D investments had spillover effects on multi-factor productivity growth in the South African manufacturing sector. All reviewed/available empirical evidence underscores the importance of innovations for firm-level productivity. However, what is missing is identifying the drivers of innovations and connecting these with firms' heterogeneous performance.

Moreover, the impact of firms' innovation activities on performance is often examined without making a distinction between product and process innovations. That might be due to the ambiguity in the definitions and the lack of a clear distinction between product and process innovations. Although there is a 'grey area' between the two, it is imperative to make an analysis by dis-aggregating innovations into products and processes to avoid wholesale recommendations and deficient policy prescriptions.

3.3 Data and Estimation Strategy

3.3.1 Data-set

We used well-established panel data from the World Bank Enterprise Surveys (ES) collected in 2011 and 2015 for Ethiopian firms. The surveys were collected from manufacturing and key service sector enterprises using standardized survey instruments. The survey targets establishments that are formal (registered) firms and have five or more employees. The firms surveyed are organized in 26 sub-industries. Table 1 presents the sub-industrial categories by survey period. In the two waves, 1492 sample firms were surveyed, of which 644 firms were surveyed in the first round (2011) and 848 establishments in the second wave (2015). However, 744 firms were surveyed in both rounds, which are used in this study. The sample sub-industries (26) are classified based on the International Standard Industrial Classification (ISIC) into Mineral Ore and Stone Processing (non-metallic mineral, bare metal, and precious instruments), Industry (food, tobacco, wood, leather, textile, garment, chemical, paper, machinery and equipment, furniture, plastic and rubber, electronics, and transport machines), Construction Services, Wholesale and Retailers, Transportation Services, Finance, and Other Businesses (publishing and printing, motor vehicle services, hotels and restaurants, and IT).

As can be seen from Table 3.1, most of the sample sub-industries are drawn from the broader industry sector. Close to 68% of the sub-industries were taken from the broader industry sectors, while the remaining 32% of sub-industries were considered from the Standard Service and Allied sectors. However, in terms of the actual number of observations, the service sector dominated the sample with 58%. A sizable proportion of the sample is from Retailer and Wholesaler firms, accounting for 17.9 and 13% of the sample establishments, respectively.

3.3.2 Empirical Strategy

To establish the link between R&D, innovations, and productivity, we applied the latest model introduced by Baum et al. (2017). They estimated the association between R&D, innovations, and productivity in a single process. We have two waves of survey data that enabled us to exploit the data-set's panel nature effectively. In the GSEM, we couldn't deal with the problem of endogeneity due to self-selection and reverse causality. But we dealt with the problem endogeneity due to self-selection in the CMP estimation method. We made conclusion considering the robustness check results. To check our results' robustness, we re-estimated the relationship using the CDM specification and Roodman (2011)'s conditional mixed process (CMP) estimator.

The first equation reflects the decision to invest in innovations (knowledge production) or the decision

Table 3.1: Classification of establishments by sub-industries

Industrial sector	Year					
	2011		2015		Panel	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Food	58	9.01	89	10.50	56	7.53
Tobacco	1	0.16	1	0.12	2	0.27
Textiles	12	1.86	13	1.53	11	1.48
Garments	12	1.86	35	4.13	26	3.49
Leather	26	4.04	22	2.59	31	4.17
Wood	13	2.02	8	0.94	11	1.48
Paper	13	2.02	3	0.35	8	1.08
Publishing, printing, and media	41	6.37	27	3.18	36	4.84
Chemicals	29	4.50	14	1.65	27	3.63
Plastics & rubber	32	4.97	27	3.18	30	4.03
Non-metallic mineral products	13	2.02	63	7.43	19	2.55
Basic metals	27	4.19	13	1.53	26	3.49
Fabricated metal products	15	2.33	22	2.59	15	2.02
Machinery and equipment	17	2.64	5	0.59	13	1.75
Electronics	6	0.93	4	0.47	6	0.81
Precision instruments	1	0.16	3	0.35	2	0.27
Transport machines	10	1.55	5	0.59	10	1.34
Furniture	13	2.02	29	3.42	19	2.55
Recycling	1	0.16			1	0.13
Construction	20	3.11	53	6.25	34	4.57
Service of motor vehicles	17	2.64	41	4.83	34	4.57
Wholesale	44	6.83	127	14.98	96	12.90
Retail	161	25.00	83	9.79	133	17.88
Hotels and restaurants	29	4.50	72	8.49	50	6.72
Transport sector (services)	21	3.26	84	9.91	36	4.84
IT	12	1.86	5	0.59	12	1.61
Total	644		848		744	

Source: ES data-set with authors's computation, 2011 & 2015

to spend on R&D. Following Crépon et al. (1998), we have the following first innovation input equation:

$$g_{it}^{*} = X_{1it}'\beta + \gamma_{1i} + \mu_{1it}, \tag{3.1}$$

where g_{it}^{*} is the latent variable for firm i at time t and is only observed when a firm decides to invest in innovation inputs, $X_{it}^{'}$ are vectors of predetermined variables, and β is a vector of coefficients. Further, γ_{1i} is firm- or sector-specific unobserved heterogeneity and μ_{1it} represents the random error term. An extension of Equation (3.1) for measuring the intensity of a firm's engagement in innovation activities can be specified as in Equation (3.2). However, in this study, we do not measure the intensity of a firm's engagement in innovative activities.

$$K_{it} = X_{2it}' + \gamma_{2i} + \mu_{2it} \tag{3.2}$$

In this case, K_{it} represents the actual expenditure or investments in innovation inputs for firm i at time t while the remaining terms are the same as in Equation (3.1). However, the variables on the right side of Equations (3.1) and (3.2) are not the same.

$$S_{it} = K_{it}'\alpha + X_{3it}' + \gamma_{3i} + \mu_{3it}, \tag{3.3}$$

where S_{it} denotes innovation output and K_{it} is the predicted value of the intensity of expenditure on innovation inputs' activities. On the other hand, Equation (3.4) below presents the relationship between innovation outputs and productivity:

$$TFP_{it} = S'_{it}\sigma + X'_{4it} + \gamma_{4i} + \mu_{4it}, \tag{3.4}$$

where TFP_{it} is total factor productivity of firm i at time t and S'_{it} represents the predicted value of innovation outputs. These equations show that knowledge production is endogenous in the innovation equation, and innovation output is endogenous in the productivity equation. A firm's total factor productivity is estimated using Levinsohn and Petrin (2003)'s control function estimator. The production technology is specified as a Cobb–Douglas function. Raw data for inputs and outputs are adjusted for inflation. Information about the Consumer Price Index (CPI) is collected from the Ethiopian Central Statistical Agency. Accordingly, the nominal value of sales was adjusted by the CPI (18.1 for 2011 and 7.7 for 2015). The GDP deflator is used to adjust capital, raw materials, and energy. National Bank of Ethiopia (2019) report shows that the GDP deflator for 2011 and 2015 are 11.4 and 10.5, respectively.

All these equations are estimated step by step using a recursive data generating process, and it is assumed that the input-output relationship of innovations is fully modeled. Therefore, we can assess the connection using the Full-Information Maximum Likelihood (FIML) estimator (Roodman, 2011), which can effectively take care of the feedback effects of productivity on the innovation input equation Baum et al. (2017). The general specifications of the equation are estimated using the FIML estimator following Roodman (2011), which is specified as:

$$Y'^{*}_{1xJ} = \theta'_{1xJ} + \epsilon'_{1xJ}, \tag{3.5}$$

where $\theta'_{1xJ} = Y'_{1xJ}\Delta_{JxJ} + X'_{1xK}\beta_{JxJ}$; $Y = G(Y^*) = [g1(Y^*).......gJ(Y^*)]'$; and $\varepsilon/x \sim i.i.d$ $N(0, \Sigma)$. Further, Σ is a nxn matrix, where n is the number of equations in the system. Y' is the observed endogenous variable and Δ is strictly upper triangular, that is, the diagonal and the lower triangle are all $0s$. While β is a matrix of coefficients, ε are random vectors, and $x = (x_1......x_k)$ is a vector of predetermined random variables.

The empirical model is specified in Equations (3.6-3.8) below. In Equation (3.6) the dependent variable is a dichotomous variable whether a firm spends on formal R&D or not. Equation (3.7) is the innovation equation, and like Equation (3.6), the left-hand side variable is dichotomous: whether the firm introduced new products or significantly improved its products and processes in the last three years or not. Equation (3.8) is total factor productivity (TFP), estimated using the Levinsohn and Petrin (2003) estimator and subscript (i) refers to a firm and (t) is time:

$$\begin{aligned} R\&D_{it} = \alpha_0 + \alpha_1 logEmp_{it} + \alpha_2 Skl_{it} + \alpha_3 Export_{it} + \alpha_4 Freign_{it} + \\ + \alpha_5 Import_{it} + \alpha_6 Loan_{it} + \alpha_7 Cityit + \alpha_8 \ell_{it} + \eta_t + \epsilon_{it}, \end{aligned} \tag{3.6}$$

$$\begin{aligned} Innov_{it} = \gamma_0 + \gamma_1 R\&D_{it} + \gamma_2 logEmp_{it} + \gamma_3 logAge_{it} + \gamma_4 Skl_{it} \\ + \gamma_5 Exp_{it} + \gamma_6 Expr_{it} + \gamma_7 City_{it} + \eta_t + \gamma_8 \ell_{it} + \vartheta_{it}, \end{aligned} \tag{3.7}$$

$$TFPit = \delta_0 + \delta_1 R\&D_{it} + \delta_2 Innov_{it} + \delta_3 logAge_{it} + \delta_4 logExp_{it} + \delta_5 Skl_{it} + \delta_6 Foreign_{it} + \delta_7 City_{it} + \eta_t + \varphi_{it}. \quad (3.8)$$

In Equation (3.6)[3], Emp is the number of employees in logarithm, Skl is skilled labor, $Export$ is the share of exports, Foreign is the share of a foreign company, Mkt is market share, Import is the share of a firm's imports, and Loan is an indicator of a firm's financial constraints.City is a location dummy indicator. In Equation (3.7), Age is the age of the firm (in logarithm), $Expr$ is years of experience of the firm's manager, and ℓ is a latent variable capturing unobserved factors (omitted variables) that have an impact on Equation (3.7). In Equation (3.6), R&D is a dummy variable capturing whether a firm has spent some money on R&D. In Equation (3.7), $Innov$ is innovations and is a dummy variable whether a firm has introduced new or significantly improved products and processes in the last three years. In Equation (3.8), TFP stands for a firm's total factor productivity. The error terms in the equations are denoted by $\epsilon, \vartheta, and \varphi$ and are assumed to follow a multivariate normal distribution. η_t is the time trend indicator. It is important to note that some explanatory variables are included in some equations and excluded from others. The reason is that one needs to consider the exclusion restriction which means that some variables need to be unique to a specific equation. In the structural equation model, the variable in innovation input and output equation shouldn't be the same. In addition, all control variables included in the model are based on theoretical and empirical literature. Table 3.2 summarizes the variable descriptions and their respective definitions.

3.4 Results and Discussion

3.4.1 Descriptive statistics

We begin our analysis by describing key statistics for the variables of interest, such as firms spending on R&D and innovations. Table 3.3 reports the level of firms' engagement in knowledge production in the year 2011 and 2015 separately and longitudinally. If we take the sample in each year, there is a decline in the proportion of firms' engagements in R&D between years 2011 and 2015. In 2011, about 20.65 % of 644 firms expressed that they invested in R&D in the last three years, but this proportion declined to 8.14% (n = 848) in 2015. The considerable decline in the proportion might be because of new firms are included in the 2015 survey that were not part of the survey in year 2011. Those firms which are included in the second round of the survey appear to be newly established firms that might have limited capacity to spend on R&D. This can be evidenced by the fact that when we exclude those new entrants, the proportion rises to 18.4% for the firms which are surveyed in both rounds (2011 and 2015).

Table 3.4 presents firms' engagement in innovations and R&D activities. According to Oslo Manual's (2005), product innovation is described as products or services that are new to the establishment or have significant improvements in capabilities, user-friendliness, components, or sub-systems. The improvements include new or significantly improved products in terms of (i) capabilities or other func-

[3]One of the advantages of structural modeling of the relationship between R&D, innovations, and firm performance over CDM's model is that it allow to control for the feedback effect. The feedback effect (from TFP to R&D) needs to be checked in a panel specified structural model. However, we have two rounds (2011 &2015) survey data-set. Thus, it could be difficult to include the lag value of TFP in the regression considering the panel nature of the data-set. Second, the survey years (2011 &2015) are not subsequent, three years gap between the two rounds of the survey. Thus, 2011's TFP is likely to have a weak effect on 2015 R&D. For this reason, we cannot controlled the feedback effect.

Table 3.2: Definition of Variables

Variables	Definition
R&D	Dummy coded 1 if firm i spends on R&D and 0 otherwise
Product innovations	Dummy coded 1 if firm i has introduced product or service improvements in capabilities, user friendliness, components, or sub-systems in the last three years
Process innovations	Dummy coded 1 if firm i has introduced new or significantly improved processes in the last three years
Total Factor Productivity	Continuous and estimated using the Levinsohn and Petrin (2003) estimator
Firm's characteristics	
Age	Years of operating in the market in logarithm
Size	Measured by logarithm of employees in firm i
Skilled labor	Proportion of employees in firm i who have completed grade 12 education
Export orientation	Firm i's share of exports in its total sales for the given year
Import	Dummy coded 1 if firm i imports more than 10 percent raw materials and intermediate inputs from abroad and 0 otherwise
Loan	Dummy coded 1 if a firm does not have access to finance and 0 otherwise
Manager-owner's characteristics	
Experience	Number of years that a manager of firm i has worked as a manager before the survey year
Foreign ownership	Share of foreign capital in firm i's total capital
Business environment	
Market share	Share of firm i's total sales in the total sales of industry j
Location	Dummy coded 1 if firm i is not located in capital Addis Ababa and 0 otherwise
Year	2011 & 15 and the base year is 2011

Table 3.3: Firms' engagement in knowledge production

Expenditure on R&D in the last three years	2011		2015		Panel	
	Freq.	Percent	Freq	Percent	Freq.	Percent
Yes	133	20.65	69	8.14	137	18.41
No	508	78.88	778	91.75	604	81.18
Don't know (spontaneous)	3	0.47	1	0.12	3	0.40
Total	644	100	848	100	744	100

Source: ES data-set with author's computation, 2011 & 2015

tions; (ii) technical specifications; (iii) components and materials; (iv) incorporated software; and (v) user-friendliness. On the other hand, process innovation is defined as the introduction of new or significantly improved processes in the establishment, which include (a) methods for manufacturing products or offering services; (b) logistics, delivery, or distribution methods for inputs, products, or services; and (c) supporting activities. A considerable proportion of the firms were involved in product innovations (47.2%) compared to process innovations (38.4%). Close to 71% of the firms introduced new or significantly improved products did not spend on R&D. Similarly, 66% of the firms which are engaged in process innovations do not have any formal expenditure on R&D. On the other hand, 25% of the firms which spent on R&D activities could not introduce any new or significantly new products to the establishment. More than 91% of the non-innovative firms, however, did not have any formal expenditure on R&D. These descriptive statistics highlight that formal spending on R&D is essential for firm-level innovations. It is also vital to look at the firms' R&D engagement from the perspective of the market share of sub-industries. A firm's market share is calculated by the ratio of its annual sales to the total annual sales of the sub-industry.

Table 3.4: Firms' R&D expenditure on product and process innovations

Product innovation	Expenditure on formal R&D		
	Yes	No	Total
Yes#	102	247	349
Row%	29.23	70.77	100.00
Col%	75.00	40.96	47.23
No#	34	356	390
Row%	8.72	91.28	100.00
Col%	25.00	59.04	52.77
Total	136	603	739
Row%	18.40	81.60	100.00
Col%	100.00	100.00	100.00
Process innovation			
Yes#	97	186	283
Row%	34.28	65.72	100.00
Col%	71.32	30.90	38.35
No#	39	416	455
Row%	8.57	91.43	100.00
Col%	28.68	69.10	61.65
Total	136	602	738
Row%	18.43	81.57	100.00
Col%	100.00	100.00	100.00

Table 3.5 provides the market share of firms within their respective sub-industries. Electronics, Information Technology, and Transport Machinery sub-industries operated in a concentrated market while others such as Food, Publishing and Printing, Chemicals, Non-metallic Minerals, and Wholesalers and Retailers sub-industries worked in contested markets. Accordingly, a firm operating in a contested market had a market share of less than 5% of the sub-industry. The maximum market share was 16% except in the Retail sub-industry. Hence, the market structure of the latter sub-industries can be described as more competitive. Table 3.6 presents the relationship between market share and a firm's decision to engage in R&D activities. There is a significant difference in market share between firms which did spend on R&D and those that did not. The average market share of firms that spent on R&D was 46%, while those that did not spend on R&D was 25%. In other words, the market share of a firm that is engaged in R&D was almost double to that of a firm that did not spend on formal R&D. The causation could be run from market share to R&D or the other way round, i.e., from R&D to market share. But what is important to underscore here is that there is a relationship between R&D and market share.

As can be seen from Table 3.7, R&D is correlated with both types of innovations. As expected, there is a correlation between product and process innovations. Firms which engage in product innovations are likely to be engaged in process innovations as well. Product innovation is significantly correlated with all variables included in the specification except firm's share of export and foreign ownership. On the other hand, process innovations do not have significant association with firm's manager experience and accessibility of loans. Finally, total factor productivity is correlated with all variables included in the system of equations.

Moreover, one may suspect that there might be multi-collinearity between the number of employees and skilled labor of a firm, given that both variables refer to workers of a firm. However, in this study, employment is measured by the number of employees in a firm in logarithm while the skilled labor

Table 3.5: Firms' market share by industrial classification

Industry classification	Obs	Mean	Std.Dev.	Min	Max
Food	53	.009	.017	0	0.088
Tobacco	1	.998	.	.998	.998
Textiles	8	.076	.135	0	.338
Garments	24	.04	.081	0	.382
Leather	30	.028	.053	0	.26
Wood	9	.087	.119	0	.317
Paper	6	.157	.146	0	.411
Publishing, printing & media	31	.019	.024	0	.096
Chemicals	24	.029	.04	0	.16
Plastics & rubber	27	.02	.041	.001	.217
Non-metallic mineral products	17	.01	.018	0	.068
Basic metals	26	.03	.077	0	.357
Fabricated metal products	14	.044	.069	0	.243
Machinery and equipment	12	.076	.116	.003	.365
Electronics	5	.199	.282	.007	.656
Precision instruments	1	.185	.	.185	.185
Transport machines	10	.08	.186	.003	.608
Furniture	17	.05	.094	0	.261
Construction	33	.028	.084	0	.483
Service of motor vehicles	31	.029	.054	0	.246
Wholesale	88	.01	.027	0	.159
Retail	117	.007	.031	0	.243
Hotels and restaurants	44	.021	.048	0	.288
Transport	30	.027	.08	0	.416
Information technology	8	.118	.194	0	.474

Table 3.6: R&D expenditure and market share

Variables	Firm engaged in R&D	Not engaged in R&D	St_Err	p_value
Total sale	89.4	80.5	34.8	0.798
	(115)			
Value of exports	35.0	107.0	52.0	0.17
	(16)	(62)		
Market share	0.46**	0.25	0.009	0.011
	(144)	(551)		

Note: Except for the value of the market share, all the remaining figures are measured in million ETB. The values in parentheses are the sample size.

variable is constructed as the proportion labor in the firm who are completed grade 12 out of the total employees of a firm. The correlation matrix presented in Table 3.7 indicates that there is no correlation between the variable employment and skilled labor. Thus, the two variables are not linearly related.

For continuous and binary categorical variables, Pearson's and Spearman's correlation tests are identical. In our data-set, all the categorical variables are binary, and we could run a Pearson's pairwise correlation test for all variables included in the analysis. For the sake 0f convenience for the readers, we have reported Spearman's correlations tests for categorical variables in the following Table below.

Table 3.7: Pairwise correlation for continuous variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Log-employment	1.000						
(2) Log-age	0.3480	1.000					
	(0.000)						
(3) Experience	0.1514	0.3836	1.000				
	(0.000)	(0.000)					
(4) Skilled	-0-0284	-0.0155	0.0219	1.000			
	(0.3133)	(0.5592)	(0.4141)				
(5) Foreign-own	0.2303	0.0178	0.0830	0.0264	1.000		
	(0.000)	(0.5073)	(0.000)	(0.3328)			
(6) Export	0.1213	0.0725	0.0502	-0.0732	0.0976	1.000	
	(0.000)	(0.0054)	(0.0552)	(0.0057)	(0.0003)		
(7) TFP	0.6954	0.2119	0.1626	-0.1198	0.2347	0.1193	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 3.8: Spearman's correlation test

Variable	(1)	(2)	(3)	(4)	(5)
(1) Product-innovation	1.000				
(2) Process-innovation	0.3223	1.000			
(3) R&D	0.1914	0.2907	1.000		
(4) Import (dummy)	0.1080	0.1396	0.1530	1.000	
(5) Loan access	-0.0470	-0.0524	-0.0912	-0.0399	1.000

3.4.2 Estimation Results

We estimated the empirical models to examine the link between R&D, innovations, and productivity. Columns 1–3 in Table 3.9 below show the link between R&D, product innovations, and productivity, while Columns 4–6 show the relationship between a firm's R&D, process innovations, and productivity. In the first equation, knowledge production, the decision to allocate resources to R&D, depends on the size of employment and access to finance. In line with Schumpeter's (1982) theory, the results suggest that large firms are more likely to spend on R&D activities. The other factor determining the likelihood of a firm's engagement in R&D is loan accessibility. Accordingly, the results show that credit-constrained firms are less likely to allocate resources to R&D initiatives than firms with access to credit. The implication of this finding is that liquidity constraint is one of the impediments to firms allocating sufficient resources to formal R&D activities and innovations.

However, the remaining control variables–proportion of skilled labor, export and import orientation, the share of foreign ownership, firm's age, and location-specific indicators–do not have a significant impact on a firm's propensity to invest in R&D. It thus seems to be the case that in low-income African countries like Ethiopia, firms opt to utilize workers' skills to complement technology adoption rather than knowledge production (R&D). The second equation is the innovation output specification. A firm's innovation output is measured by a dummy indicator of product and process innovations. In this specification, all the significant variables have the expected signs. R&D investments have a positive impact on both types of innovations. This finding aligns with Schumpeter's (1982) well-established theory that R&D investments lead to innovations. It is also consistent with the findings of Crépon et al. (1998), Hall et al. (2013), and Romijn and Albaladejo (2002) that firms that spend on R&D are more likely to become innovative.

Firm size and skilled labor influence firms' propensity to engage in innovative activities. As well stated by Schumpeter (1982), as a firm's size increases, it is more likely to engage in both types of innovations. Firms with a large cohort of skilled labor are more likely to produce new or significantly improved products. Skills embedded in labor are the core of the endogenous growth theory, and are considered a driver of innovations (Aghion and Howitt, 1990; Romer, 1990b). Moreover, over time, a firm's likelihood of engaging in process innovations decreases, but there is no statistical difference between 2011 and 2015 in terms of product innovations. This finding gives us some clues about the trend of firm-level innovation activities. Over time, innovations decline possibly due to fewer resources committed to in-house R&D activities.

The last equation identifies the link between innovations and productivity. In Columns 3 and 6 in Table 3.9, both product and process innovations have a significant impact on firm's productivity. Firms which introduced new products and processes in the last three years are more productive compared to those that did not introduce new products and processes. Thus, firms that are engaged in some form of innovative activities have a payoff in terms of productivity dividends. In line with Crépon et al. (1998), Griliches (1979), and Pakes and Griliches (1984), our results confirm that there is a link between knowledge production, innovations, and firm performance. A firm's age, its share of foreign capital, the proportion of skilled labor, and time trend indicators have considerable influence on its performance. A firm's age is positively associated with TFP. In the literature, a firm's age indicates economies of scale. A firm improves its efficiency through the process of learning by doing and understanding consumer behavior. Similarly, an increase in the share of foreign capital leads to an improvement in firms' productivity.

Foreign capital flows relax firms' foreign hard currency constraints. Moreover, foreign-owned firms can also fill the skill gaps and facilitate technology transfers to domestic firms. Thus, foreign-owned firms have a positive spillover effect on domestic firms' productivity. The proportion of skilled labor is negatively associated with firm-level productivity. Hence, employees who have completed higher school grades contribute less to productivity improvements than those who have achieved lower levels of school education. Similar findings are reported by Mastromarco and Zago (2012) for Italian manufacturing firms. These authors provide two explanations for the unexpected sign of skilled labor. The first is that skilled labor might be endogenous either due to reverse causality or measurement errors. The second is that the sign is supported by empirical literature in which education enhances growth in a country that has low-level education. Of course, the second justification works for Italy, but it does not in the Ethiopian context. Bokana and Akinola (2017) found that higher educational enrolments had a negative effect on TFP growth in 21 sub-Saharan African countries. There could be multiple reasons for the possibility that skilled labor is negatively contributed to firm productivity improvement. First, due to mismatch between skills and available jobs in Africa. Morsy and Mukasa (2019) revealed that 17.5% of employed youth are over-skilled, 28.9% under-skilled, 8.3% over-educated and 56.9% under-educated in Africa. The education system does not seriously consider the employ-ability of students. There is a mismatch between the skills the students have and demand of skills in the labor market. Thus, less efficient use of skilled labor will ultimately leading to lower productivity. Second, firms may not invest sufficiently on skilled labor to improve productivity through training and development. This limit skilled labor to perform to their best level. Finally, inadequate infrastructure in Africa could constrained skilled labor mobility to a higher productive sector.

Table 3.9: R&D, innovations, and productivity: Evidence from Baum et al. (2017) GSEM specifications

Variables	(1) (R&D)	(2) Prod. inno.	(3) TFP	(4) R&D	(5) Proc inno.	(6) TFP
Employment (in log)	0.525**	0.259***		0.542**	0.380***	
	(0.177)	(0.0705)		(0.177)	(0.0701)	
Skilled labor	0.00521	0.00860**	-0.0130***	0.00531	0.0107**	-0.0132***
	(0.00731)	(0.00307)	(0.00350)	(0.00737)	(0.00330)	(0.00351)
Exports (% Sale)	-0.00548	0.000465	0.00380	-0.00644	0.00347	0.00322
	(0.00967)	(0.00367)	(0.00448)	(0.00960)	(0.00382)	(0.00448)
Foreign ownership	0.00731		0.0281***	0.00114		0.0284***
	0.00113		(0.00422)	(0.00695)		(0.00421)
Imports	0.00863		0.00939			
	(0.00579)		(0.00582)			
Loan access (constrained)	-1.079*			-1.105*		
	(0.448)			(0.451)		
Age of firm (in log)	-0.463	0.0354	1.355***	-0.466	-0.0666	1.368***
	(0.418)	(0.187)	(0.201)	(0.419)	(0.202)	(0.201)
Manager's experience		0.00716			-0.000319	
		(0.00848)			(0.00926)	
City (Not Addis Ababa)	-0.595	0.205	-0.181	-0.605	0.0347	-0.155
	(0.460)	(0.174)	(0.204)	(0.462)	(0.186)	(0.204)
Year (2015)	-1.682***	0.276	1.711***	-1.644***	-0.793***	1.885***
	(0.481)	(0.183)	(0.200)	(0.483)	(0.181)	(0.201)
R&D		1.654***	1.351***		1.754***	1.220***
		(0.481)	(0.286)		(0.362)	(0.293)
ℓ		-0.594			-0.225	
		(0.666)			(0.602)	
Product innovations			0.825***			
			(0.195)			
Process innovations						0.992***
						(0.220)
var(e.lptfp)			7.857***			7.840***
			(0.364)			(0.364)
N			931			930

Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. [a]

[a] We have re-estimated this model including investment into the innovation equation. We have included both investment (total annual expenditure for purchases of equipment) and investment per labor (permanent worker) into the innovation equation. Both gross investment and per labor investment are statistically insignificant, and the significance of the key and control variables are also not affected. Thus, to save space we skip presenting the Table here.

Moreover, the trend indicator is also important in explaining firms' productivity differences. Over time, firms' productivity has been improved. However, firms allocate fewer resources to R&D. This is in line with the general trend of technological improvements that have only a capital deepening effect. As we know from the classical theory, advances in technology dampen wages through substitution effects but are expected to affect TFP positively. In sum, R&D is strongly associated with innovations and productivity. Finally, the latent variable (L) is not significant in the innovation equation, which indicates no endogeneity problem due to omitted variables between R&D and innovations.

We also re-estimated the empirical specification considering firms which are engaged in both types of innovations as innovative. Our estimation result finding is similar to what we found for separate estimations presented in Table 3.9 above. The estimation results from Table 3.10 further affirm that R&D enhances firm-level innovations and, in turn, innovations improve firm-level productivity. Hence, there is a strong relationship between R&D, innovations, and firms' performance.

Table 3.10: R&D, innovation, and productivity

Variables	(1) R&D	(2) Innovation	(3) Productivity (TFP)
Employment (in log)	0.542***	0.416***	
	(0.176)	(0.0869)	
Skilled labor (proportion)	0.00564	0.0105***	-0.0128***
	(0.00743)	(0.00399)	(0.00351)
Foreign ownership (percentage)	0.00142		0.0284***
	(0.00695)		(0.00423)
Imports (share of raw materials)	0.0104*		
	(0.00587)		
Exports (percentage of total sales)	-0.00728	0.000343	0.00381
	(0.00959)	(0.00440)	(0.00449)
Loan access (credit constrained)	-1.126**		
	(0.451)		
Firm's age (in logarithm)	-0.465	-0.115	1.377***
	(0.420)	(0.221)	(0.201)
City (outside Addis Ababa)	0.626	0.102	0.139
	(0.465)	(0.214)	(0.205)
Year (2015)	-1.676***	-0.448**	1.799***
	(0.484)	(0.210)	(0.200)
Manager's experience		0.00487	
		(0.0101)	
Innovation			0.969***
			(0.246)
Constant	-0.977	-3.432***	0.301
	(1.602)	(0.737)	(0.649)
Observations	929	929	929

Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. In this case innovation refers to both type of innovations.

3.5 Robustness Checks

To check the consistency of our estimates, we re-estimated the relationship between R&D, innovations, and productivity using two different specifications. We applied Roodman's (2011) conditional mixed process (CMP) and Crépon et al.'s (1998) estimation approaches. Table 3.11 shows the CMP estimation results. As can be seen, R&D does not have a statistically significant impact on innovations, while innovations enhance firms' productivity significantly. This result strengthens the finding from GSEM that innovations boost firm-level productivity. However, some of the control variables, which were not statistically significant in GSEM, become significant in the CMP estimation. For instance, in the first equation, the share of imports has a substantial impact on R&D investments. Thus, some difference between GSEM and CMP estimates can be observed. In the former, firms that spend on R&D are more productive than those that do not spend on R&D, while in the latter, R&D has no significant impact on productivity. Further, foreign capital and a firm's age have weak impact in improving firms' productivity in CMP model but not in theGSEM estimation method.

Roodman's (2011) CMP estimation approach also accounts for endogeneity due to self-selection bias. The results are presented in the last three rows of Table 3.11, and are indicated by atanhrhos. For instance, $atanhrho12$ is significant in Columns 1 and 4, suggesting that some unobserved covariates have negative impact on R&D and innovations. Moreover, $atanhrho13$ and $atanhrho23$ are significant in all four models. Hence, unobserved omitted variables negatively affect the endogenous and outcome variables. In sum, there are endogeneity problems due to a self-selection bias in R&D, innovations, and productivity equations, but they are taken care of in the estimation.

Table 3.11: Evidence from Roodman's (2011) CMP estimation

Variables	(1) R&D	(2) Prod. inno.	(3) TFP	(4) R&D	(5) Proc. inno.	(6) TFP
Employment	0.196***	0.135**		0.190***	0.227***	
	(0.0569)	(0.0431)		(0.0571)	(0.0462)	
Skilled labor	0.00223	0.00615**	-0.0656*	0.00179		-0.0315*
	(0.00268)	(0.00208)	(0.0297)	(0.00267)		(0.0149)
Exports	0.00192	0.00179	-0.0125	0.00245	0.00316	-0.0134
	(0.00305)	(0.00264)	(0.0293)	(0.00295)	(0.00260)	(0.0174)
Foreign ownership	0.000282		0.000134	0.000241		0.000248
	(0.00242)		(0.00247)	(0.00238)		(0.00247)
Imports	0.00507**			0.00506**		
	(0.00195)			(0.00190)		
Loan access	-0.417*			-0.402*		
	(0.165)			(0.163)		
Age of firm	-0.270	0.00127	0.0462	-0.268	0.121	0.801
	(0.152)	(0.119)	(1.246)	(0.152)	(0.126)	(0.742)
Manager's Experience		0.000128			0.000204	
		(0.000668)			(0.00112)	
City	-0.339*	0.127	0.133	-0.331*	-0.0945	0.133
	(0.165)	(0.126)	(0.846)	(0.164)	(0.133)	(0.846)
Year (2015)	-0.451**	-0.0631	2.538*	-0.462**	-0.485***	4.863***
	(0.161)	(0.120)	(1.261)	(0.161)	(0.124)	(0.929)
R&D		0.00823			0.0125	
		(0.0273)			(0.0472)	
Product innovations			10.41**			
			(3.355)			
Process innovations						6.172***
						(1.280)
cons	-0.335	-1.040**	13.07*	-0.309	-0.918*	7.932**
	(0.596)	(0.401)	(5.105)	(0.593)	(0.420)	(2.747)
$Insig3 - cons$	2.347***	1.825***				
	(0.319)	(0.202)				
$atanhrho12 - cons$	0.317**			0.452***		
	(0.0996)			(0.110)		
$atanhrho13 - cons$			-0.324***			-0.463***
			(0.0962)			(0.100)
$atanhrho23 - cons$		-2.897***			-2.371***	
		(0.325)			(0.212)	
N	521	521				

Standard errors in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05.

As mentioned earlier, the relationship between R&D, innovations, and productivity is also re-estimated using the CDM specification, that is, estimating equation by equation while taking the predicted probability of the first two equations (innovation inputs and innovation outputs). As can be seen from Table 3.12, the share of a firm's imports has an impact on the likelihood of the firm spending on R&D. However, unlike the estimation results from GSEM and CMP , firms' spending on R&D does not have a significant impact on their propensity to engage in innovative activities, but innovations have a significant impact on firm-level productivity. In the productivity equation, strangely, a firm's share of exports has a negative and significant impact on its productivity while the remaining control variables' direction of coefficients and statistical significance of GSEM and CDM estimates are almost comparable. The link between R&D, innovations, and productivity is not strong enough to be statistically significant in the CDM and CMP models but strong in the GSEM.

Table 3.12: Estimation results of Crépon et al.'s (1998) CDM specification.

Variables	(1) R&D	(2) Product innov.	(3) Process innov.	(4) Product-TFP	(5) Process-TFP
Employment	0.555**	0.257	0.403**		
	(0.202)	(0.133)	(0.145)		
Skilled labor	0.00522	0.0118**	0.00959*	-0.0565***	-0.0289***
	(0.00759)	(0.00453)	(0.00473)	(0.00371)	(0.00289)
Skilled labor	0.00522	0.0118**	0.00959*	-0.0565***	-0.0289***
	(0.00759)	(0.00453)	(0.00473)	(0.00371)	(0.00289)
Foreign ownership	0.000287			0.000465	0.000606
	(0.00688)			(0.00264)	(0.00253)
Imports	0.0162*				
	(0.00647)				
Exports	0.00782	0.00241	0.00634	-0.00720	-0.0170***
	(0.00867)	(0.00550)	(0.00562)	(0.00393)	(0.00398)
Loan access	-1.135*				
	(0.511)				
Firm's age	-0.796	-0.0349	-0.168	0.0689	0.721***
	(0.473)	(0.274)	(0.292)	(0.165)	(0.153)
City	-0.829	0.343	-0.153	-1.734***	-0.00615
	(0.501)	(0.279)	(0.290)	(0.170)	(0.172)
Year	-1.251*	-0.164	-0.904**	2.195***	4.215***
	(0.491)	(0.265)	(0.300)	(0.161)	(0.189)
Predicted R&D		0.641	0.980		
		(1.694)	(1.744)		
Experience		0.0106	0.000544		
		(0.0122)	(0.0126)		
Predicted product innovations				23.75***	
				(1.082)	
Predicted process innovations					17.17***
					(0.739)
cons	-0.994	-2.169*	-2.080*	0.605	-0.102
	(1.733)	(0.915)	(0.955)	(0.564)	(0.555)
$lnsig2u$	1.565*	0.230	0.194		
	(0.673)	(0.816)	(0.856)		
N	521	510	508		280

Standard errors in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05.

3.6 Concluding Remarks

This paper examines the relationship between R&D, innovations, and firm-level productivity using the World Bank's Enterprise Survey panel data-set for Ethiopia. All estimation techniques, GSEM , CMP , and CDM , show that innovations improve firms' productivity. This, in turn, suggests that innovative firms are more productive than non-innovative ones. However, the impact of R&D expenditure on innovations is less clear, as it is significant in the GSEM estimation method only. Firm-level innovations (both of products and processes) are determined by the proportion of skilled labor and employment size. A firm's size is positively correlated with its propensity to innovate. The results also show that skilled labor is an important input for firm-level innovations.

As a policy remark, we have robust evidence that innovations are strongly associated with firm-level productivity. Large firms should allocate some resources to knowledge production activities. By minimizing and sharing the risks of innovative initiatives, the Government of Ethiopia can encourage firm-level innovations. Furthermore, a strategy for promoting firms' innovations needs to support human capital development. Therefore, such a strategy should include key factors like the upgrade of workers' education level, the promotion of exports, and the improvement of loan accessibility.

This study is conducted on sample firms from Ethiopia using two survey rounds and the relationship between knowledge production, innovations, and firm performance is estimated using a robust methodological approach. The study uses all firm types without disaggregating by size and sector. Thus, the findings of this paper remain valid for all types of firms, irrespective of size and sector. On top of this, given the broad sectoral composition of the Ethiopian economy, which is dominated by the service sector, the findings of this study provide pertinent information for countries that have similar or comparable broad sectoral compositions. Finally, in the context of Ethiopia, so far, there is no policy instrument in place that encourages firm-level innovations. Therefore, the findings of this study are expected to provide some insight for countries that are at the stage of crafting or developing innovation policies and strategies. In general, Ethiopia is not unique, and most African countries have similar characteristics in terms of R&D investment and innovative activities. So, our findings might provide a perspective for a policy approach to encourage firm-level innovations in Africa.

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Chapter 4

THE LINK BETWEEN ICT, INNOVATIONS, AND PRODUCTIVITY: EVIDENCE FROM AN ETHIOPIAN FIRM-LEVEL PANEL DATA-SET[1]

Abstract
This paper uses two rounds of the World Bank's Enterprise Survey for Ethiopia, and a robust empirical methodology in the form of general structural equation modeling, to contribute to the scant and inconclusive literature investigating the impact of information and communication technology (ICT) on firm-level innovation and productivity in an African context. We find evidence (i) of a positive impact of ICT adoption on a firm's propensity to innovate, in terms of both product and process innovation; (ii) of a positive association of both types of innovation with a firm's total factor productivity; and (iii) of a positive direct effect of ICT adoption on total factor productivity. This suggests that, in developing countries like Ethiopia, ICT diffusion could play a key role in driving firm-level innovation and productivity. It could thus be a viable alternative to potentially costly and risky in-house research and development (R&D) activities undertaken by firms. Finally, the paper discusses the theoretical and policy implications of the presented findings.
Keywords: ICT, Innovations, Productivity, Developing countries, Ethiopia.

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4.1 Introduction

Innovations are considered a source of competitive advantage and growth (Romer, 1990b; Schumpeter, 1982; Solow, 1956). However, it is important to underscore that firm-level innovation in DCs is mostly triggered by external knowledge investments and technology diffusion from advanced economies, rather than formal spending on in-house research and development (R&D)–a strategy more widely practiced in firms from developed economies (Keller, 2004; Piva and Vivarelli, 2005; Vivarelli, 2014). Related to that, there is empirical evidence showing that knowledge spillovers from advanced economies have a significant impact on firm performance in DCs (Coe et al., 2009; Coe and Helpman, 1995). More specifically, according to some estimates, more than 90 percent of firms' productivity growth in DCs is related to foreign technology applications (Keller, 2004). Technology diffusion, in turn, has been shown to be facilitated by a firm's information and communication technology (ICT) infrastructure (Karshenas and Stoneman, 1993; Keller, 2004; Venturini, 2015).

While there is ample empirical evidence from advanced economies on the importance of ICT adoption for firm-level innovation and productivity (Brynjolfsson and Hitt, 2003; Jorgenson et al., 2008; Hall et al., 2013; Higón, 2012), very little is known about this link in a developing country, and in particular, in an African context. Moreover, the existing evidence is rather inconclusive (see Chowdhury and Wolf, 2003; Cirera and Sabetti, 2019) and to some extent lacks a robust methodological approach. Cirera and Sabetti (2019) investigated the relationship between ICT, innovations, and labor productivity for selected African countries using cross-sectional data at the firm level. In the Ethiopian context, literature is extremely limited. To mention related literature, for instance, Gebreeyesus (2011) assessed the relationship between innovation and firm profitability using cross-sectional data. He finds that innovative firms are more profitable compared to non-innovative firms. Using Ethiopian firm-level panel data from two rounds (2011 and 2015) of the World Bank's Enterprise Surveys, the purpose of this study is to conduct an empirical test of the relationship between ICT, innovations, and productivity in Africa, using Ethiopia as a case study.[2]

Unlike previous studies in Ethiopia and elsewhere in Africa, this study takes a fresh look at the link between ICT, innovations, and productivity in two ways: Firstly, we applied a more robust methodological approach and more rigorous estimation strategy than existing studies conducted on this topic in a developing-country setting. More precisely, we follow Baum et al.'s (2017) estimation approach and model the relationship between ICT, innovations, and productivity. To verify the robustness of our findings, the equations are re-estimated using Crépon et al.'s (1998) otherwise CDM specification, and Roodman's (2011) conditional mixed process (CMP) estimator. Methodologically, our study draws on Díaz-Chao et al. (2015), who applied Structural Equation Modeling (SEM) to identify the relationship between ICT, innovation, and productivity for Spanish firms. They found that co-innovation does not affect small firms productivity but large firms. Secondly, we differ from previous firm-level studies in an African context in the way we conceptualize innovation: following Morsy and El-Shal (2020), we argue that the ICT infrastructure could accelerate external knowledge diffusion and can hence be seen as the driving force of firm-level innovation in developing economies or enable adoption of innovations, at least. For instance, Spiezia (2011) found that web facilities are highly correlated with innovation activities in OECD countries. Moreover, ICTs could substantially reduce transaction costs which provide an incentive for the firms to find more efficient methods of production and marketing that could initiate

[2] Cf. World Bank (2021). Enterprise Surveys. World Bank Group, Washington, DC. Retrieved from this link.

firm-level innovations (Koellinger, 2005).

The rest of the paper is organized as follows. Section 4.2 discusses relevant theoretical and empirical literature. Section 4.3 presents a brief review summary of ICT use in Africa. Section 4.4 presents the data and estimation strategy. In Section 4.5 the results are discussed, which is followed by robustness checks in Section 4.6. Finally, Section 4.7 provides conclusions and implications.

4.2 Theoretical and Empirical Literature Review

It is well documented that innovation is a major source of economic growth and driver of productivity growth (e.g., Easterly, 2000; Romer, 1990b; Solow, 1956). At the firm level, the importance of innovations for firm performance is highlighted in Griliches (1979) and Crépon et al. (1998) works. Jorgenson et al. (2011) argued that post-2000 US rapid total factor productivity growth is associated with a surge of innovation activities. Klette and Kortum (2004) introduced theoretical frameworks for a micro-level analysis of innovations, firm behavior,and performance. Keller's (2004) model of technological diffusion can be considered as theoretical base for this study assuming that ICT does facilitate firm-level technology diffusion. Innovations-firm performance relationship is an extensively studied topic with more or less a conclusive finding while relationship of ICT with innovations and to that of productivity is less spotted in the theoretical and empirical literature. Thus, we found that it is more appealing and worthy to review the later relationships in this section than innovations-productivity nexus. In the subsequent two subsections, we presented the the review of literature that focuses on the relationship between ICT and innovations and, ICT and firm-level productivity, respectively.

4.2.1 ICT and innovations

ICT adoption improve information and knowledge management within a firm (Ongori and Migiro, 2010), and has a role of a dis-intermediation–eliminating the middlemen (Wigand and Benjamin, 1995) that creates to access new market for the firms–it is one aspect of innovations. There are multiple channels through which ICT could influence or enhance firm-level innovations. First, ICT is considered as a general purpose technology (GPT) that enable product, process and organizational innovations in the firms (Bresnahan and Trajtenberg, 1995) and adopting GPT by the firms requires experimentation that could possibly leads to innovations in due course (Draca et al., 2009). Second, ICT has an important function in interoperability between firms that initiate firm-level innovations to become competitive and meet customers choices (see Gasser and Palfrey, 2007). Third, ICT reduce transaction cost substantially that incentivise firms to find further best method eventually leads to innovations (Koellinger, 2005; Ongori and Migiro, 2010). Finally, ICT adoption improve business process and relations with customer and partners (Mustafa, 2015) that stimulate firm-level innovations through learning from interactions. In the technology transmission and diffusion strands of literature, Barras's (1986) theoretical model could reasonably explain firm-level ICT adoption and innovation in Africa and elsewhere in developing economies. First, this model itself is derived from an empirical study of adoption of information technology in service industries. Second, most of firm-level innovations in Africa are related to service improvements or adopted innovations from capital goods industries including information technology. To this end, Barras (1986) proposed 'reverse product cycle' to describe the process of innovations in the consumer or service sector once the technological changes or innovations are take place in the capital goods sector. Here, we assumed that developing countries adopt innovations that took place in the capital goods sector of advanced economies. Accordingly, Barras (1986) argue that innovations in the service sector start from improvement in efficiency–i.e.,"process improvement"–and then to process innovation–i.e., an improvement in the quality of service–and, finally reach product innovations–i.e., a new type of service is introduced. In the first two stages of the cycle, ICT is an indispensable input to realize efficiency in the service sector. As we know, ICT has already an important function in goods innovations by reducing transaction costs that incentivise firms to find the best efficient method of production (Koellinger, 2005). Presumably, ICT is even more entangled with innovations in the service sector and Barras (1986) suggested that ICT is a necessary condition for product innovation in the service industries. In general, however, there are two technology adoption/diffusion models; (1) the epidemic (i.e., the information asymmetry) model; and (2) the equilibrium model which depends on firms' rank and order (Karshenas and Stoneman, 1993). This study follows the equilibrium model of technology adoption, in which ICT adoption facilitates trade and investments and reinforces technology diffusion. Thus, our basic conjecture is that embodied and disembodied technological transfers will initiate firm-level innovations in a developing country context.

Empirical evidence from advanced economies demonstrates the importance of ICT adoption for innovations. Such evidence is provided, for instance, by Morikawa (2004) for Japanese SMEs; Koellinger (2008) for European firms; Polder et al. (2010) for Dutch companies; Higón (2012) for UK small and micro enterprises (SMEs), Hall et al. (2013) for Italian firms, Zoroja (2016) for European countries, Spiezia (2011) for OECD countries, and Alam et al. (2022) for Australia. All these studies found a significant and positive association between ICT usage and innovations, despite variations in terms of measuring ICT usage and identification strategies used in these studies. In contrast, empirical evidence on the effect of ICT on innovations in developing countries, particularly in Africa, is very scant. To mention few of them, Naidoo and Hoque (2018) found that information technology capability of employees is significantly associated with innovation capability in South Africa. Specifically, there are no existing studies that establish the effect of ICT adoption on innovations in Ethiopia.

4.2.2 ICT and firms' productivity

In the long run, productivity is everything (Krugman, 1997), and ICTs is ascribed an important function in improving firm-level productivity. ICTs changes business practices and reduce transaction costs (Koellinger, 2005). In the traditional production function, one of the inputs is capital, and the neoclassical subdivided this capital into ICT and non-ICT capital. Thus, ICT is one of the factors of production in the neoclassical approach that directly affect productivity, specifically labor productivity (see, Brynjolfsson et al., 2002; Draca et al., 2009; Jorgenson et al., 2008). For instance, Jorgenson et al. (2008) argued that labor productivity growth in the US between 1995 to 2000 was due to huge investments in the ICT sector and the rise in productivity within the ICT sector itself. Ceccobelli et al. (2012) pointed out that ICT capital has immense contribution to labor productivity growth in OECD countries. Theoretically, ICT could influence productivity directly (see, Brynjolfsson et al., 2002; Draca et al., 2009) putting ICT in the production function and indirectly through complementary innovations (see, Jorgenson et al., 2011; Koellinger, 2008). This approach– growth accounting–of estimating productivity doesn't care of the endogenous nature of ICT-capital. Because as economies become more efficient it might leads to more capital deepening, allocating more ICT-capital per worker. In other words, efficient economies could invest on ICT-capital.

There have, however, been contentions in the literature as to whether ICT can explain performance heterogeneity across firms. In this regard, the 'productivity paradox' is considered in empirical investigations after Solow (1987, p.36) remark in The New York Times Magazine state that:

> "Computers can be found everywhere except in productivity statistics".

However, one of the factors behind the performance heterogeneity of firms is related to the extent of investments in ICT capital assets. For example, Van Ark (2004) states that ICT capital is one of the drivers of growth in total factor productivity. The empirical literature on the relationship between ICT and productivity goes back to (Brynjolfsson and Yang, 1996; Brynjolfsson et al., 2002) and (Brynjolfsson and Hitt, 2003). The latter study investigated the impact of computerization on firm productivity using a dataset of 525 large firms in the US for the period 1987-94. The authors found that a firm's computerization contributed to its multi-factor productivity growth. The returns from ICT capital investments were much higher than the cost over a long period of time due to unmeasured complementary investments. Moreover, ICTS explain 20 percent of overall productivity growth in the European union countries (European Commission, 2010).

There is unclarity when it comes to empirical findings on the impact of ICT on firm productivity in African economies. For instance, Cirera and Sabetti (2019) found no significant correlation between ICT and firm productivity in sub-Saharan African (SSA) countries. However, Chowdhury and Wolf (2003) detected a positive impact of ICT on firms' productivity for East African Countries. Like Cirera and Sabetti (2019) findings, Nkama (2014) found that ICT has no significant impact on the productivity of Cameroonian firms. Lefophane and Kalaba (2020) estimated the effect of ICT on labor productivity of South African manufacturing firms for the period 1960-2016. The authors found growth of labor productivity at more ICT-intensive firms is higher compared to less ICT-intensive firms. Moreover, country-level evidence is provided by Asongu and Acha-Anyi (2020) who report a positive effect of ICT on total factor productivity for 25 SSA countries for the period 1980-2014. Thus, the findings of the previous studies in Africa are inconclusive.

This study differs from previous research in terms of its conception of innovations, the measure of productivity, and the methodological approach followed to establish a linkage between the three interrelated concepts: ICT, innovations, and productivity. In terms of the conception of innovation for a Africa, drawing on Coe et al. (2009) and Coe and Helpman (1995), we argue that ICT infrastructure boosts the diffusion of external knowledge and can therefore be considered an enabler of firm-level innovations in developing economies. Of course, in advanced economies, Polder et al. (2010) used ICT as an innovation input in parallel with R&D expenditure in establishing the impact of different types of innovations on firm-level productivity for the Netherlands. Furthermore, to some extent, our premise is supported by Morsy and El-Shal (2020) findings. They estimated the impact of ICT adoption on firm-level innovations. Their finding shows that the impact of ICT adoption on innovations is almost equivalent to the impact of R&D expenditure on innovations in the African context. Hall et al. (2013) also used ICT investments as innovation inputs parallel with R&D in the innovation input equation. As a result, they found no complementarity between ICT and R&D in both innovations and production. In contrast, Siegel (1997) report a significant complementary between R&D and ICT capital.

Our study contributes to the empirical literature investigating the relationship between ICT, innovations, and productivity at the firm level and in a developing country, and here in particular the African context. Previous research of this type on emerging economies in Latin America provides inconclusive evidence. For example, Álvarez et al. (2016) found that ICT had a positive effect on innovation and productivity of Chilean manufacturing firms. Arza and López (2010) examined the relationship between innovations and productivity in the Argentinean manufacturing sector and found a positive relationship between innovations and firm productivity while Miguel Benavente (2006) found no relationship between innovations and labor productivity using a data-set for the period 1995-98 for Chilean firms. Similarly, using a cross-sectional data-set, Tello (2014) found that the impact of innovations on labor productivity was statistically insignificant for Peruvian firms.

To conclude, on the one hand, we reviewed theoretical literature that show how ICT could initiate and related with innovations, and the available empirical evidences for developing countries. On the other hand, we presented the prominent theoretical literature that underscores the potential of ICT for firm-level productivity enhancement. However, we have a limited source to demonstrate how strong connection between ICT with innovations and productivity simultaneously. This could be a contribution in between in the context of developing economies.

4.3 An Overview of ICT Use in Africa

There are two important classifications in the literature related with ICT, i.e., "ICT for the development"–the contribution of ICT for broader development and "ICT in the development"–how ICT could affect the context and the outcome (see Walsham and Sahay, 2006). Most international agencies subtly uptake "ICT for the development" perspective. For instance, the UN sustainable development goals of 2030, goal nine–industrialization, innovation, and infrastructure- underscore the importance of ICTs. Specifically, target nine 'c' of goal nine states "significantly increase access to information and communications technology and strive to provide universal and affordable access to the Internet in least developed countries by 2020". On top of the above, WB (2009) identified ICT as one of the core pillars to build a knowledge-based economy. Knowledge-based economy is built in four pillars: efficiency in the use of existing and new knowledge, skilled human resources that uses and produce new knowledge, efficient innovation system, and information communications and technologies (WB, 2009).

The other strands of literature focus on "ICT in the development" perspective. The recent COVID-19 pandemic, on one hand, left us with a good lesson how ICT is important for sustaining services, and saving the economies from a total collapse due to health related restrictions. On the other hand, more importantly, trigger a serious debates whether employers need more automation of their business process using ICT infrastructure which could layoff employees. In this discourse, Ponelis and Holmner (2015) posed a strong argument that ICT should enable and empower the society than expanding the economic and political interest of the establishments. They suggest that caution is needs to be taken since ICT has an impact on power relations, and could exacerbate and perpetuate the already asymmetrical distribution. The UNCTAD (2021) report revealed that globalization and technological change are considered as driving factors behind income inequality within a country.

According to UNCTAD (2021) report, income disparity between developed and developing countries started to increase since 1880s: the age of steel, electricity, and heavy engineering. Since then income inequality has been sharply increasing from the middle of age of oil, automobile, and mass production around 1950s to date, industry 4.0 (technology frontier) age. Moreover, UNCTAD (2021) developed an index that shows a country's readiness to use, adopt and adapt the new technology adaptation named it "readiness index" and ICT deployment is one of the five pillars that comprised the readiness index. It reported that most of the least ready countries are found in sub-Saharan Africa. As a result nowadays a massive income gap is observed between countries denominated as south and north of the globe.

Internet use, globally, was 51.4 percent and just 75 percent of the total world population had an active mobile broadband subscription in 2019. Moreover, fixed broadband subscription reached just over 15 percent, and 72 percent of urban and 37 rural households had access to the internet. On average more than 57 percent of households today have Internet access at home and more than 84 percent of the world population is within reach of 4G signal (ITU, 2021). While the figure for Africa ICT utilization indicators is much lower than the global average. Majority of African countries lacks ICT infrastructure that meet the requirement for broadband internet use except Morocco, Tunisia, Senegal, Mauritius, and South Africa which invested substantial resource on land ICT infrastructure (PIDA, nd). PIDA (nd) report further conclude that ICT infrastructure is the predominant enabler of the future competitiveness and prosperity of Africa. ICT use in Africa varies among economies of the region. For instance, internet usage was 60 percent of developed economies of the region while the figure was go down to 10 percent in the least developed economies. From the total 44 economies which were considered in the ITU (2021) report, 12 of them have a mobile subscription of 100 per 100 inhabitants. The average of the region (Africa) mobile cellular coverage was 88.4 percent, and 44.3 percent of the population was within reach of a long-term evolution (LTE) mobile broadband signal in 2019. Moreover, the percentage of individuals using the internet was 28.6 percent by the end of 2019. Only 6.3 percent of rural and 28 percent urban households had access to the Internet in 2019, compared with 28 percent of urban households. In sum, 14.3 percent of households living in Africa had access to the internet in 2019. Active mobile broadband subscriptions per 100 inhabitants reached 33.1 while the world average was 75 per 100 inhabitants in 2019. (ITU, 2021) estimated a fixed broadband subscription rate was 0.5 per 100 inhabitants for Africa in 2020-a figure that is much below the global average of 15.2 subscriptions per 100 inhabitants. In 2018, the total expenditure on telecommunications estimated about 6.7 billion USD in Africa and 50 percent this investment was in Nigeria and South Africa.

ITU (2018) forecasted that less than 25 percent of the population in LDCs will be online by 2020, and one of the reasons for low being online is related to the skill needed how to use internet. People who are living in Africa have limited skills in using ICTs (basic, standard, and advanced level). ITU (2021) report shows proportion of population of who had ICTs skills (in different skill category) for five African countries where the data is available for these five countries: Cape Verde, Cote d'Ivoire, Niger, Togo, and Zambia. Except Zambia, the proportion of population who have standard and basic ICTs skills was less than 6 and 15 percent, respectively. Similarly, excluding Zambia (6.7 %), in all the rest countries, percentage of people who had advanced skill in ICT is less than one percent. Though we don't have data for Ethiopia, but the figure for Ethiopia won't be different from those countries average. ITU (2020) study revealed that a 10 percent increase in mobile and fixed broadband penetration in the Africa region would yield an increase of 2.5 percent and 0.3 percent in gross domestic product (GDP) per capita, respectively. On trade stream, Bankole et al. (2015) analyzed the impact of ICT infrastructure on intra-trade for 28

African economies and found that investment in telecommunication infrastructure has direct impact on intra-African trade and noted the importance of ICT infrastructure for institutional quality improvement as well. However, Africa has (62) data centers, i.e., less than one percent of global data centers while more than a quarter of world population are living in Africa.

4.4 Data and Estimation Strategy

We used a secondary data-set, the World Bank's enterprise survey (ES). The WB collects data from enterprises in manufacturing and key service sectors in every region of the world using standardized survey instruments. The survey targets establishments that are formal (registered) companies with five or more employees. In this survey, about 146 countries are covered, and the survey is not held in the same year across countries. Some countries have a rich data-set while others are less frequently surveyed. For our study, we used two waves (2011 and 2015) of the survey data for Ethiopian firms. The raw data for some of the important variables were adjusted for inflation. Accordingly, the nominal value of sales was adjusted by Consumer Price Index (CPI) (18.1 and 7.7 for 2011 and 2015, respectively). CPI data was collected from the Central Statistical Agency. Capital, raw materials, and energy were adjusted by the GDP deflator. Based on the Natinal Bank of Ethiopia's (2019) report, the GDP deflator for 2011 and 2015 is 11.4 and 10.5, respectively. Usually, the impact of ICT adoption on innovations and, in turn, of innovations on firms' productivity is not observed at the same time. There is certainly a lag in the impact of innovation on a firm's productivity. Hence, in this data-set firms were asked whether they had innovations in the past three years. Therefore, we do not need to take the lag of innovations into account to establish the impact.

To establish the link between information and communication technology (ICT), innovations, and productivity, we applied the latest micro-econometric estimation procedure introduced by Baum et al. (2017). They estimate the link between R&D, innovations, and productivity in a single process. Since we have two waves of survey data for Ethiopia, we can apply the model and exploit the panel nature of the data-set effectively. Secondly, we can consider the feedback effect that goes from productivity to technology diffusion. However, the relationship goes from innovation inputs to innovation outputs to productivity, sequentially. In view of this, we have three equations: innovation inputs, innovation outputs, and productivity (total factor productivity) equations. Moreover, to check the robustness of the results we also estimated the relationship using the CDM specification and the Roodman (2011) CMP estimator, which follows a recursive data generating process.

Equation (4.1) refers to the decision to invest in innovations, in other words, it is the innovation input equation. In this case, ICT diffusion is a relevant indicator of a firm's propensity to innovate. As mentioned earlier, for the most part developing countries' innovation activities come from the spillover effects of R&D somewhere on the globe through technology diffusion (Keller, 2004). Following Crépon et al. (1998), we have the following first innovation input equation:

$$g_{it}^{*} = X_{1it}'\beta + \gamma_{1i} + \mu_{1it}, \tag{4.1}$$

where $g*_{it}$ is the latent variable for firm i at time t and is only observed when a firm decides to invest in innovation inputs, X_{it}' are vector of predetermined variables, and β is a vector of coefficients, while γ_{1i}

and μ_{1it} are firm or sector-specific unobserved heterogeneity and the random error term, respectively.

$$S_{it} = g'_{it}\alpha + X'_{2it} + \gamma_{2i} + \mu_{2it}, \tag{4.2}$$

where S_{it} denotes innovation output and g_{it} is the predicted probability of the decision to invest in innovation input activities. On the other hand, Equation 4.3 below presents the relationship between innovation outputs and productivity:

$$TFP_{it} = S'_{it}\sigma + X'_{3it} + \gamma_{3i} + \mu_{3it}, \tag{4.3}$$

where TFP_{it} represent the total factor productivity of firm (i) at time (t) and S'_{it} represents the predicted probability of innovation output. For these equations, knowledge production is endogenous in the innovation equation, and innovations are endogenous in the productivity equation. In this paper, a firm's total factor productivity is estimated using Levinsohn and Petrin's (2003) estimator control function approach, and the production technology is specified as a Cobb-Douglas function. All these equations, (4.1 to 4.3), are estimated step by step using a recursive data generating process and it is assumed that the input-output relationship between innovations is fully modeled. Therefore, we can use the Full-Information Maximum Likelihood (FIML) estimator (Roodman, 2011), which can effectively take care of the feedback effects of productivity on the innovation input equation (Baum et al., 2017). The general specifications of the equation are estimated using the FIML estimator following Roodman (2011) as:

$$Y'^{*}_{1xJ} = \theta'_{1xJ} + \epsilon'_{1xJ}, \tag{4.4}$$

where $\theta'_{1xJ} = Y'_{1xJ}\Delta_{JxJ} + X'_{1xK}\beta_{JxJ}; Y = G(Y^{)}* = [g1(Y^{*}).......gJ(Y^{*})]'$ and $\varepsilon/x \sim i.i.d\, N(0,\Sigma)$. Further, Σ is a nxn matrix, where n is the number of equations in the system. Y' is the observed endogenous variable and Δ is the strictly upper triangular, that is, the diagonal and the lower triangle are all $0s$. While β is a matrix of coefficients, ε are random vectors, and $x = (x_1......x_k)$ is a vector of predetermined random variables.

The empirical econometric model is specified as follows. In Equation (4.5), the dependent variable is a dichotomous variable to see whether the firm has its own web page. It is considered an indicator for export orientation of a firm. Equation (4.6) is the innovation equation and, like in Equation (4.5), the left-hand side variable is dichotomous of whether the firm has introduced new or significantly improved its products and processes in the last three years. The last equation, (4.7), is total factor productivity (TFP), estimated using the Levinsohn and Petrin (2003) estimator, where (i) refers to a firm and (t) is time.

$$\begin{aligned} ICT_{it} = \alpha_0 + \alpha_1 logEmp_{it} + \alpha_2 Skl_{it} + \alpha_3 Exp_{it} + \alpha_4 Freign_{it} \\ + \alpha_5 Mkt_{it} + \alpha_6 Single_{it} + \alpha_7 City_{it} + \alpha_9 \ell_{it} + \gamma_t + \epsilon_{it}, \end{aligned} \tag{4.5}$$

$$\begin{aligned} Innov_{it} = \gamma_0 + \gamma_1 ICT_{it} + \gamma_2 logEmp_{it} + \gamma_3 logAge + \gamma_4 Skl_{it} \\ + \gamma_5 Exp_{it} + \gamma_6 Expr_{it} + \gamma_7 City_{it} + \gamma_8 \ell_{it} + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{4.6}$$

$$TFP_{it} = \delta_0 + \delta_1 ICT_{it} + \delta_2 Innov_{it} + \delta_3 logAge_{it} + \delta_4 logExp_{it} + \delta_5 Skl_{it} + \delta_6 Foreign_{it} + \delta_7 City_{it} + \gamma_t + \phi_{it}. \quad (4.7)$$

In Equation (4.5), Emp is the number of employees in logarithm, Skl is skilled labor, Exp is the share of exports in annual total sales, Foreign is the share of a foreign company, Mkt is market share, Single is a dummy variable whether the firm is part of a larger firm or stands on its own, and City is a location dummy (1 if the firm is located in the capital Addis Ababa and 0 otherwise). In Equation (4.6), Age is the age of a firm (in logarithm), $Expr$ is years of experience that the firm's manager has, and L is a latent variable capturing unobserved factors (omitted variables). In Equation (4.5), ICT[3] is a dummy variable capturing the availability of ICT infrastructure in the firm. At the country level, the World Bank collected two indicators for measuring the country's ICT status. These are mobile penetration and internet penetration rates. Higón (2012) used the existence of a web page as an important indicator of ICT adoption. Gallego et al. (2015) also used having a web page as an indicator of firm-level ICT adoption in their analysis for Colombian firms, and Spiezia (2011) for OECD countries. Moreover, Spiezia (2011) provide evidence that web facilities are correlated with a firm's intensity of ICT utilization. Thus, we used the availability of a firm's web page as an indicator of ICT use in the firm. In Equation (4.6), $Innov$ stands for innovations and is a dummy of whether a firm has introduced new or significantly improved products and processes in the last three years. Finally, in Equation (4.7), TFP stands for a firm's total factor productivity. The error terms in the equations are denoted by ϵ, ε, and ϕ. They are assumed to follow a multivariate normal distribution, and γ_t is the time trend indicator. The variable definitions are presented in Table 4.1 below.

Table 4.1: Definition of Variables

Variables	Definition
ICT	Dummy coded 1 if firm i has its own web page otherwise 0
Product innovations	Dummy coded 1 if firm i has introduced product or service improvements in capabilities, user friendliness, components, or sub-systems in the last three years
Process innovations	Dummy coded 1 if firm i has introduced new or significantly improved processes in the last three years
Total Factor Productivity	Estimated using the Levinsohn and Petrin (2003) estimator
Firm's characteristics	
Age	Years of operating in the market in logarithm
Employment (in log)	Measured by logarithm of employees in firm i
Skilled	Proportion of employees in firm i who have completed grade 12 education
Export orientation	Firm i's share of exports in its total sales for the given year
Corporate status	Dummy coded 1 if firm i is part of a large firm and 0 if it is a single unit
Experience	Number of years that a manager of firm i has worked as a manager before the survey year
Foreign ownership	Share of foreign capital in firm i's total capital
Business environment	
Market share	Share of firm i's total sales in the total sales of industry j
Location	Dummy coded 1 if firm i is not located in capital Addis Ababa and 0 otherwise
Year	2011 & 2015 and the base year is 2011

[3]Indeed, website as the proxy for ICT adoption appears to be very narrow. This is a limitation of this paper and mentioned in the first chapter. However, in the data-set we couldn't find any better proxy to measure ICT than this. But a firm must have at least a computer and an internet to have its own web-page. We can say web-page is a derivative of tangible part of ICT.

4.5 Results and Discussion

In this section, the empirical findings of the link between ICT, innovations, and productivity are presented. To establish the relationship between the three equations, we adopted the general structural equation model (GSEM) estimation technique because two of the left-hand side variables are dichotomous, i.e., in Equation (4.5 & 4.6), while in the last Equation (4.7) the outcome variable TFP is continuous. The first equation is innovation input or the knowledge production function equation. We used ICT as an innovation input. Thus, to some extent, the concept of knowledge production is attached to technology diffusion and is measured by ICT adoption/usage (availability of the firm's web page). Hall et al. (2013) have also used ICT in parallel with R&D as innovation inputs.

The second equation is innovation output, which is measured by whether a firm introduced new or significantly improved products and processes in the last three years. We adopt the OECD (2018) manual's definition of innovations to distinguish between product and process innovations. However, the impact of ICT on process innovations and productivity is not presented in GSEM because the estimation does not converge. Nonetheless, we show the impact of ICT on process innovations and productivity using CDM and CMP estimators. In estimating TFP, raw materials and energy (electricity) are used as proxies for unobserved productivity shock indicators because these are intermediate inputs (see Levinsohn and Petrin, 2003). All the variables included in the production equation have been adjusted for price inflation and transformed into their logarithm values. Summary statistics of the variables that are included in the equations are presented in Table 4.2. The descriptive statistics presented in Table 4.2 are based on firms

Table 4.2: Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
ICT	744	.483	.5	0	1
Product innovation	740	.472	.5	0	1
Process innovation	739	.383	.486	0	1
Corporate status	744	.228	.42	0	1
Share of foreign ownership	678	7.934	25.069	0	100
Firm's age (in log)	732	2.998	0.465	1.792	4.554
Employment (in log)	665	3.804	1.367	1.792	8.936
Proportion of skilled labor	714	72.147	27.778	1	100
Share of exports	739	7.321	22.459	0	100
Manager's experience	737	15.695	10.341	1	60
Market share	666	.029	.081	0	.998
TFP	538	5.726	3.337	1.945	16.444
Location	744	.716	.451	0	1

surveyed in the years 2011 and 2015. In other words, this is not a year-specific description and is instead a panel data-set description. More than 48[4] percent of the establishments had their own web pages. A little more than 38 and 47 percent of the establishments introduced new or significantly improved processes and products, respectively, in the last three years. TFP ranges between 1.95 and 16.4. Therefore, there is a large variation in terms of firms' efficiency.

The GSEM estimate in Table 4.3 below shows that a firm's decision to invest in ICT infrastructure

[4]It is a legitimate concern that one may raise about the margin of firms that have their own website given role of digital economy in the overall economic system of the country. This poses a serious concern about the representativeness of the World bank enterprise survey data-set. However, it is clearly stated in the methodology section of the survey instrument that large firms are disproportionately represented.

depends on its size (captured by the logarithm of employment), the proportion of skilled labor, export orientation (share of exports), and corporate status (whether the firm is part of a large establishment). Location and year-specific indicators' coefficients are also significant. Theoretically, it is expected that large firms will have higher payoffs to spend on ICT due to rank effects (Karshenas and Stoneman, 1993). The core assumption of the equilibrium model of technology adoption is that there is no information asymmetry in technology adoption. Hence, larger firms have incentives to adopt ICT since their monitoring and coordination costs are expected to be high. Moreover, the effect of firm size on ICT adoption has theoretical underpinnings which are consistent with Battisti and Stoneman (2005) and Commander et al. (2011) findings. But it is not conclusive that firm size and technology adoption are always positively correlated. For instance, Battisti and Stoneman (2005) found no significant relationship between firm size and ICT intensity in French firms. The other important covariate that affects firms' ICT adoption is the percentage of skilled labor in a firm. Firms that have a higher proportion of a qualified labor force can easily adopt and diffuse technology and they also have advantages in absorbing and assimilating external knowledge (Cohen et al., 1990). It is crystal clear that technology and human capital complement each other.

Exports and corporate status are also positively correlated with ICT. Firms which target both local and international markets are more likely to invest in ICT infrastructure and in adopting technology. This result is consistent with Lal's (1996) findings for India and Battisti and Stoneman's (2005) findings for UK. Export-oriented firms are more likely to invest in ICT infrastructure. Organizational structure is another important determinant of technology adoption since it can change a firm's payoff structure.

In this paper, organizational structure is captured by whether the firm is part of a large firm or is on its own. It is expected that multi-unit organizations are more likely to adopt ICT compared to single unit establishments to minimize the costs of monitoring and coordination. However, our results show that single unit firms are more likely to invest in ICT compared to multi-unit firms. It is expected that capital cities are ICT hubs. Firms in Addis Ababa are more likely to adopt ICT technology compared to firms that are in regional cities. However, our results unexpectedly show that firms' use of ICT has been worsening over time as indicated by the year dummy. A possible explanation for this is related to the sampling and data-set. The data-set is unbalanced, and the descriptive statistics also show that more ICT-equipped firms exit from the industry over time and less ICT-equipped firms joined the industry in 2015. This finding provides some signals that firms pay little attention to developing their web pages.

The aim of Equation (4.6) was to establish the linkage between ICT adoption and innovations. The coefficient of ICT is positive and statistically significant. Hence, there is strong evidence that ICT usage has a positive impact on firm-level innovations. ICT adoptions enhance firm-level product innovations in all specifications and process innovations in CMP and CDM method of estimations. The relationship between ICT, process innovations, and productivity does not converge in the GSEM estimation method, however. This finding is in line with previous empirical studies (Álvarez et al., 2016; Cirera and Sabetti, 2019; Hall et al., 2008; Higón, 2012). Thus, we state that ICT can be considered a driving force for firm-level innovations in developing countries. The proportion of skilled labor has a statistically significant impact on the likelihood of product innovations. As the share of skilled labor increases, firms are more likely to engage in product innovations. However, Van Uden et al. (2017) found that employees' schooling levels had a negative effect on innovations in sub-Saharan African countries.

Table 4.3: The link between ICT, innovations, and productivity: $GSEM$ estimation results

Variables	(1) (ICT)	(2) Product innovations	(3) Productivity (TFP)
Employment (in log)	0.828***	0.206	
	(0.0895)	(0.111)	
Skilled labor	0.0153***	0.00993*	-0.0128***
	(0.00379)	(0.00504)	(0.00354)
Exports (share of output)	0.0256***	-0.0105	0.00183
	(0.00485)	(0.00687)	(0.00463)
Foreign ownership (percentage)	0.00736		0.0270***
	(0.00417)		(0.00427)
Market share	0.0143		
	(1.309)		
Corporate status (single unit)	1.184***		
	(0.264)		
Age of firm (in log)		0.0117	1.317***
		(0.293)	(0.204)
Manager's experience		0.0156	
		(0.0137)	
ICT adoption		2.886**	0.744***
		(0.960)	(0.208)
Product innovations			0.925***
			(0.194)
Location (outside Addis Ababa)	-0.861***	-0.136	-0.136
	(0.215)	(0.208)	(0.208)
Year (2015)	-1.205***	0.449	1.658***
	(0.234)	(0.302)	(0.201)
Latent variable(ℓ)		-2.266**	
		(0.827)	
Cons	-5.776***	-3.752**	0.426
	(0.653)	(1.289)	(0.679)
var(e.lptfp)	7.955***		
	(0.369)		
N	928		

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Firm characteristics like size, age, and export orientation do not have a significant impact on the likelihood of firms' engagement in product innovations while the coefficients are still positive. This is in line with Schumpeterian arguments and Hue's (2019) findings for Vietnamese firms where large firms had a high propensity to engage in innovations due to resource availability and economies of scale. Moreover, there is no significant difference between firms located in the capital city and elsewhere. The results in Table 4.3 also confirm that there was no significant change in firms' product innovation activities over a period of four years (2011-2015). Finally, except for exports, all the variables have expected signs. However, most empirical studies show that exports enhance a firm's propensity to engage in innovative activities through learning by exporting and knowledge/information spillovers. In contrast, Harris et al. (2003) found that exports did not have a significant impact on a firm's propensity to innovate in Australia using a probit model.

The final equation establishes the link between innovations and productivity. As can be seen in Table 3, innovations have a positive impact on a firm's TFP. This result is supported by the findings of Álvarez et al. (2016) who shows that innovations improved the productivity of Chilean manufacturing firms. Besides its indirect effects on productivity, ICT can also boost productivity directly (Jorgenson et al., 2008). Accordingly, our finding is consistent with Commander et al.'s (2011) finding that ICT has a direct positive impact on productivity of Indian and Brazilian manufacturing firms; Chowdhury and Wolf (2003) for East African countries; and Asongu and Acha-Anyi's (2020) findings for 20 SSA countries. This result further strengthens the conclusion of Álvarez et al. (2016) that ICT not only has indirect (spillover) effects on productivity through innovations, but it also enhances productivity directly. However, our finding contrasts with the findings of Díaz-Chao et al. (2015) for Spain's small firms that shows that ICT did not have a direct impact on productivity and cleared doubts that arise in Cirera and Sabetti's (2019) findings for six SSA countries.

Moreover, foreign ownership, the firm's age, and skilled labor have a significant impact on its productivity. A higher level of foreign ownership share leads to a higher TFP. A firm's age is positively correlated to its productivity suggesting that firms can improve their productivity (efficiency) through learning by doing. Surprisingly, a firm's human capital (proportion of skilled labor) is negatively correlated with productivity. Similar findings are reported by Mastromarco and Zago (2012) for Italian manufacturing firms. These authors provide two explanations for the unexpected sign of skilled labor. The first is that skilled labor might be endogenous either due to reverse causality or measurement errors. The second is that the sign is supported by empirical literature in which better education only enhances growth in a country that has low education levels. Of course, the second justification works for Italy, but it does not in the Ethiopian context. Bokana and Akinola (2017) found that higher educational enrolments had a negative effect on TFP growth in 21 sub-Saharan African countries. Finally, the latent variable ℓ) is significant in the innovation equation, which indicates that there are variables that affect ICT adoption and innovations negatively but are not included in the model. Therefore, our estimation approach takes care of this endogeneity problem.

4.6 Robustness checks

To check the consistency of our estimates and to confirm our findings, we re-estimated the relationships in two different estimation methods. We applied Roodman's (2011) Conditional Mixed Process Estimation and Crépon et al.'s (1998) estimation to establish the linkage. The results are presented in Table 4.4 and 4.5, respectively.

In the CMP estimation, output also confirms that ICT drives innovations and innovations enhance productivity. All the control variables that are significant in GSEM remain significant. However, some of the control variables that are not statistically significant become significant. For instance, in the first equation, market share and percentage of export have a significant impact on technology adoption/usage. In the innovation output equation, the CMP estimation results show that over time firms are more likely to engage in product innovations, but in GSEM the coefficient of time trend is statistically insignificant. Similarly, CMP's estimation results also show that firms that are located outside the capital city are more likely to become innovative than otherwise. In sum, the specification does not affect the key variables' statistical significance.

The Roodman (2011) CMP estimation approach also accounts for endogeneity due to selection bias.

Table 4.4: Roodman's (2011) conditional mixed process (CMP) estimation results

Variables	(1) (ICT)	(2) Product	(3) (TFP)	(4) (ICT)	(5) Process	(6) (TFP)
Employment	0.356***	0.111*		0.358***	0.121	
	(0.0363)	(0.0474)		(0.0360)	(0.0756)	
Skilled labor	0.00714***	0.00394*	-0.0573***	0.00717***	0.00397	-0.0524***
	(0.00167)	(0.00185)	(0.0154)	(0.00167)	(0.00239)	(0.0120)
Exports	0.0101***	-0.00177	-0.00637	0.0101***	-0.00161	-0.0167
	(0.00203)	(0.00233)	(0.0168)	(0.00203)	(0.00280)	(0.0129)
Foreign owner	0.00350		0.00493	0.00344		0.00335
	(0.00187)		(0.00657)	(0.00181)		(0.00718)
Market share	0.875*			0.764*		
	(0.392)			(0.355)		
Corporate status	0.302*			0.279*		
	(0.119)			(0.110)		
Firm's age	-0.0163		0.259		-0.0714	0.559
	(0.0943)		(0.800)		(0.100)	(0.618)
Experience		0.000850			0.00119	
		(0.00098)			(0.00133)	
ICT adoption		0.259*			0.443*	
		(0.122)			(0.177)	
Product inno.			8.514***			
			(1.366)			
Process inno.						6.180***
						(0.785)
Location	-0.337***	0.206*	-0.554	-0.344***	0.156	0.426
	(0.0960)	(0.104)	(0.782)	(0.0960)	(0.121)	(0.627)
Year (2015)	-0.531***	0.239*	0.000806	-0.526***	-0.293*	4.072***
	(0.0997)	(0.0982)	(0.787)	(0.0987)	(0.127)	(0.634)
cons	-1.912***	-0.983**	10.81***	-1.902***	-0.807	8.392***
	(0.216)	(0.376)	(3.132)	(0.212)	(0.490)	(2.313)
lnsig3-Cons			2.160***			1.865***
			(0.157)			(0.118)
atanhrho12-cons		-0.105		-0.229		
		(0.131)		(0.194)		
atanhrho13-cons			-0.185**			-0.257***
			(0.0573)			(0.0595)
atanhrho23-cons			-1.646***			-1.193***
			(0.292)			(0.295)
N	1024			1024		

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

The results are presented in the last rows of Table 4.4, which are indicated by $atanhrhos$. For instance, $atanhrho - 12$ in columns 2 and 3 columns are not significant indicating that there is no evidence of self-selection bias between ICT adoption and innovations. In other words, there is no omitted variable that affects both ICT and innovations. However, $atanhrho - 13$ and $atanhrho - 23$ are significant in both columns. Hence, unobserved omitted variables will negatively affect the endogenous and outcome variables. In sum, there were endogeneity problems due to self-selection bias in the innovation and productivity equations, however, the problems are considered in the estimation process. Thus, there is a cross-correlation between the error terms due to omitted variables. In this specific case, the CDM model is not appropriate for estimation. By contrast, GSEM is suitable, as it allows a cross-error correlation between equations.

Further, as mentioned earlier, the model is also re-estimated using the CDM specification, that is, estimating equation by equation while taking the predicted probability of the first two equations (innovation inputs and innovation outputs). CDM's specification results also strengthen our findings that there is a link between ICT adoption, innovations (products and processes), and firm productivity. However, there are variations between GSEM and CDM estimates for control variables, mostly in terms of statistical significance.

In Table 4.5 below, CDM's estimation results show that firm size is negatively correlated with the adoption of ICT, which is against evidence from the GSEM estimate and, of course, contrary to most empirical evidence. Likewise, export-oriented firms are less likely to become innovative. Location and time trend indicators are also significant in the latest estimation method. In the last productivity equation, foreign capital does not have a significant influence on firm productivity. Firms outside Addis Ababa are more productive compared to those in the capital. In general, GSEM estimates of output and CDM estimates are comparable except for some difference in the level of statistical significance for the control variables. However, from a theoretical and empirical point of view, GSEM is preferable to the CDM approach of estimation.

But the remaining control variables' direction of coefficients and the statistical significance of GSEM and CDM estimates are almost comparable. Moreover, CDM's results also show that innovations have a significant impact on firm productivity. To conclude, all methods of estimation show that ICT drives innovations (products and processes) and innovations boost productivity.

4.7 Conclusion and Policy Implications

This paper examined the linkage between ICT, innovations, and firm productivity in an Ethiopian context. We use two rounds ES data collected by Wb. GESM, CMP, and CDM model estimates showed that ICT adoption enhances the likelihood of innovation in relation to both products and processes. A firm's ICT usage in turn depends on its size, the proportion of skilled labor, its share of exports, and corporate status. In addition to ICT, we find some evidence that product innovation is determined by the proportion of skilled labor in a firm. Thus, ICT's adoption is a viable option for enhancing a firm's propensity to engage in innovative activities in Ethiopia.

Next, we find strong evidence that product, as well as process innovation, improves firm-level productivity. Hence, innovative firms are more productive than less innovative ones. Besides, we find that ICT adoption not only has an indirect impact on productivity through innovation but also a direct impact on productivity. Hence, ICT adoption is not only a driving force for firm-level innovation but also for productivity. Therefore, Solow's (1987) productivity paradox is clarified when we introduce innovations in-between ICT and productivity equations. The key theoretical implication of this study is that firm-level innovation in developing countries may not necessarily require potential internal R&D activities but could be created based on technology adoption. This suggests a key role of ICT in transmitting technological information and facilitating technology diffusion. Thus, ICT can be considered an important ingredient of the input function for innovation. Beyond that, our findings suggest that the extent of ICT utilization and application in a company is not only indicative of its propensity to innovation but also of

Table 4.5: Crépon et al. (1998) otherwise (CDM) model estimation results

Variables	(1) ICT	(2) Product innov.	(3) Process innov.	(4) TFP-Product	(5) TFP-Process
Employment	0.968***	-0.337*	-0.345*		
	(0.138)	(0.171)	(0.155)		
Skilled labor	0.0178***	-0.000823	-0.00210	-0.0368***	-0.0307***
	(0.00453)	(0.00421)	(0.00405)	(0.00351)	(0.00341)
Exports	0.0248***	-0.0165**	-0.0153**	-0.00111	-0.00579
	(0.00558)	(0.00579)	(0.00505)	(0.00404)	(0.00414)
Ownership	0.00940			0.00298	0.00435
	(0.00492)			(0.00429)	(0.00433)
Market share	0.613				
	(1.613)				
Corporate stat.	1.026***				
	(0.304)				
Location	-0.927***	0.958***	0.794***	-0.513**	-0.0459
	(0.275)	(0.260)	(0.236)	(0.196)	(0.198)
Year	-1.337***	0.937***	-0.0740	0.307	2.743***
	(0.260)	(0.249)	(0.215)	(0.164)	(0.176)
Predicted ICT	6.100***	6.623***			
	(1.403)	(1.276)			
Firm's age	-0.0962	-0.0564	0.682***	0.780***	
	(0.209)	(0.192)	(0.191)	(0.192)	
Experience		0.0116	0.00449		
		(0.00949)	(0.00883)		
Predicted product innov.				13.94***	
				(0.791)	
Predicted process innov.					11.61***
					(0.687)
cons	-6.244***	-2.407***	-2.359***	0.306	0.142
	(0.941)	(0.662)	(0.638)	(0.610)	(0.616)
$lnsig2u$	1.235***	0.327	-1.183		
	(0.371)	(0.493)	(1.266)		
N	1024	1002	1000	834	1005

Standard errors in parentheses. * p < 0.05, ** p < 0.01, and *** p < 0.001.

its productivity. Our findings are based on a novel and robust empirical methodology because, unlike previous studies conducted in Africa and elsewhere in developing countries, we model the relationship between technology diffusion, innovations, and productivity structurally with a feedback effect. This is a valid contribution to the empirical literature in establishing the nexus between those variables.

This study has two major policy implications. First, in developing countries like Ethiopia, in-house R&D spending is costly and risky for firms. However, ICT diffusion by firms has an impact on innovations and productivity. Liberalizing the ICT sector which is under the monopoly of the Ethiopian government is an important move to promote innovations and enhance productivity. The Ethiopian government has already started opening the ICT sector: see the following link Connecting Africa. The government should also commit to undertaking serious liberalization of the ICT sector in a way that encourages firms to invest in ICT infrastructure and related services (Federal Government of Ethiopia, 2019). Second, the Government of Ethiopia should develop a strategy on how to encourage firm-level innovations, and ICT development should be an indispensable element of this strategy. However, upgrading workers' educational levels, enhancing export potential, and loan accessibility are also important factors that need to be included in the strategy.

This study has some limitations that need to be addressed by future investigations. First, we used, to some extent, a twisted version of ICT measurement, nevertheless, it is quite relevant in the context of Africa. Second, in most previous empirical works, ICT is measured either through the amount of investment in ICT and related facilities or broadband internet use per worker. By contrast, we used the availability of a web page for the firm as an indicator of ICT utilization/adoption. Due to data constraints in the World Bank Enterprise Survey, we do not have much freedom to change our measurement of ICT. Finally, we used firms' self-reported innovations as a dummy variable. It would have been still more insightful to instead use the value of innovative products and services to provide numerical rather than probabilistic information to policymakers. We encourage future studies to address these limitations. More research needs to be conducted that considers different aspects of ICT for establishing the relationship between ICT, innovations, and productivity. Moreover, the mechanism through which ICT enhances or impedes technology diffusion requires deeper investigation.

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Chapter 5

INNOVATION AND EMPLOYMENT: NEW FIRM-LEVEL EVIDENCE FOR AFRICA[1]

Abstract

Does innovation expand or reduce employment? This issue has been investigated both for advanced and developing economies. This paper provides novel evidence on this important relationship using firm-level data from the World Bank Enterprise Survey (ES) for six African economies. The results of the difference-in-differences estimations show that both product and process innovations significantly expand job opportunities in Africa. In addition, there are significant intra-industry innovation spillover effects on employment. In conclusion, this study confirms that innovation does enhance employment in the analyzed African economies. Accordingly, policymakers need to promote and provide incentives for firm-level innovations to enhance productivity and expand job opportunities.

Keywords: Innovation, Employment, Sub-Saharan, Spillover effects, DID, Matching approach
JEL: XY

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5.1 Introduction

The nexus between employment and innovation[2] is a classical controversy. Broadly speaking, there are two channels through which innovation can influence employment. The first channel is via labor productivity, and the second is through price mechanism (Peters et al., 2014). In the latter case, innovation reduces the per unit cost of production and consequently reduces the price of products, which causes employment to rise to meet higher demand (Pigou, 1962). While Say (1964) argues that innovations lead to reallocating jobs from one sector to another sector. Thus, job losses in one sector are compensated by gains in other sectors.

Regarding productivity effect of innovations, technology augmenting innovations cause labor productivity of a firm to increase. Thus, firm-level employment could be influenced negatively by substitution effects while due to the income effect employers might hire more workers. Hence, the net effect of innovations on employment depends on the relative strength of these two opposite effects. As a consequence, economic theories are ambiguous regarding the relationship between innovation and employment.

So far studies have investigated the nexus between innovation and employment mainly in the context of advanced economies (e.g., Petit et al., 1993; Pianta, 2003; Vivarelli, 2014, 2015).[3] For example, Van Roy et al. (2018) and Stare and Damijan (2015) show that innovation enhances employment while Gagliardi (2019) find negative employment effects from external technology shocks. As another example, Pantea et al. (2017) find that ICT does not have a significant impact on labor substitution. The relationship between innovation and employment in the context of developing countries has been studied much less, see also Vivarelli (2014). To the best of our knowledge, the available evidence for Africa are the studies by Medase and Wyrwich (2021); Avenyo et al. (2019); Okumu et al. (2019); Gyeke-Dako et al. (2016); Cirera and Sabetti (2019). Okumu et al. (2019) perform an analysis for 27 selected African countries, while Gyeke-Dako et al. (2016) provide evidence for Ghana. Overwhelmingly, these studies rely on cross-sectional data, which can be seen as a severe limitation to study the impact of innovation on employment.

Our study aims to overcome this limitation by using longitudinal analysis. We contribute to the existing literature in several aspects. Firstly, we adopt a quasi-experimental approach by combining longitudinal cross-country data to identify the impact of innovation on firm-level employment. Secondly, we extend previous studies by including inter- and intra-industry spillover effects into the analysis to be able to infer on the aggregated impact of innovation on employment. Finally, the paper distinguishes innovation types and also employment forms in order to obtain a more complete picture regarding the relationship between innovation and employment.

[2]While we sometimes use the term technological progress instead of innovation, following the Oslo manual (OECD, 2018) innovation is not the same as technological change. There are many types of innovations which would not be described as technological change, like marketing and organizational innovations. In this study, the major types of innovation we are referring to are product and process innovations.

[3]See also Gagliardi (2019) for Great Britain; Van Roy et al. (2018) use 22 European countries; Pantea et al. (2017) perform their analysis for seven European countries, and Stare and Damijan (2015) provide evidence for Spain regarding the impact of innovation on employment at the micro level. However, the results are mixed. For earlier studies, we refer the reader to the surveys of Pianta (2003) and Calvino and Virgillito (2018) of the empirical literature on the nexus between innovations and employment.

Our empirical analysis employs the Difference-in-Difference (DID) estimator in combination with matching. The estimation results, using firm-level data of the World Bank Enterprise Survey, confirm that both product and process innovations expand firm-level employment. The estimates for the intra-industry spillover effects from innovations support that there is an indirect positive effect of innovation even on the employment of non-innovating firms in the same industry. In contrast, the inter-industry spillover effect is not statistically significant.

These results have important policy implications in the context of developing countries. Policymakers may consider promoting and enhancing firm-level innovation given its positive impact on employment. The African Union, specifically the Economic Commission for Africa (ECA) may aim to develop strategies to encourage firm-level innovation in Africa as one instrument to ease the pressure of unemployment, in particular of young persons, in Africa.

The paper proceeds as follows. Section 5.2 presents a literature review. Section 5.3 describe the innovation indicators and extent of job opportunities in the continent and, specifically, for the countries included in this study and followed by the presentation of the methodology in Section 5.4. Section 5.5 gives results and discussion. Finally, the conclusion and policy implications are presented in Section 5.6.

5.2 Innovations and Employment

While the innovation-employment relationship has been a classical issue, it recently has gained the attention of some scholars due to advancements in information and communication-technology (ICT) and automation technologies in the 21st century. For instance, Acemoglu (2021) in the International Monetary Fund (IMF) spring issue suggested that innovations, like for example automation, have a negative impact not only on employment but also on firms' productivity. He further pointed out that now, after the Covid-19 pandemic, employers are seeking labor-saving technology and showing a tendency of displacing workers. The pandemic enhanced innovation but also created involuntary unemployment. On the other hand, Fox and Oviedo (2013) highlighted that employment growth in SSA countries is associated with technology. Thus, it is interesting to know how innovation and employment interplay in the context of Africa.

To investigate this interplay, Okumu et al. (2019) use labor productivity as an outcome variable. However, labor productivity can be improved due to forward effects, i.e., a firm that engages in innovation activities more likely invests in its human capital, and in turn, human capital enhances firm-level innovations. Another critical shortcoming of Okumu et al.'s (2019) study is the measurement of innovations in the African context. They use R&D as a binary indicator for innovation for both product and process innovations. From the data-set it is difficult to differentiate between whether the R&D expenditure is allocated for product or process innovations. Second, few firms are investing in in-house R&D activities in Africa, and there are firms that are engaged in innovative activities without formal spending on R&D. Moreover, R&D fails to capture imitator and adopter firms (Pianta, 2003), which mostly explains firms' behavior in developing countries. In the ES data-set, there is a binary question of whether a firm has introduced new or significantly improved products or processes in the last three years. We used this information as an indicator of innovation activities within a firm. To mention another study, Cirera and

Sabetti (2019) investigated the relationship between innovations and employment in their cross-country study by taking some sample firms from Africa. Cirera and Sabetti's (2019) study is designed as a cross-sectional and, as a result, it is hard to disentangle the impact of innovations on employment. Furthermore, Cirera and Sabetti (2019) did not discuss the spillover effect of innovations on employment.

According to De Bondt (1997), spillover effects can be described as side effect of a business strategy. It can be involuntary leakage or voluntary transmission of important technological information from one firm/industry to others. On the one hand, important information is transmitted from innovator firms to competing firms. On the other hand, it may also inflict negative externalities on rival firms, like reducing the profit margin and market share (De Bondt and Veugelers, 1991). Thus, the impact of innovations on employment is not limited to the firms that are involved in the innovation activities. Rather, it has policy relevance to look at the spillover effects of innovations on the employment of rival firms. However, previous studies on the spillover effect of innovations in advanced countries are focused on the mechanisms and magnitudes of it(Acs et al., 1994; Braunerhjelm et al., 2018; Griliches, 1991; Harabi, 1997; Mansfield, 1985; Nadiri, 1993). Knowing the side effects of innovation with respect to jobs in rival firms would enable policymakers to assess the potential impact of innovations on the competitiveness of rival firms. However, so far, we know very little, if not nothing, about spillover effects of innovations on employment in the context of Africa.

One possible explanation for this scant empirical literature is maybe related to the proposition that developing countries are mere recipients of new technologies. In other words, innovation in Africa is almost equivalent to the import of machinery and capital goods. Due to this underlying assumption, much attention has been given to the spillover effects of R&D investment of developed countries on developing countries economic performances (Grossman and Helpman, 1995; Coe et al., 1997). Moreover, earlier empirical studies on Africa concentrated on the relationship between innovations and trade, foreign direct investment (FDI), or productivity, instead of the relation with employment (Coe et al., 1997; Mazorodze and Tewari, 2018).

Besides that, empirical evidence available for developing countries is mostly related to the impact of firms' innovations on skill composition. There are, for instance, the studies of Conte and Vivarelli (2011) for 23 Low and Middle Income Countries (LMIC), of Le Roux (2018) for South Africa, and of Zhu et al. (2021) for China. Most of the empirical evidence from developing countries are from Latin America:Aboal et al. (2015) for Uruguay; Benavente and Lauterbach (2008) and Álvarez et al. (2011) for Chile; Castillo et al. (2014), De Elejalde et al. (2015), and Novick et al. (2013) for Argentina.

Empirical literature on the relationship between innovations and employment in Africa is scant. To mention the available studies, Naidoo et al. (2023) investigated the impact of product and process innovations on employment using the South African National Innovation Survey (NIS) data-set of the period 2005-2016. They found that process innovations enhance employment more than product innovations. Medase and Wyrwich (2021) examined the effect of innovations on employment growth of Nigerians firms using the Nigerian Innovation Survey (NIS) data-set over the 2005-2020 period. They found both product and process innovations to promote employment growth. Avenyo et al. (2019) studied the impact of product innovations on employment on five Central African countries, namely; Democratic Republic of Congo, Ghana, Tanzania, Uganda, and Zambia. Their findings show that there is a positive correlation between employment and product innovations. They combined Innovation Survey (IS) data with Enterprise Survey (ES) data and applied dose response model to check the intensity of the impact of innovations on employment. This study, however, has some limitations. First, the study used a cross-sectional data-set, which makes it difficult to disentangle the impact of innovations with associated variables and establish causal impact. But they generated statistical twins for the treated firms. Second, this study provides evidence for product innovations only, and it is less debatable in its impact on employment (see Pianta, 2003). Moreover, there is less experience for African firms in engaging in product innovations due to limited in-house development and firms investment on R&D (Oberdabernig, 2016; Vivarelli, 2014, 2015).

Furthermore, Okumu et al. (2019) found that both product and process innovations are positively associated with employment using the WB Enterprise Survey data-set for 27 African countries. Yet, their analyses are confined to firms in the manufacturing sector only. The authors pointed out there is complementarity between product and process innovations in their effect on the increase of employment, and employment is conditioned by the size of a firm. Similarly, Gyeke-Dako et al. (2016) found that product innovations have a positive impact on employment but process innovation is employment neutral using cross-sectional data of Ghanaian firms. Moreover, Sithole and Buchana (2021) found product innovations have a positive effect on employment growth of manufacturing firms while process innovations have a negative impact on manufacturing and service sector employment growth. In sum, empirical literature from Africa shows that product innovation is positively associated with employment, but the impact of process innovations on employment is not conclusive. Thus, it is worthy to add more evidence to existing empirical literature and figure out the net effect of both types of innovations on employment.

Moreover, one of the most important studies on this topic is Cirera and Sabetti's (2019) work. The authors found that product innovations have a positive impact on employment but not process innovations. However, Cirera and Sabetti's (2019) study also has some weaknesses. First, their study did not check the possibility of simultaneity between output growth and the price of product because the value of output is not deflated. Nevertheless, they have used R&D as instrumental variable (IV) for output growth. And yet, this IV has little relevance and probably most African countries dropped out from the regression given limited firm-level investment on R&D. Second, employment growth can be confounded with the time trend. As a result, the coefficient of the estimate may not be well identified due to the cross-sectional design of their research. Hence, their result might not be robust for other types of specifications and modelings. Thus, the issue needs a thorough investigation with a more robust methodological approach.

On related literature, Anakpo and Kollamparambil (2021) identified that automation is positively associated with unemployment using a panel data-set of a sample of ten countries in southern Africa countries over the period 2004-2017. Seemingly contrary to Anakpo and Kollamparambil's (2021) finding, Metu et al. (2020) report that ICTs reduce youth unemployment for SSA countries. Their study covers 48 SSA countries from 1991 to 2018. Similarly, Ebaidalla (2014) investigated the effects of ICTs–measured by mobile subscription and Internet penetration–on youth unemployment using a panel data-set of 30 SSA countries over the 1995-2010 year series. The results indicate that ICTs have a positive impact on youth employment in Africa. Hence, the effect of innovations on (un)employment is contested and needs in-depth investigation.

Along the same lines, evidence from other developing countries have also shown a strong contention regarding the impact of process innovations on employment growth. For instance, Aboal et al. (2015) found that process innovation has a negative impact on employment using a panel data-set for Uruguayan firms while Castillo et al. (2014) have identified a positive impact of innovations on employment for Argentinian firms, and Zhu et al. (2021) found a positive effect for Chinese firms. On the other hand, De Elejalde et al. (2015) found that process innovation is not related to employment growth using a firm-level data-set of Argentina. Likewise, Álvarez et al. (2011) and Benavente and Lauterbach (2008) found that process innovations do not have a significant impact on employment growth in Chile. But, Novick et al. (2013) show that technological complexity is correlated with a higher employment dynamism using a data-set for the period 2007-2010 for Argentinian firms. Hence, the impact of process innovations on employment is less clear and needs further investigation, especially, in the context of developing countries. Moreover, to the best of our knowledge, this study is the first attempt to disentangle the impact of innovations on employment by applying a quasi-experimental method on a firm-level panel data-set of Africa. Moreover, there is no evidence from Africa that looks at the spillover effects of innovations on employment. However, this study is unable to capture the intensity of the impact of innovations on employment due to a lack of data about the values of firm-level innovative products and patent rights. This data would give us important information to check whether there is a non-linear relationship between innovations and employment. Consequently, the impact of innovations is identified using the available information.

5.2.1 Review of classical papers

In pre-industrial time, the assumption was there is a complimentary relationship between employment and technical progress (Petit et al., 1993). In the industrial period, the substitution of capital for labor has become a new reality, and the question was raised about the impact of technology on employment. As a result, in the early 19th century workers in England were protesting against the introduction of machines in textile factories because they were scared advanced machines might displace them from their workplaces. Since then, the issue has been widely discussed in the academic literature. Theoretically, however, the linkage between innovations and employment goes back to the classical theories of economic growth (Say, 1964; Ricardo, 1951) and was then rigorously discussed by neoclassical economists like Solow (1956) and Swan (1956) in relation to productivity improvement. Moreover, innovation is the core of endogenous growth theories (Romer, 1990a; Sala-i Martin, 1990). On the other hand, Griliches (1957), Aghion and Howitt (1990) and Grossman and Helpman (1991), which are extensions of the Schumpeterian school of thought, discussed the sources of technical change via diffusion of technology. Their conceptualization of innovation is in line with endogenous growth theory. There are opposing axioms between neoclassical and endogenous growth theories about the mechanisms through which innovations can be affected. The former theory argues that innovations take place due to external shocks to the economic system while the latter assumes that innovations are entirely determined by factors within the system. Nevertheless, empirical evidence regarding the relationship between innovations and employment[4] at the macro level has been well documented since the 1980s while micro-level studies started later (Vivarelli, 2014).

Broadly speaking, compensation theory is the bare-bones nexus between innovations and employ-

[4]This refers to general employment without making a distinction between different types of employment. First, in the data-set, the data for individual countries are not organized by the types of employment except for categorizing firms' total employees as production and administrative workers. Second, the magnitude of the impact of innovations on blue-collar and white-collar jobs might vary, one could even expect a contradictory effect. Thus, it is the net effect that is important for policymakers.

ment. The concept of innovations is highly entrenched with the classical-neoclassical and Schumpeterian schools of thought (Say, 1964; Schumpeter et al., 1942; Ricardo, 1951). According to classical and neoclassical theories, the transmission mechanisms of innovations that influence employment are mainly through price, wage, and profit. On the other hand, the Schumpeterian and, of course, Keynesian pass-through channels are income–due to productivity increment–as well as consumption of new products. Generally, the classical theories correspond to compensation theory regarding the nexus between innovations and employment while Neo-Schumpeterians and Kaldorians pay much attention to the disequilibrium aspect of the innovation-employment interaction due to large productivity shocks. Alternatively, the jobs-dislodge effects of innovations might not be compensated, and general employment may not be self-adjusted. However, microeconomics theoretical literature extends the debate by adding structural dimensions as well. Accordingly, the impact of innovations on employment is dis-aggregated by types of innovations (product, process, organizational, and marketing) (Hamermesh, 1993; Petit et al., 1993; Stoneman, 1983; Vivarelli, 2014); Sector (Dosi and Nelson, 2010; Marsili et al., 2001) and qualitative aspects of employment, like skill compositions (Acemoglu and Autor, 2011; Chennells and Reenen, 1998; Haskel and Slaughter, 2002). Yet, this study is limited to investigating the impact of process and product innovations on employment. These are the two most important types of innovations that need to be understood in the context of Africa. Most often, product innovations are expected to have a positive impact on employment through demand expansion but it is still not straightforward (Pianta, 2003; Vivarelli, 2015). On the other hand, the effect of technical progress on employment is more complicated. For instance, Schumpeter et al. (1942) and Marx (1959) argued that innovations displace jobs by substituting capital for labor because a drastic improvement in productivity ultimately leads to structural or technological unemployment. Moreover, Edquist et al. (1992) and Edquist et al. (2001) contribute to the theoretical literature with what they called "System Innovation" (SI) approach which combines both evolutionary and institutional economic perspectives while the basic assumption is in line with the new-growth theory in conceptualizing innovations. They provide an analytical framework to examine the effect of innovations on employment that fits to the developing countries context. On further elaboration, the authors strongly argue that the most important step (type) of innovation is diffusion. The three main anchors in Edquist et al.'s (1992) theoretical framework are learning by doing, learning by using, and learning via interacting. They underscore the importance of making distinctions between product and process innovations since it has ramifications for the type of production technology.

The other important issue that we addressed in this paper is the spillover effect of innovations on employment. There are many mechanisms through which information or knowledge about new technology could be leaked and create potential spillovers. Some of the channels, through which information is leaked, are: in the process of licensing technology, patent disclosure, technical meetings, conversations with and hiring of employees of innovative firms (i.e., learning by hiring), and reverse engineering (see Harabi, 1997; Mansfield, 1985). A firm might, however, be engaged with its rival firms in cooperation in R&D, marketing, productions of components, or information systems, which leads to symmetric spillover effects (De Bondt, 1997). R&D is an input to generate innovation outputs (see Crépon et al., 1998; Griliches, 1979). However, small firms do have a resource constraint to engage in knowledge production and instead get involved in innovative activities through knowledge spillovers. Most often, knowledge spillovers from large firms' and universities' R&D expenditures are critical elements for the innovation activities of small firms (Acs et al., 1994; Audretsch and Vivarelli, 1996). Notably, the learning-by-hiring effect is much more important for small firms than for large firms (Braunerhjelm et al., 2018). In any case, innovations have spillover effects, and hence, the benefits of innovations are not limited to the innovative firm (Nadiri, 1993). In this study, therefore, we investigated the impact of innovations' spillover effect, in other words, the knowledge/information effect on the employment of rival firms. We considered both intra- and inter-industry spillover effects of innovations and their impact on employment.

5.3 Innovations and Employment in Africa

5.3.1 Innovations in Africa

African Union (AU) Assembly calls Heads of State and Government to invest at least one percent of the gross domestic product (GDP) on science, technology, and innovations (STI). In 2003, the ministerial council of Africa developed a common set of indicators of STI for Africa, and about 43 member states have implemented these indicators in 2019 (Sithole, 2020). The African Union adopted a ten-year (2014-2024) STI strategy for Africa (STISA-2024). The strategy paper identified, among others, areas of priority and investments to meet the envisaged development of STI in Africa. Accordingly, the third African innovation outlook (AIO-3) report provides information for 23 countries based on innovation indicators developed by the ministerial council. It is worthy, therefore, to present a summary of the report to understand the status of innovation activities in the continent.

One of the biggest challenges in Africa is not only knowing the actual amount of investments on R&D in each country but also where that investment took place. For convenience, sectors are divided into four categories. These are government, business, higher educations, and private non-profitable institutions that are engage in innovation activities, whereas information about R&D expenditure is limited for Africa (AIO-3, 2019). Out of 23 countries, where data were collected for STI indicators, reliable information has been found for only 11 countries. Almost all African countries spend less than one percent of GDP on R&D. Three countries, namely, South Africa, Ethiopia, and Botswana, do invested a little more than 0.5 percent GDP on R&D. The source of finance for R&D activities in Africa mainly originates from the governments. It ranges from the lowest government contribution of 35 percent in Eswatini to 97 percent in Ethiopia. In Uganda (53%) and Mozambique (42.7%), R&D investment is financed mainly by external sources. An overwhelmingly large amount of R&D resources are allocated to public research institutions with exception of South Africa where 46 percent of R&D expenditure is allocated to the business sector. On the other hand, the business sector itself does not spend economically meaningful resources on R&D activities. For instance, in Eswatini and Ethiopia, the business sector spends only 0.002 and 0.003 percent of GDP on R&D, respectively, while the South African business sector allocated more than 0.3 percent of GDP on R&D. In the African context, the business sector does not invest adequately in knowledge production, though the business sector is an incubator and epicenter of innovation activities in advanced economies. Looking at the type of R&D engagement, out of the seven countries included in the survey, four countries spend more than 20 percent of R&D investment on basic research. On the other hand, with exception of Ethiopia, which spends more than 74 percent on experimental research, the remaining countries spend less than 30 percent of the total R&D expenditure on experimental research.

In terms of personnel working in the R&D department, R&D personnel is concentrated in higher education and in the government sector with exception of Seychelles (38 percent) and South Africa (26 percent), where R&D personnel is also found in the business sector. Moreover, the ratio of researchers per million persons in Africa ranges from 27 in Uganda to 715 in Egypt, and, on average, is comparable to some Latin American countries, like Mexico (244) and Chile (533). The report further sheds light on the innovative performance of firms, which are found in 10 African countries. Accordingly, low-level innovation activities were reported for Cape Verde (3.9) and the highest was registered for Uganda (91.7) percent. Categorized by type of innovations, process innovation (33.4) takes the lead followed by product innovations in goods (21.6) and services (17) percent. However, close to 64 percent of Kenyan firms were engaged in organizational innovations related to workplace responsibility. Remarkably, R&D expenditure is ranked as the second option for a firm to be innovative while the first mechanism is through embedded technology transfer through importing. Moreover, the report provides evidence that innovative firms hire more employees with higher education than non-innovative firms.

On top of the above, we used the World Bank (WB) data-set to observe the intensity of engagement in innovation activities of each country considered in this study. Most often, be it for macro- or micro-level analysis, innovations can be measured in terms of the amount of resources spent on R&D–measuring the input side (knowledge production)– or in terms of the number of applications submitted to get patent rights or the number of granted patent rights–measuring the innovation output. Accordingly, data for R&D expenditure as a percentage of GDP and patent applications differentiated by residency are available in the WB data-set.

Nevertheless, information on patent applications is available for only three countries: Kenya, Rwanda, and Zambia. In addition, the size of observations for each country varies. We found a data series from 2002 to 2020 for Kenya and Zambia, and a five-years data series for Rwanda, i.e., 2014-2019. Over 19 years (2002-2020), Kenya and Zambia submitted a total of 3613 and 508 patent applications, respectively. On average, annually, Kenya has applied for 190 innovative products for the past 19 years while Zambia has submitted applications for close to 27 products. Moreover, Rwanda has submitted 37 patent rights applications within five years, which is about 7.4 applications per year. However, information is not available for the rest countries: Cameroon, Mali, and Niger with regard to patent rights applications.

Similarly, expenditure on R&D for Cameroon, Kenya, Niger, and Zambia is not available at all while observations for a few years are available for Mali and Zambia. For the years between 2007 and 2019 for five-point observations, the average expenditure on R&D as a ratio of GDP for Mali was 0.313 percent, which is below the target set by the AU. The figure for Zambia was even much lower than in Mali, i.e., 0.051 percent for seven years of observation over the period 1996-2008.

5.3.2 Employment in Africa

Labor force participation rate in Africa was 63.1% and higher than the world average (60.7%) in 2019. Total employment has grown annually between 2.5 and 3.0 percent within two decades, i.e., 2000-2019 (Shawa et al., 2020). Regionally, employment in Eastern Africa has grown by just above 3 percent between 2000-2019 with the exception of 2009, where growth was slightly below 3 percent. Central African employment growth in these two decades has similar trends to that of Eastern Africa while between 2006-2012 the growth was less than 3 percent. Employment growth in Western Africa region was between 2.4 and 3 percent for the entire period with an exception in 2017, when it reached its peak at 3.2 percent. Looking at the trends, all three regions have shown stable and consistent employment growth for the last two decades. However, the employment growth trend of the Southern Africa region was cyclical with sharp peaks hit in 2005, 2007, and 2014 at more than 3 percent, and negative growth was registered in 2001, 2008, and 2009. Similarly, the Northern Africa employment trend was volatile, but the growth rate never exceeded 3 percent and was negative from 2006 onward.

In Africa, more than half of all employment was projected to be generated by the agriculture sector in 2020 which is a slight decline after a decade long trend of growth. However, there is disparity between regions with regard to the sectors that absorb most of the labor force. For instance, agriculture is the main source of employment in Eastern, Central, and Western Africa while service and industry absorbed more labor force in South and North African countries, respectively (ILO, 2020). It is noteworthy to mention that the African labor market is characterized by high informality–from 40.2 percent of the total employment in Southern Africa to more than 90 percent in Eastern, Central, and Western Africa. Nevertheless, regional level unemployment rate is low with 6.8 percent in 2019 (ILO, 2020). On the other hand, it is relevant to know the effects of being employed on workers welfare. In other words, understanding the return of labor sheds light on how the growth achieved between 2016 and 2020 has improved workers' living standards. Shawa et al. (2020) reported that more than 63 percent of workers in Africa were considered as working poor, though labor productivity in Africa has grown except in Central African countries (Shawa et al., 2020). Also, it should be noted that labor productivity in Africa has been measured with errors.

The unemployment figure for Africa does not show the extent of people who are looking for a job given that a huge part (85.8 percent) of the total employees are working in the informal sector (Shawa et al., 2020). Thus, looking at the employment trends and figures gives a good picture of the regional economies in terms of creating job opportunities and labor supply absorption. As a result, we opted to look at the ratio of employment to the total population age 15 and above using the World Bank data-set. Due to data constraints, a series of data over 1991-2021 is available for Niger and Mali while for the other four countries random observations are available. The average employment-population ratio for over three decades in Niger and Mali was close to 76.5 and 65.4 percent, respectively. The ratio for both countries has been declining over time. It was just more than 78 and 67.9 percent in 1991 and it became 72.3 and 63.2 percent in 2021 for Niger and Mali, respectively. Thus, employment was reduced by close to 6 percent in Niger and by more than 4.5 percent in Mali over thirty-one years. Surprisingly, employment to population ratio for Rwanda in 1996 was 94.3 percent but started to decline in 2017 (based on the data available) and fell to 49.6 percent in 2020. To put it another way, more than half the population of Rwanda aged above 15 were not employed in 2020, either they were in education or training. On the other hand, the employment-population ratio for Zambia increased from 49.5 percent in 2017 to 64.1 percent in 2021.

There is no recent information for Cameroon since 2015 while the ratio was 69.6 percent in 2014. Similarly, random information is available for Kenya. For instance, the proportion of the labor force who are employed was 72.3 percent in 2016 and declined to 64.4 percent in 2019. In sum, per available information, the percentage of employed population declined over time, except in Zambia. Thus, African economies need to be employment oriented to absorb future labor supply who are either in education or training now.

5.4 Empirical approach

5.4.1 Identification strategy

To identify the impact of innovations on employment, we adopt the standard neoclassical model of profit maximization. The demand for labor is a derived demand from firm's profit maximization function. Accordingly, the paper follows the Van Reenen (1997) specification of a competitive firm. A firm operating under a Constant Elasticity Substitution (CES) production function is specified as follows:

$$Y = T[(A_l L)^{(\frac{\sigma-1}{\sigma})} + (B_K K)^{(\frac{\sigma}{\sigma-1})}]^{\sigma(\sigma-1)}, \tag{5.1}$$

where L is employment, K is capital, Y is output, T is the Hicks-neutral technology parameters, A_l is labor augmenting Harrod-neutral technology, and A_k is the Solow-neutral technical change. In a perfectly competitive market, wage is equal to marginal productivity of labor, and given by:

$$MP_l = \frac{W}{P}, \tag{5.2}$$

where MP_l, is the marginal product of labor, W is the wage rate, and P is the price of product. Taking the first order condition for labor, substituting $Eq(2)$ by $Eq(1)$, taking the logarithm of $Eq(1)$, and then solving for L, we obtain the following:

$$LogL = LogY - \sigma Log(\frac{w}{p}) + (\sigma - 1)LogA_l. \tag{5.3}$$

Next, substituting the marginal product of capital with the real price of capital and substituting in the labor demand function of $Eq(2)$, we obtain the following:

$$LogL = (\sigma - 1)Log(\frac{A_l}{A_k}) - \sigma Log(\frac{W}{P} + LogK + \sigma LogR, \tag{5.4}$$

where R is the price of capital. Van Reenen (1997) substituted the unobserved technology shock terms $(\sigma - 1)Log(A_L/A_K)$ with innovations and specified a stochastic labor demand function.

On the other hand, we followed a similar method of Stare and Damijan (2015), but we adapted it to our context to capture the spillover effect of innovations. They are much interested in vertical innovations' spillover effect. Accordingly, innovations' spillover effect is constructed as follows:

$$Z^{kmt} = \sum_{m,j=1}^{n} (\alpha_{mjt} \times sIN^k_{mt}), m, j = 1, \ldots, n, \tag{5.5}$$

where Z^{kmt} is the weight of the sum of the share of innovative firms in total population of firms in two-digit industry of (m), and sIN^k_{mt} is the share of innovative firms in total population of firms in the two-digit industry of (m). α_{mjt} is a weight measurement which is the share of output of industry (m) purchased by firms in industry (j). Unfortunately, we do not have data on transactions that take place between two or multiple industries to attach weights for each. Therefore, our spillover-effect measurement considers the share of innovative firms to the total population only. Thus, our empirical identification strategy that examines the impact of innovations and its spillover effect on employment in Africa is described below.

To identify the impact of innovations on employment, we applied a Fixed Effect (FE) estimator after matching[5]. As we know, the standard fixed effect estimator has clear limitations in disentangling the impact of some interventions. The crucial parallel trend assumption is likely to be violated in the FE estimation method. Therefore, there is a need to reduce the model dependency of the estimate (Ho et al., 2007) by reducing the link between the treatment and covariate variables. Thus, the result of estimates is likely to be independent of different model specifications. However, the combination of the FE with a matching estimation method can solve the model dependency problem by finding statistical twins for the treated firms.

FE estimation with matching is executed in a two-step estimation procedure. First, the matching of treated (innovative) firms with control (non-innovative) firms is done based on the variables included in the empirical specification that influence the outcome variable, i.e., employment. In our case, matching is done based on the following variables: log of firm age, log of sale, log wage, log of capital, proportion of skilled labor, firm size, share of export and foreign ownership, and location dummy. We applied a nearest-neighbor matching algorithm to match between treated and control firms. Second, based on the matched sample, FE estimation is applied. We have added indicators of spillover effect variables in the second regression. Once again, we re-estimated the empirical model by applying the FE estimator without matching and pooled OLS: ignoring the time dimension of the data-set as a mechanism to check the sensitivity and robustness of our findings. The variables included in our empirical model specification are based on the empirical literature that we reviewed.

$$Emp_{ijct} = \alpha_1 Innov_{ijct} + \alpha_2 Splov_{jct} + X'_{ijct}\beta + \gamma_i + \eta_j + \delta_c + \vartheta_t + \mu_{ijct}, \tag{5.6}$$

where Emp_{ijct} is employment indexed for a firm (i), industry (j), country (c), and at time (t). $(Innov)$ is innovation and represents both types of innovations (process and product). $(Splov)$ are industry level innovations to capture the spillover effect. To capture inter-industry spillover effects of innovation, we estimated innovations in the two-digit industry (h) on employment of firm's (i) in the (j) industry, where $(j \neq h)$. Similarly, intra-industry spillover effects of innovations are included to highlight their impact on the employment of rival firms of the same industry. X'_{1ijct} is the vector of predetermined variables that affect employment, like annual sales revenue, wage, and other firm specific characteristics, and β the associated vector of coefficients. Finally, firm, industry, and country specific unobserved heterogeneity are captured by γ, η, and δ, respectively, and ϑ is the macroeconomic shocks indicator. Finally, μ is the random error term. $Eq(6)$ is estimated using the FE estimator after matching. However, initially we estimated the model using a flexible double difference model, but we could not retrieve a coefficient of DID estimate of the impact. As a result, we switched to FE with matching to fit the data-set available for African countries. Since innovation, the treatment variable, starts at different times in each country, and the time gap between two survey periods is also not constant across all countries included in this study, a FE estimator with matching was a better fit. Otherwise, it is more appropriate to estimate the impact using flexible DID. For details on flexible double difference and associated STATA commands, one can

[5] It is legitimate concern that the causality could be running in the opposite direction, i.e., large firms are more likely to engage in innovation as compared to small firms. Causal ordering is an important concern needs to be clarified. Broadly speaking, in developing economies, innovations and technological changes are somehow related to advanced economies' knowledge production. Some estimates indicate that more than 90 percent of firm performance improvement in developing countries is related to the application of foreign technology (see Keller, 2004). It is hard to say innovations in developing economies are entirely an endogenous process. In this thesis, we considered innovation as quasi-exogenous variable. Thus, seemly, we treated firm-level innovation as exogenous process while firms have some stake in the process. Moreover, it is important to note that we considered innovation as "new or significantly improved product or service to the firm" not to the market. However, one can employ instrumental variable approach to instrument innovation to overcome identification problem, but this is beyond the scope of current analysis.

see (Dettmann et al., 2019).

5.4.2 Sample and variable description

We use the Enterprise Survey (ES) data-set. It is a secondary data collected by the World Bank. The ES collects data from enterprises in manufacturing and key service sectors in every region of the world by standardized survey instruments and a uniform sampling methodology. The survey sample frame is constructed from a list of enterprises made available by Central Statistical Agency (CSA), the country's statistical office, the Tax and Business Licensing Authority, and Business Associations and Marketing Database. A stratified random sampling approach was followed to select enterprises into the ES sample. Strata are made based on firm size, business sector, and geographic region. Firm size is categorized based on the number of employees working in the firm; 5-19 (small), 20-99 (medium), and 100 and above employees (large firms). Large-sized firms are over-sampled to reduce the negative proportion effects while underscoring the importance of large firms for employment and growth. Sectoral strata are manufacturing, retail, and other services while geographic regions within a country are selected based on which cities/regions collectively contain most of the economic activity.

The survey targets establishments which are formal (registered) companies and have 5 or more employees. All the sample firms are either fully or partially owned by the private sector. The survey is conducted at establishment level which is advantageous for micro-level analysis. The survey instrument has 15 sections (A-N) organized by topics. Section (H) is entirely left for innovation-related issues. However, the ES uses two instruments that are designed for manufacturing and key service sectors separately. In this survey about 146 countries are covered but it is not conducted in the same years across countries. Some countries have rich data-sets while others were included in fewer rounds. For this study, we considered countries that have at least three rounds in the survey data-set. We found 7 African countries that meet this criterion–namely, Cameroon, Kenya, Mali, Niger, Nigeria, Rwanda, and Zambia. However, Nigeria was dropped from our sample because it has only one-period observation for our key variable, innovation. Accordingly, our sample firms are drawn from six African countries. The values of sales revenue, capital, and labor cost of each country are changed into their equivalent in USD for each year, and extreme values of the top one percent are trimmed using $Winsor$ outlier fixation technique. Details of the variables we used for this study are presented in Table 5.1.

Table 5.1: Variable Definitions

Variables	**Definition**
Product innovations	Dummy coded 1 if firm i has introduced products or services that are new or have significant improvements in capabilities, user friendliness, components or sub-systems in the last three years
Process innovations	Dummy coded 1 if firm i has introduced new or significantly improved processes in the last three years
Inter-industry spillovers	The ratio of the total number of innovative firms in the two-digit "(J)" industry to the total number of innovative firms in the country in each year
Intra-industry spillovers	The ratio of total number of innovative firms in the two-digit "J" industry to the total number of firms in the same industry in each country and year
Firm's characteristics	
Age	Years of operating in the market in logarithm
Employment	Number of employees in firm (i) in logarithm
Export orientation	Firm (i)'s share of exports in its total sales for a given year
Sale	Annual sale of firm (i) measured in USD
Firm size	Dummy coded 1 if firm (i) is in the large category and 0 otherwise
Wage	The total amount of wage paid to labor in USD in logarithm
Capital	The book values of a firm (i)'s total assets in USD in logarithm
Manager-owner's characteristics	
Foreign ownership	Share of foreign capital in firm i's total capital
Business environment	
Market share	Share of firm (i)'s total sales in the total sales of industry (j) in country (c)
Location	Dummy coded 1 if firm (i) is not located in capital county (c) and 0 otherwise
Year	The survey year, which varies from country to country

5.5 Results

5.5.1 Descriptive statistics

In this subsection, we present the descriptive statistics of the data-set comparing innovative with non-innovative firms in different firm-specific characteristics.

A summary of the sample size in each country and the survey year is presented in Table 5.2 below. As can be seen, a total of 7736 firm-level observations are being considered for this study. A relatively large sample size comes from Kenya, which is 2439 with the latest round of survey data for the year 2018, while the smallest sub-sample of firms comes from Niger 439. In 2006, we have survey data for two countries: Cameron and Niger. Similarly, Kenya, Mali and Zambia were surveyed in the year 2007. Furthermore, in the year 2009 we have survey data for Cameron and Niger, and in 2013 for Zambia and Mali. Finally, we have the latest survey data from 2019 for Rwanda and Zambia.

In Table 5.3 below, we present employment growth of firms over three years. In the enterprise survey (ES) data-set, we have two periods of information. Firms are asked to declare the number of permanent employees three years ago and the number of permanent employees in the survey period. We followed

Table 5.2: Summary of sample size in each country and survey period

Survey year	Selected Countries						
Year	Cameroon	Niger	Rwanda	Zambia	Mali	Kenya	Total
2003	-	-	-	-	155	-	155
2005	-	138	-	-	-	-	138
2006	207	-	212	-	-	-	419
2007	-	-	-	603	490	657	1750
2009	363	150	-	-	-	-	513
2010	-	-	-	-	360	-	360
2011	-	-	241	-	-	-	241
2013	-	-	-	720	-	781	1501
2016	361	-	-	-	185	-	546
2017	-	151	-	-	-	-	151
2018	-	-	-	-	-	1001	1001
2019	-	-	360	601	-	-	961
Total	931	439	813	1924	1190	2439	7736

Fisman and Svensson's (2007) firm-level employment growth calculation, i.e., the logarithm difference between the two periods gives us the growth (percentage change) of employment over three years. To know the annual average, we can divide it by three. Accordingly, employment growth ranges from -253 percent to 340 percentage points. Thus, some firms have cut employment by more than 253 percent while others have increased permanent employment more than threefold within three years. However, on average there is a positive employment growth rate in all countries. Within three years, on average, employment growth is registered to range from 11 percent in Zambia to close to 21 percent in Rwanda. Overall, on average, employment has grown by 12.2 percent over three years. Hence, annually, firms' employment size is expanded by seven percent in Rwanda and close to 3.67 percent in Zambia while the overall annual growth is close to 4.1 percent. This descriptive statistic is somehow close to the ILO (2020) report where the average employment growth ranges between 2.5 and 3.0 percent for Africa. Of course, the ILO (2020) report refers to total employment for all sectors while we used permanent employment for industry and service sectors only. As a result some marginal deviation on average employment is observed.

Table 5.3: Firm-level employment growth over three years in sub-Saharan African countries

Country	Obs	Mean	Std.Dev.	Min	Max
Cameroon	840	.123	.344	-2.436	2.06
Rwanda	674	.209	.385	-1.744	2.485
Zambia	1584	.11	.364	-1.609	2.639
Mali	986	.16	.349	-1.386	3.401
Kenya	2180	.128	.406	-2.526	2.526

Moreover, it has practical and academic relevance to see which type of firms are creating more job opportunities. For this consideration, average employment growth is broken down by firm size to see whether there is variation in terms of employment growth between different firm sizes. For convenience, firms are grouped into three sizes; small (less than 20 employees), medium (20-99 employees), and large (above 99 employees). Relatively speaking, a large proportion of the sample firms are in the 'small' category followed by medium-sized firms.

As can be seen from Table 5.4, the relationship between employment growth and firm size is less clear. On average, large firms' employment grew by 15.2 percent over the three-year interval followed

Table 5.4: Employment growth vis-à-vis firm size

Firm size	Obs	Mean	Std.Dev.	Min	Max
Small	3337	.139	0.391	-2.526	2.639
Medium	2003	.126	0.377	-2.303	3.401
Large	924	.152	0.326	-2.408	2.303

by small firms with 13.9 percent. Thus, from this descriptive result, it may be difficult to establish the relationship between firm size and growth while, unequivocally, large firms create more job opportunities compared to small firms. This contribution of large firms to a high employment growth might be due to our consideration of permanent employment. The growth rate could be different if we take into account temporary employment as well.

As can be seen from Table 5.5 below, the overall sample statistics presented in column (1) indicate that except for the share of foreign ownership, all variables included in the empirical model have a significant difference between innovative and non-innovative firms before matching. The descriptive statistics for innovative and non-innovative firms after matching are also presented in the subsequent tables. Specifically, innovative firms create more job opportunities for permanent and temporary workers compared to non-innovative firms. However, when we look at the average industrial wage per firm, non-innovative firms are paying a significantly higher wage compared to innovative firms.

Innovative firms in Zambia and Kenya have hired more employees compared to non-innovative firms. Similarly, innovator firms are generating a large amount of revenue and are more export oriented in both countries. Moreover, large firms[6] and firms that are situated in the capital cities are more innovative compared to their counter part, i.e., small firms that are located outside the capital cities. Firms located in the political and economic center are more innovative than ones outside the center, except in Mali. On the other hand, there is no statistically meaningful difference between innovators and non-innovators in terms of total and temporary employment, engagement in the export market, and market share in Cameroon, Niger, Rwanda, and Mali. As a result, this cross-country study gives us a better understanding about the possible impact of innovations on employment than single-country studies.

From Table 5.6 after matching, there is no statistically significant difference in mean distribution between innovative[7] and control groups of firms for all covariates included in our empirical model specification. Our final estimation is based on these matched sample firms. As a result, to some extent our regression estimates are less likely to be affected by self-selection bias. Moreover, our sample met the basic assumption of randomness in providing treatment. In other words, one of the two basic assumptions of propensity score matching is conditional independence, i.e., the outcome variable is independent of the treatment given the covariates. Based on the test statistics, our estimation result based on the above sample firms is statistically desirable. The finding out of this sample can be considered as a quasi-

[6]In this data-set, firms are categorized into four groups. These are micro firms, which have less than five employees; small firms with five to 19 employees; medium firms having between 20 and 99 employees; and large firms, which have 100 or more employees. In this paper, we reduced these four categories of firm size to two. The first two categories are considered as small while the last two are labelled as large firms. Thus, "large firm" is referring to firms that have twenty or more employees.

[7]Here, "innovative" refers to firms that introduce new or significantly improved goods and services, i.e., product-innovative firms. Similarly, we have done a test for firms that are engaged in process innovations as well. The descriptive statistics are similar to what we have presented here in Table 5.6. Hence, to save space and avoid redundancy of information, we prefer to skip presenting the results here.

Table 5.5: Overall descriptive statistics before matching

	1 Overall	2 Cameroon	3 Niger	4 Rwanda	5 Zambia	6 Mali	7 Kenya
Permanent Emp							
Innovators	61.419***	54.405*	33.34	45.2	53.3***	32.8	72.646***
	(2264)	(200)	(50)	(145)	(548)	(131)	(1190)
Non-innovators	40.512	39.594	35.10	59.78	36.5	24.573	46.587
	(2089)	(293)	(58)	(46)	(694)	(164)	(834)
Temporary Emp							
Innovators	17.349***	8.31	15.16	16.79	9.1***	7.633	23.776***
	(2286)	(200)	(49)	(144)	(560)	(120)	(1213)
Non-innovators	8.928	8.728	10.17	6.69	5.7	4.973	12.367
	(2139)	(286)	(58)	(46)	(726)	(147)	(876)
Total Emp							
Innovators	83.919***	62.672	49.38	68.32	66***	38.779	103.44***
	(2189)	(186)	(48)	(142)	(532)	(118)	(1163)
Non-innovators	54.004	49.428	45.28	87.93	47.5	27.717	64.433
	(2032)	(269)	(58)	(45)	(694)	(145)	(821)
Sales in (1000)							
Innovators	625.3***	4208.3	6620.5	3486.1	245400***	4762.5	10347.3**
	(2126)	(203)	(38)	(128)	483)	(127)	(1147)
Non-innovators	370.7	2192.7	5512.2	25239.2	103276.6	1389.5	5231.8
	(2003)	(307)	(44)	(49)	(658)	(158)	(797)
Wage							
Innovators	277617.4	7263.7	2459.1	11520.1	1149548.8***	3494	5042
	(2389)	(216)	(51)	(149)	(568)	(136)	(1269)
Non innovators	345600.4***	7624	2978**	12822.2	1061751.2	3173.5	4981.7
	(2,202)	(312)	(58)	(50)	(709)	(170)	(903)
Ownership							
Innovators	0.143	0.106	0.108	0.159	0.264	0.096	0.098
	(2375)	(213)	(49)	(148)	(574)	(136)	(1255)
Non-innovators	0.148	0.091	0.184	0.130	0.234	0.144	0.099
	(2,218)	(312)	(56)	(50)	(731)	(169)	(900)
Export							
Innovators	0.071***	0.037	0.04	0.059	0.044***	0.026	0.095***
	(2,367)	(215)	(47)	(148)	(570)	(132)	(1255)
Non-innovators	0.050	0.067	0.049	0.036	0.021	0.044	0.071
	(2,201)	(308)	(57)	(50)	(730)	(165)	(891)
Market share							
Innovators	0.015***	0.022	0.059	0.031	0.012***	0.022	0.012***
	(2145)	(208)	(39)	(128)	(494)	(130)	(1146)
Non-innovators	0.009	0.018	0.040	0.018	0.006	0.018	0.005
	(1,961)	(308)	(43)	(37)	(619)	(158)	(796)
Firm size							
Small firms							
Innovators	1,046	94	32	90	322**	78	430***
	(2,309)	(146)	(51)	(149)	(582)	(112)	(1269)
Non-innovators	1,201	147	37	28	349	93	442
	(2,095)	(213)	(58)	(50)	(734)	(123)	(903)
Large firms							
Innovators	1,263***	52	19	59	261	34	839
	(2,309)	(146)	(51)	(149)	(582)	(112)	(1269)
Non-innovators	894	66	21	22	284	40	461
	(2,095)	(213)	(58)	(50)	(734)	(123)	(903)

Sample size in parentheses, and *** p<0.01, ** p<0.05, * p<0.1.

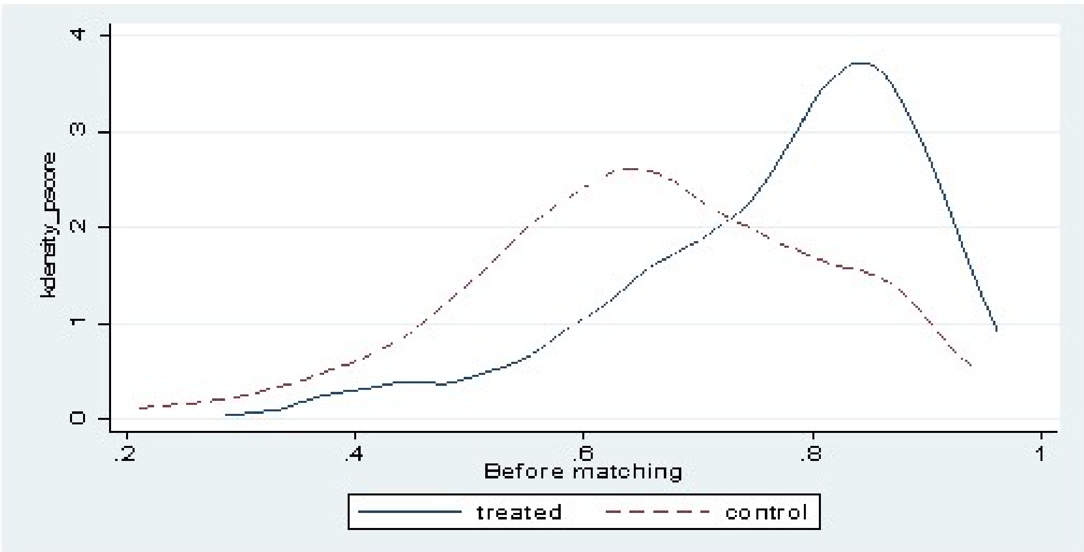
Table 5.6: Descriptive statistics after matching

Variable	mean		bias	T	t-test	
	Treated (Innovative)	Control (Non-innovative)			p>t	V(T)/V(C)
Log of annual sale	14.722	14.554	5.8	1.040	0.296	1.030
Log of labor costs	12.503	12.345	5.5	1.000	0.318	1.060
Percentage of export	0.090	0.089	0.6	0.100	0.917	0.880
Foreign ownership	0.122	0.131	-2.900	-0.460	0.646	0.890
Log of capital	13.203	13.046	5.3	0.950	0.344	1.20*
Log of firm's age	2.902	2.974	-8.800	-1.520	0.128	1.040
Percentage of skilled labor	0.635	0.601	11.100	1.860	0.064	0.850
Firm size (category)	1.715	1.736	-4.300	-0.750	0.454	1.050
City (dummy)	1.340	1.444	-21.400	-3.500	0.000	0.910

*if variance ratio outside [0.84; 1.18]

experimental investigation.

Figure 5.1: Propensity score distribution before matching



If we look at the two figures closely, after matching (see Figure 5.2), the propensity score distribution for control firms is relatively smoothed compared to before matching (see Figure 5.1). The distribution of the propensity score for innovative and non-innovative firms looks similar after matching. We have already shown in descriptive statistics that after matching innovative and non-innovative firms have similar characteristics.

As can be seen from the Table 5.7 above, from the total of sample firms, more than (725) firms are found on common support region either for permanent or total employment as an outcome variable. Both types of innovations (product and process) have significant impact on both types of employment (permanent and total). The size of the Average Treatment Effect (ATE) of innovation is higher for overall employment. More precisely, firms that are engaged in product innovations create 54.6 and 57.6 percentage point more job opportunities for permanent and total employment than their counterpart, respectively.

Figure 5.2: Propensity score distribution after matching

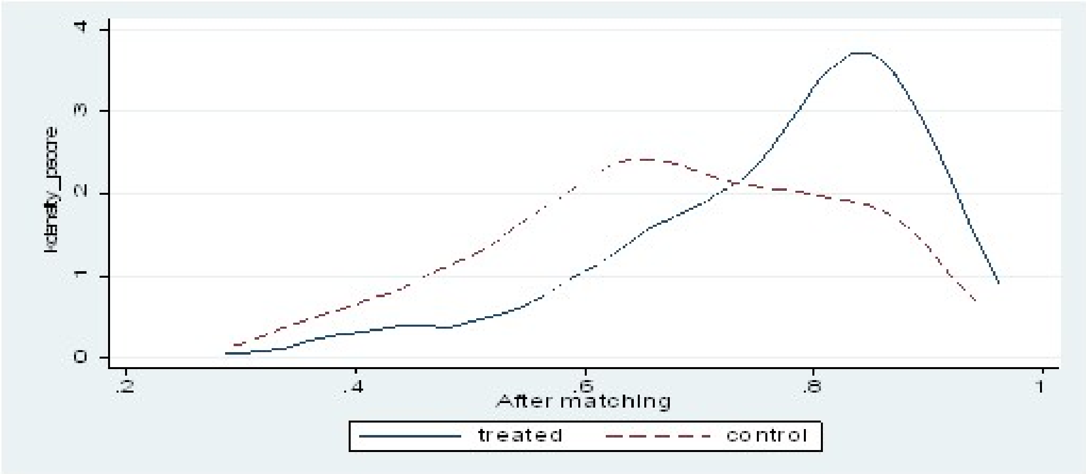


Table 5.7: Average Treatment Effect (ATE) of innovations on employment

	Product innovations		Process innovations	
	(1)	(2)	(3)	(4)
Employment type	Permanent	Total	Permanent	Total
Innovation	0.546***	0.576***	0.611***	0.667***
	(5.70)	(5.80)	(6.76)	(7.14)
cons	3.257***	3.450***	3.232***	3.412***
	(39.64)	(40.66)	(43.10)	(44.14)
N	725	741	733	750

t statistics in parentheses and * p<0.05, ** p<0.01, *** p<0.001

Process innovations have a positive impact on both categories of employment with a higher magnitude of impact compared to product innovations.

5.5.2 Estimation Results

We have estimated three different models to disentangle the impact of innovations (product and process) on employment (permanent and total). Column 1&4 in Table 5.8, attached in the annex, present fixed effect estimates on the matched sample for the impact of product innovations on permanent and total employment, respectively. Results in columns (2&5) are fixed effect estimates for the whole sample without matching. Finally, columns 3&6 present pooled OLS estimates results while ignoring the time dimension of the panel but it is clustered by firm's unique number. Here, we present, however, fixed effect estimates without matching and pooled OLS estimate to check the strength and susceptibility of our findings for different model specifications.

As can be seen from Table 5.8, product innovations have a positive and significant impact on employment (permanent and total). Theoretically speaking, these results give some signal that the compensation effect of product innovations via pricing mechanism is higher than the displacement effect via demand contraction for old products. In other words, the net effect of product innovation on employment is positive.

Table 5.8: The impact of product innovations and its spillover effect on employment

	Log of permanent employment			Log of total employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Matched	Full	Pooled	Matched	Full	Pooled
Product Innovation	0.233**	0.142**	0.264***	0.266**	0.131**	0.303***
	(0.108)	(0.0599)	(0.0364)	(0.114)	(0.0630)	(0.0373)
Inter-Spillovers	-1.079**	-0.215	0.542***	-0.647	-0.262	0.562***
	(0.516)	(0.313)	(0.113)	(0.436)	(0.300)	(0.116)
Intra-Spillovers	3.913***	0.860	1.960***	3.530**	1.331**	2.275***
	(1.243)	(0.617)	(0.161)	(1.427)	(0.668)	(0.165)
2006	0.455***	0.104	0.521***	0.678***	0.506	0.370
	(0.141)	(0.282)	(0.190)	(0.251)	(0.308)	(0.232)
2007	0.486*	0.394**	-0.271*	0.150	0.643***	-0.545***
	(0.272)	(0.162)	(0.154)	(0.230)	(0.188)	(0.197)
2009	0.400	-0.180	0.205	-0.221	-0.117	-0.00242
	(0.267)	(0.155)	(0.236)	(0.409)	(0.142)	(0.267)
2013	0.00323	0.189	-0.315**	-0.156	0.401*	-0.597***
	(0.179)	(0.199)	(0.159)	(0.126)	(0.227)	(0.202)
2017	-0.169		0.315	-0.641		0.154
	(0.284)		(0.222)	(0.431)		(0.258)
2018	0.0526	0.174	-0.253	-0.0545	0.401*	-0.460**
	(0.199)	(0.202)	(0.165)	(0.151)	(0.230)	(0.207)
2005		-0.249	-0.143		0.0654	-0.0867
		(0.177)	(0.213)		(0.234)	(0.261)
2011		-1.150***	0.0773		-0.551	-0.0574
		(0.360)	(0.184)		(0.394)	(0.224)
2016		-0.00498	0.157		0.262	-0.298
		(0.239)	(0.165)		(0.257)	(0.207)
2019		0.179	0.0550		0.445*	-0.139
		(0.210)	(0.165)		(0.238)	(0.207)
Constant	1.909***	2.784***	2.313***	2.350***	2.555***	2.598***
	(0.630)	(0.304)	(0.159)	(0.735)	(0.346)	(0.202)
Observations	1,298	3,874	3,874	1,306	3,914	3,914
R-squared	0.185	0.049	0.098	0.121	0.050	0.123
Number of Panelid	623	3,318		627	3,352	

Robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

The magnitude of its impact is higher on matched sample firms than the other optional specifications. Innovative firms created more than 23 percentage points more permanent job opportunities compared to less-innovative firms. Firms engaged in product innovations not only create more jobs for permanent workers but also for temporary workers as well. In sum, there is no trade-off between product innovations and employment, rather firm-level product innovations in Africa create more job opportunities. Accordingly, our finding is in support of the previous empirical evidence of Medase and Wyrwich (2021) for Nigeria for firms in the manufacturing sector; of Okumu et al. (2019) for 27 African countries; and of Cirera and Sabetti (2019) for developing countries. They all concluded that product innovations have a significant and positive impact on employment.

Further, as firm-level innovation has a positive impact on firms' employment, it will be interesting to examine its impact on other firms that are in the same or different cohorts of two-digit industries. According to Schumpeter et al. (1942), innovations have also a business-stealing effect. To capture this effect, we included and intra-industry and inter-industry spillover effects of innovations in our regression.

In all estimation approaches, the intra-industry spillover effect of product innovation is positive and significant for permanent employment. Thus, firm-level product innovation in Africa has a positive intra-industry spillover effect. The implication of this finding is twofold. First, this result provides evidence that product innovations do not have a business-stealing effect in the African context. This may be due to the fact that less-innovative firms in Africa are reluctant to respond to market share reduction in the short term due to an imperfect market structure. Another possible justification could be that a firm's innovation may incentivize other firms in the same industry to engage in innovative activities. It is well documented that knowledge spillovers from large firms are important elements in the innovative activities of small firms (see Acs et al., 1994; Audretsch and Vivarelli, 1996). On the other hand, the coefficient of the inter-industry spillover effect is negative in all model specifications and significant in matched and pooled cross-section samples for permanent employment. Our finding contrasts with Stare and Damijan's (2015) findings, though their investigation is a macro-level analysis, they found a positive impact of product innovation on the employment of vertically connected firms.

Table 5.9: The impact of process innovations and its spillover effect on employment

	Log of permanent employment			Log of total employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Matched	Full	Pooled	Matched	Full	Pooled
Process innovation	0.174*	0.0770	0.306***	0.142	0.0685	0.328***
	(0.0976)	(0.0575)	(0.0394)	(0.105)	(0.0629)	(0.0408)
Inter-Spillovers	-0.849	-0.316	0.557***	-1.068**	-0.357	0.557***
	(0.519)	(0.301)	(0.117)	(0.495)	(0.289)	(0.123)
Intra-Spillovers	3.667***	1.051*	1.381***	3.878***	1.411**	1.906***
	(1.326)	(0.590)	(0.222)	(1.312)	(0.657)	(0.235)
2005		-0.241	0.0590		0.0680	0.176
		(0.184)	(0.157)		(0.239)	(0.161)
2006	0.561***	0.129	0.621***	0.408*	0.284	0.533***
	(0.181)	(0.307)	(0.149)	(0.224)	(0.356)	(0.166)
2007	0.305	0.209	0.0673	0.613**	0.203	-0.247
	(0.216)	(0.139)	(0.146)	(0.304)	(0.150)	(0.159)
2009	0.463	-0.162	0.193	0.247	-0.110	0.108
	(0.432)	(0.158)	(0.160)	(0.247)	(0.147)	(0.175)
2011		-0.189*	0.145		-0.0943	0.0251
		(0.106)	(0.129)		(0.114)	(0.141)
2013	0.0396	0.00123	-0.122	0.114	-0.0435	0.375***
	(0.180)	(0.0788)	(0.121)	(0.179)	(0.0800)	(0.134)
2016		0.0411	0.339***		0.0638	0.0167
		(0.267)	(0.106)		(0.310)	(0.120)
2018	0.148	-0.0131	0.0355	0.206	-0.0460	-0.161
	(0.196)	(0.0923)	(0.134)	(0.194)	(0.0935)	(0.148)
2017	0.212		0.191	-0.110		0.142
	(0.293)		(0.144)	(0.386)		(0.164)
2019			0.215*			0.0674
			(0.119)			(0.131)
Constant	1.982***	2.942***	2.365***	2.060***	3.004***	2.548***
	(0.667)	(0.244)	(0.105)	(0.618)	(0.280)	(0.118)
Observations	1,192	3,990	3,990	1,236	4,001	4,001
R-squared	0.097	0.023	0.083	0.164	0.024	0.103
Number of Panelid	601	3,398		624	3,403	

Robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

On the other hand, the impact of process innovations on employment is positive in all model specifications and significant for permanent employment for matched and cross-section design samples (see

Table 5.9 in the annex). Like product innovation, process innovations could expand firm-level job opportunities in the context of Africa. This is a remarkable finding given the ambiguity and contentions about the relationship between process innovations and employment, theoretically and empirically.

However, our study's finding is in line with earlier studies documented by Medase and Wyrwich (2021) for Nigerian employment growth; Castillo et al. (2014) for Argentinian firm-level employment, and Zhu et al. (2021) for Chinese firms in that process innovations create more job opportunities. On the other hand, our finding does not support the findings of Álvarez et al. (2011) and Benavente and Lauterbach (2008) for Chile, Gyeke-Dako et al. (2016) for Ghana, De Elejalde et al. (2015) for Argentina stating that process innovations do not have a significant impact on employment. In general, it is clear from the results that firm-level innovations in Africa create more employment than layoffs.

Process innovations have also a positive intra-industry spillover effect on employment while the inter-industry spillover effect is negative in total employment for matched sample. It gives a signal that, potentially, process innovations in one industry might have a negative impact on employment in firms of some other two-digit industry. This result is consistent with Stare and Damijan's (2015) finding for Spain. But, in related empirical literature, Wang et al. (2020) found that internet technology progress promotes within industry and inter-industry employment in China.

5.6 Conclusions and Policy Implications

Nowadays, employment is a burning economic and political issue in Africa and elsewhere in developing economies. Concurrently, it is a recent phenomenon that policy makers in Africa realized that innovation is not something to be sidelined for developing economies instead it is a key to attain stability, growth, and fair income distribution in Africa (see Asongu et al., 2016; Zanello et al., 2016). But Africa spends a very small fraction of GDP on knowledge production–only 0.3 percent of global R&D expenditure–and its export was less than 1.5 percent of the global high- and middle-tech exported products in 2019 (Hamid et al., 2021). Furthermore, the average innovation score index for Africa was 22.4 in 2020 which is below emerging economies' average (Hamid et al., 2021). And yet, advancements in information and communications technology stimulate firm-level innovations in Africa. For instance, Rwanda and Malawi are ranked as 1st and 3rd in the top three innovative countries in the low-income category in 2021 (WIPO, 2021). Thus, in this paper we attempt to investigate whether there is a trade-off between innovations and employment in the African context using a firm-level survey panel data-set for six African countries. We have a total of close to 4,000 firms that are considered for this study while more than 725 firms are on support region are used for our estimation. We apply a two-way fixed effect estimator with matching to identify the impact of innovations on employment. The results indicate that innovations (product and process) have a strong positive impact on firm-level employment in Africa. Broadly speaking, the results confirm that there is no trade-off between innovations and employment in Africa. Firm-level innovations could have a positive intra-industry spillover effect on employment. On the other hand, firm-level innovations in Africa do not have a positive inter-industry spillover effect on employment. Thus, firm-level innovations have a positive spillover effect on firms operating within the same two-digit industry but not in another two-digit industry.

As policy remarks, this study indicates the potential of innovations for employment creation in Africa. Accordingly, policymakers need to promote and provide incentives for firm-level innovations to enhance productivity and expand job opportunities. Policy interventions need to be designed to promote firm-level innovations in a coherent manner throughout the African continent while underscoring the enabling environment of each country. The African Union, specifically the Economic Commission for Africa (ECA), should develop strategies to encourage firm-level innovations in Africa as a mechanism to ease the pressure of youth unemployment in Africa.

In this study, we attempted to exploit the panel nature of the data-set, as recommended by Avenyo et al. (2019), to disentangle the impact of innovations on employment. However, further studies need to be conducted to know the potential impact of innovations on employment in Africa by merging Innovations Survey (IS) and the ES data-set for a long panel. Moreover, the spillover effect of innovations on employment and market share considering the volume of trade within and between industries needs a thorough investigation for developing economies. Due to data constraints, we could not deal with all these issues in detail. However, this study is the first attempt in applying a quasi-experimental approach of using a fixed effect estimator with matching to identify the impact of innovations in the African context, but experimental studies on this issue will give us more reliable and clear information for policy makers. Moreover, firm-level employment might increase or decrease due to firms' entry and exit outside of the panel. Thus, appropriate methodology needs to be designed to deal with this issue while in this study we were unable to control for it.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter presents a synthesis summary of each essay's conclusions and policy recommendations in a compact manner. For the convenience of readers, we preferred to organize conclusions and policy remarks for each essay chronologically. They are presented as follows. For the first essay, we used four waves (2009-2012) of an unbalanced panel data-set composed of the annual census of large and medium scale manufacturing (LMSM) firms of a total of 7349 firms. Four control function estimation methods are applied to estimate TFP. Specifically, OP, LP, WLRDG, and RM estimators were employed. We found that the correlation between WLRDG productivity estimate and RM estimates is more than 98 percent. We opted to drop the WLRDG estimate because it considers a small sample size compared to the RM estimator. We found some evidence of self-selection (exit firms are less productive compared to surviving ones). Hailu et al. (2020) reports that heterogeneity in productivity performance has been observed in the manufacturing sector of Ethiopia. Motor vehicles, basic metals, fabricated metal, and food & beverages have relatively higher labor productivity compared to garment, wood, textiles, furniture, and leather & footwear industrial sub-sectors. The report further highlights labor productivity grew at an annual average of 4.9% between the year 2000 and 2016. Though, the growth trends of labor productivity are highly dispersed. Moreover, Hailu et al.'s (2020) estimated TFP of the manufacturing sector has grown an average of 2.11% per annum over the period from 1996 to 2016.

Our estimation results have indicated that the devaluation of Birr against USD did not enhance the productivity of exporting firms significantly. To conclude, currency devaluation in less-developed countries may not enhance domestic firms' competitiveness, and the long-term impact of devaluation in terms of productivity gains is hardly materialized. As a remark, in a country where domestic firms are highly dependent on foreign intermediate inputs, devaluation is a less effective policy instrument for enhancing domestic firms' competitiveness. Hence, a macroeconomic policy like devaluation is not the right policy approach to raise firm-level productivity in Ethiopia. To gain some dividend out of devaluation, the share of imports needs to be reduced.

The second essay analyzes the relationship between R&D, innovations, and firm-level productivity using two rounds of the World Bank's Enterprise Survey panel data-set for Ethiopia. For this paper, we analyzed information on more than 930 firms to establish the possible impact. The robust finding shows innovations improve firms' productivity while the impact of R&D expenditure on innovations is not strong enough to be significant. In short, innovative firms are more productive compared to less innovative ones. Firm-level innovations (both of products and processes) are determined by the proportion of skilled labor and firm size. As a firm's size increases (in terms of employment), firms are more likely to engage in innovative initiatives. Thus, the Government of Ethiopia needs to design strategies on how to provide incentives and minimize and/or share the risks of firms to support innovative initiatives. In such a strategy, firms' human development through training and education needs to be taken into account. Moreover, the strategy also needs to encompass the improvement of loan accessibility for small innovative firms. Moreover, promoting small businesses to engage in export is another indirect avenue to boost firm-level innovation due to the effect of learning from exporting. This present study, however, used all firm types without disaggregating by size and sector. Thus, the findings of this paper remain valid for all types of firms irrespective of size and sector. On top of this, given the broad sectoral composition of the Ethiopian economy, which is dominated by the service sector, the findings of this study provide pertinent information for countries that have comparable broad sectoral compositions.

The third essay examines the linkage between ICT, innovations, and firm productivity in Ethiopia using a sample of 928 firms. We adopted a similar methodology like for the second paper. The rationale behind this is to verify whether ICT could be a substitute for R&D in regard to enhancing innovations and productivity in the developing economies context. We found that ICT usage enhances the likelihood of both types of innovations–product and process innovations. ICT utilization not only has an indirect impact on productivity through innovation but also a direct impact on productivity. Therefore, Solow's (1987) productivity paradox could be clarified when we introduce innovation as a bridge between ICT and productivity. Thus, ICT's adoption is a viable alternative to R&D for enhancing a firm's propensity to engage in innovative activities in Ethiopia. Firm size, the proportion of skilled labor, share of exports, and corporate status are important factors that explain variation in firms' ICT utilization. This study might provide a theoretical contribution in drawing an alternative line toward innovation. This implies that firm-level innovation in developing countries may not necessarily require internal R&D activities but could be created based on technology adoption. A key role of ICT is the transmission of technological information and technology diffusion. Thus, ICT can be considered an important factor in the input function for innovation. Furthermore, we modelled the relationship between technology diffusion, innovations, and productivity structurally while controlling for the feedback effect of productivity. This is a solid contribution to the empirical literature in establishing this relationship in a developing-country context. This study has two major policy implications. First, in developing countries like Ethiopia, in-house R&D spending is costly and risky for firms. As we have seen above, ICT diffusion by firms has an impact on innovations and firms' competitiveness. Therefore, liberalizing the ICT sector, which is under the monopoly of the Ethiopian government, is an important milestone to promote innovations and enhance productivity. The Ethiopian government has already started opening the ICT sector: see the following link Connecting Africa. Remarkably, the Government of Ethiopia has already commenced liberalization of the ICT sector in a way that encourages firms to invest in ICT infrastructure and related services (Federal Government of Ethiopia, 2019). Second, ICT development is an indispensable element of the strategy that promotes innovations and competitiveness.

Finally, in this thesis we looked at the historically contested issue of the nexus between innovations and employment. Policymakers in Africa realized that innovation is not something to be sidelined for developing economies instead it is a key factor to attain stability, growth, and fair income distribution in Africa (see Asongu et al., 2016; Zanello et al., 2016). But Africa spends a very small fraction of GDP on knowledge production–0.3 percent of global R&D expenditure(Hamid et al., 2021). That said, advancement in information and communications technology stimulates firm-level innovations in Africa. Thus, in this paper we attempted to investigate whether there is a trade-off between innovations and employment in Africa using the firm-level ES panel data-set for six African countries. For this paper, we used a total of close to 4,000 firms while more than 725 firms are on support region and form part of our quasi-experimental analysis. We applied a two-way fixed effect estimator with matching to identify the impact of innovations on employment. The result indicated that innovations (product and process) have a strong positive impact on firm-level employment in Africa. We found no evidence of a trade-off between innovations and employment in Africa. Moreover, firm-level innovations could have a positive intra-industry spillover effect on employment but a negative inter-industry spillover effect.

This study indicates the potential contribution of innovations for employment creation in Africa. Combined with the previous findings, firm-level innovation is like "filling two needs with one deed"– enhance productivity and expand job opportunities. The African Union, specifically the Economic Commission for Africa (ECA), is expected to develop a strategy to encourage firm-level innovations in Africa as a mechanism to ease the pressure of youth unemployment in Africa. In this study, we attempted to exploit the panel nature of the data-set, as recommended by Avenyo et al. (2019), to disentangle the impact of innovations on employment. However, further studies need to be conducted to know the potential impact of innovations on employment in Africa by merging Innovations Survey (IS) and the ES data-set for a long panel. Moreover, the spillover effect of innovations on employment and market share considering the volume of trade within and between industries needs a thorough investigation for developing economies. Due to data constraints, we could not address these issues. This study is the first attempt to employ a quasi-experiment to identify the impact of innovations on employment in the African context. Experimental studies on this issue will give us more reliable and clear information for policymakers. Moreover, the size of firm-level employment might increase or decrease due to firms' entry and exit outside of the panel. Thus, appropriate methodology needs to be designed to deal with this selection issue while in this study we are unable to control for it.

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