

Essays on Firm Behavior and Performance in Ethiopian Manufacturing: Labor Demand, Capital Accumulation and International Linkages

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**Essays on Firm Behavior and Performance in Ethiopian
Manufacturing: Labor Demand, Capital Accumulation, and
International Linkages**

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Declaration

I, **Eyayu Tesfaye Mulugeta**, hereby declare that this dissertation entitled “**Essays on Firm Behavior and Performance in Ethiopian Manufacturing: Labor Demand, Capital Accumulation and International Linkages**”, is my original work and has not been submitted, in whole or in part, for the award of any degree or diploma at this or any other institution. All sources of materials and ideas used in this dissertation have been duly acknowledged.

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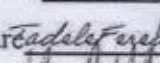
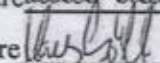
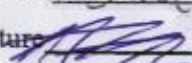
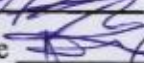
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Approval

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Dedication

To my beloved family, whose unwavering love, support, and encouragement have sustained me throughout this journey. Your patience, sacrifices, and steadfast belief in me have made this achievement possible.

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Acronyms and Abbreviations

CSE	Constant Elasticity of Substitution
CV	Coefficient of Variations
ESS	Ethiopian Statistical Services
FAO	Food and Agriculture Organization
FE	Fixed Effects
GMM	Generalized Methods of Moment
GNR	Gandhi, Navarro, and Rivers
HDFE	High Dimensional Fixed Effects
HHI	Herfindahl-Hirschman Index
ISIC	International Standard for Industrial Classification
LMMIS	Large and Medium Manufacturing Industry Survey
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
SD	Standard Deviations
2SLS	Two-Stage Least Squares
TFP	Total Factor Productivity

Chapter One

1. General Introduction

1.1. Background and Motivation

Understanding the determinants of firm performance is central to promoting economic development, structural transformation, and industrialization in developing countries. Manufacturing firms in Ethiopia operate in complex and often volatile environments, shaped by limited access to high-quality inputs, labor market frictions, and macroeconomic and policy uncertainty. These factors influence productivity, employment, and capital accumulation, with implications for both firm-level outcomes and broader industrial policy (Oqubay, 2015; Rodrik, 2014). Access to imported intermediate inputs has been recognized as a key channel for enhancing firm-level productivity. Imported inputs can improve product quality, stimulate innovation, and expand production capabilities (Bas & Strauss-Kahn, 2014; Bloom et al., 2016; De Loecker, 2011; Goldberg et al., 2010).

Empirical evidence shows that firms in low- and middle-income countries gain from high-quality imported inputs, which enhance output variety, foster technological adoption, and improve productivity (Halpern et al., 2015; Pane & Patunru, 2023). However, the benefits of imported inputs vary across firms, and ownership structure, particularly foreign ownership, can mediate this relationship. Foreign-owned firms often have superior access to high-quality inputs, managerial expertise, and international markets, enabling them to derive greater benefits from imported intermediates (Bykova & Lopez-Iturriaga, 2018; Caves, 1974; Dunning, 2015). Despite a growing literature on trade and productivity, evidence on the complementary role of foreign ownership in low-income countries remains limited, particularly in Ethiopia, where manufacturing firms are heavily reliant on imports and foreign direct investment has steadily increased over time (Abreha, 2019; Abebe et al., 2022; Asturias et al., 2021).

Labor market dynamics add another layer of complexity to firm performance. In Ethiopia, manufacturing firms face challenges such as skill mismatches, high turnover, and gaps between wages and productivity, which affects the adjustment of employment to changing economic conditions (Gebreeyesus et al., 2020; Halvorsen, 2021). Accurate estimation of labor demand is

essential for designing effective employment policies, including wage regulations, training programs, and targeted incentives. Static labor demand models often fail to capture firm-level adjustment dynamics, particularly in contexts characterized by high turnover (Falk & Koebel, 2001; Hamermesh & Pfann, 1996; Oi, 1962). Understanding how firms adjust their demand for different types of labor is central to both labor economics and development policy. However, much of the empirical literature treats labor as homogeneous or imposes restrictive assumptions on adjustment costs. The dynamic framework employed in this paper, which accounts for adjustment costs and labor heterogeneity, provides a more realistic understanding of how Ethiopian firms respond to shocks in wages and other economic factors (Haile et al., 2017).

Overlaying these dynamics is a pervasive layer of uncertainty. Firm-specific uncertainty affects investment decisions and capital accumulation, particularly in developing countries with underdeveloped financial markets and high adjustment costs (Alfaro et al., 2024; Arellano et al., 2019; Bloom et al., 2007; Dixit & Pindyck, 1994). While short-term investment responses to uncertainty have been studied extensively, evidence on the long-term effects of uncertainty on capital accumulation remains limited, especially in low-income countries. Firms may respond nonlinearly to uncertainty, with moderate uncertainty encouraging investment, but high uncertainty leading to delayed or reduced capital accumulation (Abel & Eberly, 1999; Bo & Lensink, 2005). In Ethiopia, medium and large manufacturing firms, which are critical for industrialization and employment creation, face persistent macroeconomic volatility, policy unpredictability, and limited access to secondary markets, all of which amplify firm-specific uncertainty. These conditions make understanding the impact of uncertainty on long-term capital accumulation particularly relevant for policymakers seeking to promote investment, industrial growth, and structural transformation (Asturias et al., 2021; Dinh et al., 2012; Shiferaw, 2009).

In addition to its theoretical contribution, this study is strongly motivated by its policy relevance and developmental urgency. Ethiopia has placed industrialization, foreign direct investment attraction, and export-led manufacturing at the center of its growth strategy, yet the effectiveness of these policies depends critically on how firms respond to imported input constraints, labor costs, and uncertainty. Despite the growing global literature, Sub-Saharan Africa remains underrepresented in firm-level studies, making Ethiopia a particularly valuable empirical setting due to its reliance on imported inputs, the expanding role of foreign direct investment, persistent

labor turnover in manufacturing, and the prevalence of firm-level uncertainty, all of which are central to understanding productivity, employment, and investment dynamics in developing-country manufacturing. By linking firm-level dynamics in productivity, employment, and capital accumulation to broader goals of job creation, structural transformation, and integration into global value chains, this study contributes to microeconomic analysis and long-term development strategy, highlighting its broader significance.

Collectively, the interplay of imported inputs, foreign ownership, labor demand, and firm-specific uncertainty shapes productivity, employment, and investment behavior in Ethiopian manufacturing firms. These interrelated dimensions are explored in detail across the three interrelated papers that constitute this dissertation, providing the foundation for analyzing firm behavior and informing policies that enhance productivity, employment, and industrial development.

1.2. Objectives and Research Questions

This dissertation investigates the key drivers of firm performance in Ethiopia's manufacturing sector, focusing on three interrelated dimensions: productivity, labor demand, and capital accumulation under uncertainty. These dimensions address both theoretical gaps and pressing policy concerns in low-income country contexts.

Objectives

The dissertation specifically aims to:

1. Assess the impact of imported intermediate inputs on firm-level productivity and the complementary role of foreign ownership.
2. Examine firm-level labor demand for production and non-production workers using a dynamic framework that accounts for adjustment costs and labor market frictions.
3. Evaluate the effect of firm-specific uncertainty on capital accumulation, including potential nonlinear relationships.

Research Questions

Corresponding to these objectives, the dissertation addresses the following questions:

1. How does the use of imported intermediate inputs influence firm-level productivity, and to what extent does foreign ownership complement this effect?
2. How do Ethiopian manufacturing firms adjust their demand for production and non-production workers in response to wage changes and other economic factors, considering adjustment costs and labor market frictions?
3. How does firm-specific uncertainty affect capital accumulation, and does this relationship exhibit nonlinear patterns?

Together, these objectives and research questions provide a coherent framework for understanding how trade, ownership structure, labor dynamics, and uncertainty interact to shape firm performance. The insights generated have important implications for industrial policy and structural transformation in Ethiopia and other low-income economies.

These questions are addressed in three self-contained yet thematically connected empirical papers

1.3. Overview of the Three Papers

This dissertation is structured around three interrelated empirical papers that collectively explore the determinants of firm performance in Ethiopia's manufacturing sector, focusing on productivity, labor demand, and capital accumulation under uncertainty. Each paper addresses a distinct but complementary research question, contributing to a broader understanding of the challenges and opportunities faced by firms in a low-income country context.

Paper 1: Imported Inputs and Firm Productivity: Does Foreign Ownership Matter?

The first paper examines the role of imported inputs in enhancing firm-level productivity and considers the extent to which foreign ownership amplifies this effect. Drawing on firm-level panel data, the analysis demonstrates that access to imported inputs is positively associated with productivity, reflecting the higher quality and technological content of foreign-sourced inputs. Moreover, the paper highlights that foreign-owned firms are better positioned to capitalize on these gains, given their superior access to international networks, managerial know-how, and credit markets. These findings underscore the importance of trade openness and foreign investment for

productivity growth in Ethiopian manufacturing.

Paper 2: Estimating Labor Demand Using Dynamic Framework: Evidence from Manufacturing Firms in Ethiopia

The second paper investigates firm-level labor demand in Ethiopian manufacturing, focusing on both production and non-production workers within a dynamic framework that accounts for adjustment costs. Accurate measurement of labor demand is critical for policy design, particularly in low-income countries like Ethiopia, where job creation is a key development objective and labor markets are characterized by high turnover, skill mismatches, and wage–productivity gaps. The empirical findings show that firms adjust employment relatively quickly, suggesting moderate adjustment costs. Own-wage elasticities are larger for production than for non-production workers, consistent with theory on substitutability and labor flexibility. We also find positive cross-wage elasticities, implying substantial interdependence between labor types. By highlighting these dynamics, the paper contributes to understanding how firms balance efficiency and flexibility in the face of wage fluctuations and structural transformation.

Paper 3: Idiosyncratic Uncertainty and Capital Accumulation: Evidence from Manufacturing Firms in Ethiopia

The third paper shifts the focus to the relationship between firm-specific uncertainty and capital accumulation. While most existing studies emphasize short-term investment flows, this paper adopts a longer-term perspective by examining how uncertainty influences firms' ability and willingness to build capital stock. Employing Ordinary Least Squares estimation with multiple proxies for uncertainty, the analysis reveals a nonlinear, inverted U-shaped relationship: capital accumulation initially increases with moderate uncertainty but declines once uncertainty crosses a critical threshold which is in line with the real options theory. This pattern reflects firms' risk-taking behavior under manageable uncertainty and their tendency to delay investment when uncertainty becomes excessive. The results provide evidence that firm-specific uncertainty exerts persistent effects on productive capacity, with important implications for investment and industrialization strategies in volatile environments.

Together, these three papers contribute new insights into the microeconomic foundations of productivity growth, labor adjustment, and capital accumulation in Ethiopian manufacturing. By examining imported inputs, labor demand, and uncertainty through rigorous empirical methods and rich firm-level data, the dissertation not only advances the academic literature but also generates evidence directly relevant to policy debates on trade integration, labor market reform, and industrial development in low-income countries.

1.4. Methodology and Data

1.4.1. Data Description

This dissertation utilizes firm-level data from the Large and Medium Manufacturing Industries Survey (LMMIS), an annual census conducted by the Ethiopian Statistical Services (ESS), covering the period 1996–2016. The census encompasses both public and private establishments across all regions of Ethiopia, limited to large and medium-scale firms employing at least ten workers and using electricity in production. Firms included in the survey account for approximately 50% of total manufacturing employment and over 70% of sectoral value added, including informal manufacturing activities (Asturias et al., 2021). The panel includes both continuous incumbent firms and firms that entered or exited during the census period. The survey provides rich firm-level information on production, employment, wages, inputs, investment, ownership, and financial characteristics. Importantly, it allows for consistent measurement of imported intermediates, worker composition (production versus non-production), and capital stock, which are central to the three papers. The panel structure of the data enables the estimation of dynamic relationships. This dataset has been widely used in studies focusing on firm performance, firm entry and survival, Africa’s manufacturing puzzle, and Ethiopia’s productivity report most of which are published in reputable journal.

1.4.2. Methodological Approach

This dissertation employs a combination of advanced econometric techniques and firm-level panel data covering the period 1996–2016 to address the research questions rigorously. For the analysis of productivity, the study applies the Gandhi, Navarro, and Rivers (2020) estimator and a system Generalized Method of Moments (GMM) approach (Blundell & Bond, 1998) to estimate production functions and productivity effects. These methods allow for precise measurement of

output elasticities and the interaction between imported inputs and ownership structure while addressing potential endogeneity and selection biases.

For labor demand, this paper employs a dynamic framework that distinguishes between production and non-production workers. Using a System-GMM estimation strategy, it captures firms' responses to wages and other economic factors under conditions of labor market frictions and high turnover. Long-run labor demand elasticities are then derived from the short-run estimates.

To investigate the impact of firm-specific uncertainty on capital accumulation, Ordinary Least Squares (OLS) regression is applied to time-averaged cross-sectional firm-level data, complemented by multiple backward-looking proxies for uncertainty. The analysis explicitly tests for nonlinear effects, including inverted U-shaped relationships, consistent with the real options framework. This methodology captures the cumulative effects of uncertainty on capital formation while accounting for firm heterogeneity and sectoral characteristics.

Together, these methodological strategies combine structural estimation, dynamic panel modeling, and nonlinear capital investment analysis, leveraging rich firm-level data to generate robust insights into the determinants of productivity, labor demand, and capital accumulation in Ethiopian manufacturing. By integrating multiple dimensions of firm behavior within a single empirical framework, the dissertation provides internationally comparable, policy-relevant evidence on how low-income country firms respond to trade integration, labor market dynamics, and economic uncertainty.

1.5. Contributions of the Papers

This dissertation makes several contributions to the literature on firm dynamics, trade, labor markets, and investment in developing economies, with a particular focus on Ethiopia's manufacturing sector.

First, it contributes to the literature on trade and productivity by highlighting the complementary role of ownership structure in shaping the productivity effects of imported inputs. While previous studies emphasize the importance of imported intermediates for technological upgrading and efficiency gains, this dissertation shows that foreign ownership substantially magnifies these effects, reflecting differences in absorptive capacity and access to global knowledge networks.

This finding advances the “learning by importing” hypothesis by situating it in the context of low-income countries, where ownership heterogeneity is particularly salient.

Second, this dissertation contributes to the literature on labor demand in developing countries by applying a dynamic framework to firm-level panel data and distinguishing between production and non-production tasks. While applied to Ethiopia, the framework is broadly applicable and provides a foundation for future research on labor market dynamics in other contexts. The empirical results yield robust estimates of both short- and long-run labor demand elasticities and quantify the role of adjustment costs. By providing precise evidence from Ethiopia’s manufacturing sector, the study enhances understanding of how firms adjust employment in environments characterized by high turnover, skill mismatches, and wage–productivity gaps. These findings are particularly relevant for designing effective labor policies in economies undergoing structural transformation.

Third, the dissertation extends the literature on uncertainty and investment by examining how firm-specific idiosyncratic uncertainty shapes long-term capital accumulation. Unlike most existing studies that focus on aggregate or macroeconomic uncertainty, this study employs firm-level indicators and provides evidence of a nonlinear (inverted U-shaped) relationship between uncertainty and capital formation. This result deepens the understanding of investment behavior under irreversibility and adjustment costs, showing that moderate uncertainty can stimulate risk-taking and capital accumulation, while excessive uncertainty deters investment.

Taken together, the three papers provide a comprehensive account of how Ethiopian manufacturing firms respond to trade integration, labor market frictions, and uncertainty. The findings contribute to academic debates on productivity, labor dynamics, and investment under risk, while also offering actionable insights for policymakers concerned with industrial development, job creation, and economic resilience in low-income countries.

1.6. Structure of the Dissertation

This dissertation follows an article-based format, with each empirical chapter designed as a self-contained paper. Together, the chapters address different but interrelated aspects of firm performance in Ethiopian manufacturing. The structure is as follows:

Chapter 1: General Introduction

Chapter 2: Imported Inputs and Firm Productivity: Does Foreign Ownership Matter?

Chapter 3: Estimating Labor Demand Using Dynamic Framework: Evidence from Manufacturing Firms in Ethiopia

Chapter 4: Idiosyncratic Uncertainty and Capital Accumulation: Evidence from Manufacturing Firms in Ethiopia

Chapter 5: General Conclusion and Policy Implications

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Chapter Two

2. Imported Inputs and Firm Productivity: Does Foreign Ownership Matter?

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Abstract

This paper provides evidence on whether the relationship between imported inputs and productivity in Ethiopia depends on foreign ownership. The study uses a nationally representative firm-level unbalanced panel dataset for the period 1996–2016. Methodologically, this paper adopts two complementary empirical approaches: the Gandhi, Navarro, and Rivers (2020; henceforth GNR) two-step approach for estimating the gross output production function, and the System GMM approach for estimating the gross output production function. Our results indicate that the use of imported inputs enhances productivity among manufacturing firms with foreign ownership. For domestically owned firms, the effect of imported inputs is relatively small and marginally significant. We thus find evidence that foreign-owned firms have a premium in terms of productivity gains from the use of imported inputs, compared to domestically owned firms. Our results suggest that reducing trade barriers for imported inputs will benefit foreign-owned firms more than domestically owned firms.

JEL codes: D22, D24, F14, F61, L60, O12

Keywords: Trade, Imported Inputs, Foreign Ownership, Firm Productivity, GNR, translog, Ethiopia

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2.1. Introduction

International trade has been declared as one of the most important ways to improve firm-level productivity. From a theoretical perspective, several channels explain the positive effect of trade on productivity growth, one of which is the increased availability of a broader range of imported inputs. According to Bloom et al. (2016) and De Loecker (2011), better access to imported intermediate inputs can promote innovation, reward technological adoption, and increase productivity. Additionally, the use of imported inputs significantly influences important firm-level outcomes like product range (Goldberg et al., 2010) and exports (Bas and Strauss-Kahn, 2014). A number of empirical studies have examined the effect of importing on firm productivity. Studies by Abreha (2019), Amiti and Konings (2007), DAVIS and Milgram-Baleix (2009), Forlani (2017), Halpern et al. (2015), Kasahara and Rodrigue (2008), Luqman and Murtaza (2023), Lööf and Andersson (2010), Pane and Patunru (2023), and Smeets and Warzynski (2013) revealed evidence of productivity gains from importing. In contrast, Muendler (2004), Van Biesebroeck (2008), and Vogel and Wagner (2010) found weak evidence for the claim that importing enhances productivity.

The mixed empirical findings are partly attributable to methodological choices or inherent differences in the nature of the import–productivity nexus across countries and over time (Abreha, 2019). In addition, previous empirical studies often do not simultaneously consider the role of complementary factors such as ownership structure in the underlying relationship. Failure to account for such factors may lead to biased estimates and potentially incomplete or misleading conclusions (Okafor, 2021; Muris & Wacker, 2022).

Foreign ownership affects firm productivity both directly and indirectly through channels such as firm size, age, and trade activity (Webster et al., 2022; Yang & Tsou, 2020; Javorcik & Poelhekke, 2017; Teng et al., 2021; Xu et al., 2022). Consistent with theory, foreign-owned firms tend to be more productive than domestically owned firms do (Le et al., 2019; Ullah et al., 2014; Wang & Wang, 2015). Foreign investors' superior technology, marketing networks, and resource allocation capabilities explain these differential performance outcomes (Caves, 1974; Dunning, 1980; Lemi & Wright, 2020). Furthermore, compared to domestically owned firms, foreign-owned firms are more productive partly because they utilize high-quality foreign inputs in their production processes. These firms may benefit more from import spending, as they are familiar

with foreign markets and have access to more affordable or efficient suppliers (Halpern et al., 2015). Accordingly, one significant factor complementary link between trade and productivity is foreign ownership (Bykova and Lopez-Iturraea, 2018). However, the complementary role of ownership status in the import-productivity nexus hitherto relatively remained scantily explored.

Manufacturing firms in Ethiopia represent an informative case study for this purpose due to their high reliance on imported inputs and the steady inflow of foreign direct investment into the sector over time (Abebe et al., 2022; Abreha, 2019). Over the past two decades, the manufacturing sector has received a substantial amount of foreign direct investment (FDI), largely due to generous government incentives such as tax exemptions offered to foreign investors. Following the rise in FDI inflows, foreign-owned firms accounted for more than 21% of manufacturing value added by 2016 (up from 5.6% in 1996) and more than 13% of employment (up from just under 1% in 1996) (Asturias et al., 2021).

According to the Central Statistics Agency (1996–2016), on average, 95% of foreign-owned firms and more than 60% of domestically owned manufacturing firms rely on imported inputs. In contrast, only 6% of manufacturing firms in Ethiopia export their products. Hence, the integration of Ethiopia's manufacturing sector with the rest of the world is primarily through imports. Viewed through this lens, Moller and Wacker (2017) argued that an overvalued exchange rate contributed to economic growth in Ethiopia by making imported inputs relatively cheaper. Despite the significant role of imports in the economy in general—and for manufacturing firms in particular—most of the literature on Ethiopian firms has focused on the export side (Bigsten & Gebreeyesus, 2009; Esmaille, 2018; Shiferaw & Söderbom, 2018; Siba & Gebreeyesus, 2016).

Ethiopia's concentration of trade with high-income countries makes imported technology, as opposed to research and development spending, potentially the key source of stimulating productivity (Abreha, 2019). Even though imported inputs are essential to a firm's productivity, empirical evidence on manufacturing firms in Ethiopia is scant. In this study, we examine the effect of imported inputs on firm productivity and the complementary role of foreign ownership in the underlying relationship. This is motivated by a sense that firms with foreign ownership may be in a better position to benefit from imported inputs than firms that are fully domestically owned. Such an advantage may arise because firms with foreign ownership are more familiar

with international markets and have better access to low-cost and/or high-quality input suppliers there. It could also be that firms with foreign ownership have a relatively stronger absorptive capacity, enabling them to use imported inputs more productively than domestically owned firms.

Several studies in the literature show that having access to high-quality inputs allows firms to improve the quality of their output (Kugler & Verhoogen, 2012; Pane & Patunru, 2023) and upgrade their export products (Bas & Strauss-Kahn, 2015; Fan et al., 2018; Kugler & Verhoogen, 2012; Hallak & Sivadasan, 2013). Furthermore, empirical evidence also shows that high quality imported inputs and firm characteristics complement each other and have an impact on output quality. For instance, Bas and Paunov (2021) and Fieler et al. (2018) find evidence that imported input quality and firms' skill composition jointly boost firms' output quality. There is also some empirical evidence for high and middle-income countries that foreign-owned firms are more productive because they use high-quality foreign inputs in their production process (e.g., Halpern et al., 2015; Bykova & López-Iturriaga, 2018).

However, the complementary role of ownership status in the import–productivity nexus remains largely unexplored in low-income countries. In our empirical analysis, we distinguish two roles of intermediate inputs: we consider that total intermediates are the relevant inputs for total production, while the share of imported intermediates in total intermediates is a potential productivity shifter. This distinction is motivated by the idea that imported inputs may have a different effect on output compared to domestic intermediates. Moreover, we allow the effect of imported inputs to vary with ownership.

While there is a considerable body of evidence on the relationship between imported inputs and productivity in developed countries (e.g., Halpern et al., 2015), much less is known about this connection for low-income countries. Our paper thus contributes to the existing international trade literature by examining the complementary role of foreign ownership in the import-productivity nexus in a developing country context. Indeed, there is a dearth of empirical studies investigating the import-productivity nexus for African manufacturing firms, partly due to the unavailability of data (Aberha, 2019), so we fill a gap in the empirical literature.

We use two distinct approaches for our empirical analysis. Our first approach uses the estimation framework developed by Gandhi, Navarro, and Rivers (2020; henceforth GNR) for estimating

the gross output production function and subsequently productivity. Results from the GNR estimator imply output elasticities that are quite reasonable and precisely estimated. In a second step, estimated productivity is regressed on a set of firm variables including foreign ownership, imported inputs, and the interaction between these two variables. The OLS estimates suggest that increasing the fraction of use of imported intermediates by a firm from 0 to 100% would increase the productivity of domestically owned firms and foreign owned firms by 2.8% and 10.3% respectively. However, a potential weakness of estimating the parameters in two stages is that the results may be biased if the covariates of productivity are correlated with the instruments that are used to identify the production function. To investigate if this is a serious problem in our application, we also obtain results from a system GMM estimator (Blundell and Bond, 1998) of a gross output production function, where the production function parameters and the effects of foreign ownership and imported inputs are estimated in a single step. Using a relatively flexible functional form (translog) to approximate the production function, we obtain results indicating that if the use of imported intermediates increases from 0 to 100%, productivity would rise by 4% for domestically owned firms and by 13 % for firms with foreign ownership. Hence, the results from our two approaches are similar, which is reassuring.

Our results support the hypothesis that firms learn by importing, which is consistent with existing evidence from developing countries (see Okafor, 2021, on Ghana; Edwards et al., 2020, on South Africa). Previous studies in this literature find a positive effect of international sourcing on productivity growth. This effect operates through several channels: variety effects from an expanded set of available inputs (Bas & Strauss-Kahn, 2014; Elliott et al., 2016; Halpern et al., 2015); quality-ladder effects from higher-quality imports (Halpern et al., 2015; Zhong, 2023); and learning from superior foreign technologies embodied in imported inputs (Pane & Patunru, 2023; Mo et al., 2021; Zhong, 2023). The results also suggest that foreign ownership plays a significant role in shaping the effect of imported intermediates on firm productivity. The superior performance of foreign-owned firms reflects their use of high-quality foreign inputs, greater knowledge of foreign markets, and access to cheaper suppliers abroad relative to domestically owned firms (Halpern et al., 2015). Overall, our results suggest that foreign ownership magnifies the effect of trade on productivity, which is in line with theoretical and empirical intuition (see, for example, Halpern et al., 2015; Bykova & López-Iturriaga, 2018).

The remainder of the paper is organized as follows. Section 2 presents our empirical approach, including the identification strategy and estimation procedures. Section 3 presents the data and descriptive statistics, Section 4 reports the empirical results, and Section 5 concludes

2.2. Empirical Approach

Our analysis of the relationship between productivity and imported inputs is based on a three-factor gross output production function of the following form,

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + v_{it} \text{ --- (1)}$$

where y_{it} denotes log gross output, k_{it} is log physical capital (e.g. machines and equipment), l_{it} is log labor, m_{it} denotes log intermediate inputs (henceforth “intermediates”), f is a production function, v_{it} represents total factor productivity (TFP), and i, t are firm and time indices, respectively. The main purpose of this paper is to provide evidence on whether the relationship between imported intermediates and productivity depends on foreign ownership. We thus distinguish two roles of intermediate inputs: we consider total intermediates the relevant input in the production function f , while the share of imported intermediates in total intermediates is a potential productivity shifter. This distinction is motivated by the idea that imported inputs may have a different effect on output compared to domestic intermediates.³ Next, we discuss our methods for estimating the production function f .

2.2.1. The Gandhi, Navarro and Rivers (GNR) Approach

Building on earlier work by e.g., Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2020; henceforth GNR) develop a sequential approach for estimating the gross output production function. Productivity v_{it} is decomposed into a potentially persistent term ω_{it} , which is known to the firm at time t , and a serially uncorrelated ‘ex post’ productivity shock ε_{it} which is realized after all input decisions for time t have been made:

$$v_{it} = \omega_{it} + \varepsilon_{it} \text{ --- (2)}$$

³ An alternative approach could be to break up total intermediate inputs into domestic and imported intermediates and enter these as separate inputs in the production function. However, given that a substantial share of firms in our dataset have zero imported intermediates (and some firms have zero domestic intermediates), for a logarithmic production function of the form in equation (1) such an approach would be somewhat awkward.

An important theoretical distinction underlying this approach is made between inputs that are fully flexible and inputs that are not.⁴ Following GNR, we assume that intermediates is a flexible input, while labor and capital are not. Assumed that firms are price takers in output and intermediate-input markets, the demand for intermediates m_{it} is specified as

$$m_{it} = M(k_{it}, l_{it}, \omega_{it}) \text{ --- --- (3)}$$

Where the demand function M is strictly monotonic in ω_{it} . Exploiting the firm's first-order condition for intermediate inputs, GNR show that the production elasticity with respect to intermediate inputs $\frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it})$, is closely related to the (observable) share of expenditures on intermediate inputs in total revenues. Based on this insight, GNR propose estimating $\frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it})$ from a of non-linear least squares regression, where the log of the revenue share of intermediate inputs is expressed as a non-linear function of the inputs k_{it}, l_{it}, m_{it} .⁵ Next, define

$$y_{it} \equiv \psi_{it} - \varepsilon_{it} - \int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it}. \text{ --- --- (4)}$$

Note that y_{it} is equal to log output minus the ex-post productivity shock and the contribution of intermediates, where the latter two terms derive from the share equation. By the fundamental theorem of calculus, $\int \frac{\partial}{\partial m_{it}} f(k_{it}, l_{it}, m_{it}) dm_{it} = f(k_{it}, l_{it}, m_{it}) + C(k_{it}, l_{it})$, where C is a function. Hence, (4) can be developed into the following expression:

$$y_{it} = -C(k_{it}, l_{it}) + \omega_{it}. \text{ --- --- (5)}$$

Persistent productivity is expressed as $\omega_{it} = h(\omega_{i,t-1}) + \eta_{it}$, where η_{it} is a productivity innovation and h is a function.⁶ This implies that (5) can be developed into the following expression

⁴ Inputs that are subject to adjustment costs will be non-flexible inputs in the GNR framework.

⁵ Further details regarding this estimation step are provided in Section IV in Gandhi, Navarro and Rivers (2020), see especially equations (12)-(14).

⁶ See Section II in GNR for details.

$$y_{it} = -C(k_{it}, l_{it}) + h(y_{i,t-1} + C(k_{i,t-1}, l_{i,t-1})) + \eta_{it} \text{ --- (6)}$$

Using a second order polynomial to approximate C , and expressing $h(\omega_{i,t-1}) = \sum_{j=1}^3 h_j \omega_{i,t-1}^j$, we develop (6) into an equation that we can use for estimating the capital and labor elasticities. Following GNR, we assume that the firm's decision on capital and labor for period t is made in period $t-1$, i.e., before the realization of η_{it} . This assumption implies that moments of the form $E(\eta_{it} k_{it}^a l_{it}^b) = 0$, $a = 0,1,2, b = 0,1,2$, identify the capital and labor elasticities. These elasticities can thus be estimated by means of generalized methods of moments (GMM).⁷ Finally, based on the production function estimates, we can estimate persistent productivity as

$$\hat{\omega}_{it} = \hat{y}_{it} + C(\widehat{k_{it}, l_{it}}). \text{ --- (7)}$$

We proceed by investigating how imported inputs and foreign ownership are related to productivity. As noted by several authors, one should be cautious in interpreting results from regressions of estimated productivity on firm characteristics. Estimated productivity is the production function residual, so if the covariates of productivity are also correlated with the instruments that are used to identify the production function, the results will be biased. It may be possible to address this problem by extending the GNR estimator to allow for the inclusion of a (potentially large) set of firm characteristics, but we leave this task for future research. Instead, we report results from a simple OLS regression, while acknowledging that these estimates could be biased.

2.2.2. The System GMM Approach

Our second empirical approach is to use a system GMM estimator proposed by Blundell and Bond (1998) to estimate the production function parameters and the effects of foreign ownership and imported inputs on productivity in a single step. We specify the production function as translog, augmented with a vector of firm characteristics x_{it} , a firm fixed effect u_i and time effects τ_t :

⁷ We obtain GMM estimates using the Stata ado program "gmm_prod", which is part of the Supplemental Material made available by Gandhi, Navarro and Rivers (2020). This program estimates the parameters of the h function from a regression of ω_{it} on $\omega_{i,t-1}$, $\omega_{i,t-1}^2$, and $\omega_{i,t-1}^3$.

$$y_{it} = \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + \beta_{KK} k_{it}^2 + \beta_{LL} l_{it}^2 + \beta_{MM} m_{it}^2 + \beta_{KL} k_{it} l_{it} + \beta_{KM} k_{it} m_{it} + \beta_{LM} l_{it} m_{it} + \rho y_{i,t-1} + x_{it} \theta + u_i + \tau_t + \epsilon_{it}, \quad (8)$$

Where the terms ϵ_{it} and u_i denote time varying, and time invariant, unobserved productivity respectively.⁸ The term $x_{it} \theta$ captures effects of observable variables on output, conditional on inputs. Therefore $x_{it} \theta$ is interpretable as the observable determinants of productivity, and includes ownership, imported inputs and their interaction, as well as some additional variables (see below).

The system GMM approach involves combining the levels equation (8) with a first-differenced version of the equation to form a system of two equations, and using different instruments for the two different equations (Blundell and Bond, 1998). Capital, labor and intermediates expressed in levels are potentially correlated with the fixed effect u_i , but differences of these inputs are assumed uncorrelated with u_i . Hence, we use differenced inputs as instruments for the levels equation. The differenced equation does not contain the fixed effect u_i , so lagged levels of inputs are potential instruments for the differenced equation. We allow intermediate inputs m_{it} (and all terms on the right-hand side of (8) that contain m_{it}) to be correlated with the unobserved productivity shock ϵ_{it} . Capital and labor, on the other hand, are assumed uncorrelated with ϵ_{it} , although they are potentially correlated with $\epsilon_{i,t-1}$. These assumptions are similar to those underlying the GNR estimator, i.e. intermediates is “endogenous” while capital and labor are “predetermined”. Consequently, we use as instruments for the first-differenced equation one period lags of $k_{it}, l_{it}, k_{it}^2, l_{it}^2$ and $k_{it} l_{it}$, and two period lags of $m_{it}, m_{it}^2, k_{it} m_{it}$ and $l_{it} m_{it}$; while for the levels equation we use as instruments contemporaneous values of $\Delta k_{it}, \Delta l_{it}, \Delta k_{it}^2, \Delta l_{it}^2$ and $\Delta k_{it} l_{it}$, and one period lags of $\Delta m_{it}, \Delta m_{it}^2$ and $\Delta k_{it} m_{it}, \Delta l_{it} m_{it}$. Additional moment conditions are of course required to identify the parameters associated with the x_{it} vector and the time effects, an issue to which we return below.

The approach just described differs from that proposed by GNR in terms of functional form and theoretical underpinnings, and some remarks on these differences are in order at this point. First, the GNR estimator specifies persistent productivity as a non-linear first-order Markov process, while in our translog specification the dynamics in the error term ϵ_{it} are left unspecified. Of course,

⁸ Alternative interpretations are also possible, e.g. ϵ_{it} may reflect output measurement errors.

serial correlation in ϵ_{it} would undermine the credibility of our identification strategy of the translog model (lagged inputs would not be credible instruments). We address this potential concern in two ways: we include a lagged dependent variable in the translog specification, which should capture at least some of the serial correlation in unobservable factors (if there is any), and we test for serial correlation following estimation. Second, our translog model includes firm fixed effects while the GNR estimator does not. It is not obvious how to extend the GNR framework to allow for fixed effects while still modeling persistent productivity as a non-linear Markov process.⁹

Third, while the assumption that intermediate inputs is a flexible input is central for the GNR framework, this assumption is not necessary for identification of the translog model. On the other hand, the latter model would be under-identified if intermediates are a flexible input and the intermediate-input price is constant across firms (Bond and Söderbom, 2005; Akerberg, Caves and Frazer, 2015). Tests for under-identification can shed some light on whether this is a concern. Rather than attempting to establish which of the two methods described above is preferable, we take the view that they are in some sense complementary in our analysis. If results on the relationship between foreign ownership, imported inputs and productivity are reasonably invariant to our choice of estimator, we would be more confident that our results are robust.

2.2.3. Productivity, imported inputs and foreign ownership

We now turn to the relationship between productivity and imported inputs, and the role of foreign ownership. We express productivity as a linear function of import intensity (denoted *Import_intensity*), foreign ownership (*Foreign*), and their interaction (*Import_intensity* x *Foreign*). For domestically owned firms the effect of imported inputs is thus given by the parameter on *Import_intensity*, while for firms with foreign ownership it is given by the parameter on *Import_intensity* plus the parameter on the interaction term *Import_intensity* x *Foreign*. *Import_intensity* is import intensity measured by the ratio of the real value of imported inputs to the value of total intermediate inputs.¹⁰ In the empirical analysis, we use the lag of import intensity throughout. The foreign ownership variable is a dummy, where a firm is categorized as foreign-

⁹ Gandhi, Navarro and Rivers (2020) show how to extend their estimator to allow for fixed effects if persistent productivity is modelled as a *linear* Markov process.

¹⁰ The total intermediate inputs are the sum of raw materials, energy, and services.

owned if the share of initial paid-up capital to total capital exceeds 10%.¹¹ Additional covariates of productivity include a proxy for labor quality or absorptive capacity (*Skill_intensity*), firm age (*Firm_age*), location in the capital city Addis Ababa (*Capital_city*). Location is a dummy variable that takes the value 1 if the firm is located in the capital city, and 0 otherwise. *Skill_intensity* is defined as the share of wage bill for non-production workers in the firm's total wage bill. This variable is included to capture the effect of labor quality (Aberha, 2019; Fox & Smeets, 2011). This is motivated by the findings of Fox and Smeets (2011), who show that wages potentially capture the quality of workers used in the production process. Okafor (2021) argued that firms with a higher level of absorptive capacity are potentially closer to the technology frontier and, thus, better placed to assimilate technology spillovers from the use of imported inputs. For GNR-based productivity, we add controls for time and industry (such effects are controlled for directly in the translog specification).¹²

2.3. Data and Descriptive Statistics

2.3.1. Data Description

This paper utilizes firm-level data from the Large and Medium Manufacturing Industries Survey (LMMIS), an annual census conducted by the Ethiopian Statistical Services (ESS), covering the period 1996–2016. The census encompasses both public and private establishments across all regions of Ethiopia, limited to large and medium-scale firms employing at least ten workers and using electricity in production. Firms included in the survey account for approximately 50% of total manufacturing employment and over 70% of sectoral value added, including informal manufacturing activities (Asturias et al., 2021). The dataset provides comprehensive firm-level information, including output, employment, domestic and export sales (both value and quantity), location, ownership type, and wages. It allows identification of the value and quantity of raw materials used, distinguishing between domestic and imported sources, and their share in total firm

¹¹ Our dataset has information on the paid-up capital contribution of Ethiopians and non-Ethiopians, which is important to define the ownership status of the firm. A foreign investor who directly owns at least 10% of the shares of a firm is said to have influence ownership. Having greater than 50 percent share for control ownership and 100 percent share for ultimate ownership (Broniatowska & Strawiński, 2021). Although the rate of foreign share ownership in a firm consists of several thresholds, this study refers to the 10 percent threshold, which is a standard threshold used in the literature to denote foreign owned (Alfaro and Chauvin, 2020; Broniatowska & Strawiński, 2021; OECD, 2008; Javorcik & Poelhekke, 2017). Per OECD guidelines, an equity-based investment with greater than 10% holding by a foreigner investor is the minimum requirement to qualify as foreign-owned (Dayan et al., 2023).

¹² Note that the translog specification controls for firm fixed effects, which encompass industry fixed effects.

expenditure. Additionally, the survey includes information on the share of capital held by foreign nationals, enabling the identification of foreign-owned firms.

In this study, we focus on industries with ISIC Revision 3.1 codes from 1511 to 3610, which correspond to the manufacturing sector. The panel includes both continuous incumbent firms and firms that entered or exited during the census period. All nominal values are deflated using manufacturing sector-specific deflators from the FAOSTAT (2021) database. Firms with missing data on key variables—production, capital, employment, and intermediate inputs necessary for production function and total factor productivity (TFP) estimation, are excluded. The final empirical dataset comprises 16,276 firm-years over the period 1996–2016, providing a robust foundation for analyzing the topic.

This dataset has been widely used in studies on Ethiopia’s manufacturing sector. Applications include analyses of firm performance (Bigsten & Gebreeyesus, 2007; Söderbom, 2012; Bigsten et al., 2016; Siba & Gebreeyesus, 2016; Haile et al., 2017; Shiferaw & Söderbom, 2018; Aberha, 2019; Erena et al., 2021; Fiorini et al., 2021; Tsaedu & Chen, 2021), firm entry and survival (Shiferaw, 2006), Africa’s manufacturing puzzle (Diao et al., 2024), and Ethiopia’s productivity report (Gebreeyesus et al., 2020).

2.3.2. Descriptive Statistics

Before presenting the empirical results, we provide descriptive statistics in Table 2.1, which compares firm characteristics by ownership type over the period 1996–2016. On average, foreign-owned firms are larger than domestically owned firms do, with higher values of production, labor, and capital. For instance, the mean logarithm of production is 12.2 for foreign-owned firms compared to 10.9 for domestic firms, a difference that is statistically significant at the 1% level. Foreign-owned firms also rely more on imported inputs compared to domestic firms, and their mean value of imports is substantially higher.

In addition, foreign-owned firms participate more actively in export markets, with an average export share of 3.3% versus 1.8% for domestic firms, while being older and having larger firm sizes. All differences across ownership types are statistically significant at the 1% level, highlighting systematic heterogeneity in firm characteristics. These differences are important as

they may affect production and productivity motivating the need to control for firm ownership in subsequent analyses.

Table 2.1: Comparison of firm characteristics between domestic and foreign-owned firms

VARIABLES	(1)	(2)	(3)	(4)
	All firms	Domestically Owned	Foreign Owned	Difference
Ln(value of production)	11.2 (2.1)	10.9 (0.01)	12.2 (0.04)	1.3***
Ln(labor)	8.6 (1.8)	8.4 (0.02)	9.5 (0.03)	1.1***
Ln(capital)	9.7 (2.5)	9.3 (0.02)	10.8 (0.04)	1.5***
Ln(intermediate input)	11.5 (4.8)	9.2 (0.02)	11.5 (0.04)	2.3***
Ln(value of import)	6.6 (4.9)	5.7 (0.04)	10.2 (0.08)	4.5***
Imported Input Share (%)	40.0 (39.0)	32.0 (0.00)	65.0 (0.01)	33.0***
Export Share (%)	2.1 (11.8)	1.8 (0.01)	3.3 (0.03)	1.5***
Firm size	114 (285)	95 (2.4)	184 (4.8)	89***
Firm age	14.8 (15.2)	14 (0.13)	17 (0.26)	3***
N	16276	12832	3444	

*Notes: Labor is measured as the real total wage cost, and firm size is proxied by the number of workers. Capital is measured as the real total book value of fixed assets at year-end. Intermediate inputs include expenditures on raw materials, energy, and services. Variables in logarithmic form are calculated by adding one to zero values to reduce data truncation. Standard deviations are reported in parentheses. *** is significant at the 1% level of significance.*

Table 2.2 presents the distribution of firms using imported inputs by ownership type. We observe that participation through importing is substantially more common than exporting among Ethiopian manufacturing firms. Imported input dependence is particularly pronounced for foreign-owned firms (96.4%) compared to domestically owned firms (61.3%). These results indicate that, while both domestic and foreign-owned firms rely heavily on imported inputs, foreign ownership is associated with a markedly higher integration into global input markets. This pattern has important implications for understanding productivity differences and the potential channels through which foreign ownership may enhance firm performance.

Table 2.2: Distribution of firms by importing status and ownership structure

Importing status of firms	Ownership status of firms		
	Domestic Owned	Foreign Owned	Total
Non – Importer	38.7	3.6	31.3
Importer	61.3	96.4	68.7

Notes: The “Total” column shows the share of all firms that are importers or non-importers, regardless of ownership. Percentages in the Domestic Owned and Foreign Owned columns show the distribution of firms within each ownership type.

Table 2.3 presents trade participation and firm characteristics of Ethiopian manufacturing firms (1996–2016) by ownership type. Firms active in both importing inputs and exporting output (“two-way” firms) are generally larger, older, and more productive than firms engaged solely in domestic sales, importing, or exporting. This pattern is consistent with prior evidence showing that two-way traders tend to exhibit higher productivity (Edwards et al., 2020; Okafor et al., 2017).

Ownership differences are also evident. The wage share of non-production workers, which can serve as a proxy for absorptive capacity by reflecting the relative presence of professional and technical staff in the firm (Fox & Smeets, 2011; Gujarati & Dars, 1972), is higher for foreign-owned importing firms than for domestically owned firms. This suggests that foreign-owned importing firms are better positioned to leverage imported inputs for productivity gains through technology transfer and learning from international markets. In contrast, domestically owned firms generally have lower non-production wage shares, indicating lower levels of skilled labor and potentially limited capacity to benefit from importing (Okafor et al., 2017; Aberha, 2019; Akay & Yuksel, 2009; Teal, 2000).

Overall, the descriptive evidence highlights that both trade participation and ownership structure are closely associated with firm size, age, productivity, and absorptive capacity. These patterns provide important context for the subsequent empirical analysis on how foreign ownership shapes the productivity benefits of importing intermediate inputs.

Table 2.3: Trade participation and firm characteristics of manufacturing firms in Ethiopia

Variable	Domestic Only	Import Only	Export Only	Two-Way	All Firms
Import Intensity (%)	0	44.2	0	57.7	40
Wage Share Non-Production (Foreign, %)	26.4	35.7	33.1	33.4	35.1
Wage Share Non-Production (Domestic, %)	28	34.4	32.7	35.5	36.0
Ln (value of Production)	14.4	15.1	16.2	17.5	15.0
Firm size	55	109	193	525	105
Firm age	12.7	15.1	17.2	23.6	14
N	4936	10396	161	783	16276

Notes: “Foreign” denotes foreign-owned firms and “Domestic” denotes domestically owned firms. Trade participation is categorized as follows: “Domestic Only” refers to firms serving only the domestic market (neither importing nor exporting); “Import Only” refers to firms serving the domestic market and importing inputs; “Export Only” refers to firms serving the domestic market and exporting but not importing; and “Two-Way” refers to firms active in both domestic and export markets while importing.

2.4. Results and Discussion

Table 2.4 reports the average input elasticity estimates for the gross output production function based on the GNR approach. The estimates appear reasonable and the sum of the elasticities, a measure of the local returns to scale, is also sensible. Standard errors, obtained by means of bootstrapping, indicate that the elasticities are reasonably precisely estimated.¹³ For reference, we also show OLS results (col. 2). The results differ quite substantially across the two estimators. The OLS estimate of the output elasticity of intermediate inputs is much higher than the corresponding GNR estimate. This is consistent with the hypothesis that OLS will suffer from transmission bias. The intuition is that a flexible input responds strongly to productivity shocks, which generates a high positive correlation between that input and unobserved productivity (Gandhi et al., 2020). This bias seems to contaminate the OLS estimates of the elasticities for capital and labor, which are lower than the GNR estimates.

¹³ Because the GNR approach involves a two-step procedure (see Section 2), we use a bootstrap procedure to estimate standard errors. This involves drawing 200 bootstrapped samples (“clustering” on firm) and repeating the entire GNR estimation procedure 200 times. Standard errors for the OLS estimator are also bootstrapped.

Table 2.4: Estimates of the gross output production function (GNR versus Uncorrected OLS)

Variables	(1)	(2)
	GNR	OLS
<i>Ln(Capital)</i>	0.16*** (0.01)	0.08*** (0.00)
<i>Ln(Labor)</i>	0.43*** (0.02)	0.24*** (0.01)
<i>Ln(Intermediates)</i>	0.38*** (0.01)	0.71*** (0.01)

*Notes: All variables are in natural logarithms. Standard errors are computed using bootstrap with 200 replications and are reported in parentheses. The gross output production function is specified as a complete polynomial series of degree two. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Next, we estimate productivity based on the GNR estimates, and regress it on the productivity covariates as explained in Section 2. OLS results are shown in Table 2.5.¹⁴ The coefficient on import intensity is estimated at 2.8 % and we reject at the 10% significance level the null hypothesis that the parameter is zero. Thus, there is some evidence that imported inputs enhances productivity for domestic firms. The estimated coefficient on imported inputs interacted with foreign ownership is positive and the effect is statistically significant at the 5% level. The result shows that foreign-owned firms' productivity gain from the use of imported intermediates is 10.3%, which is 7.5% higher than the productivity gains of domestically owned firms. This suggests that the relationship between imported inputs and productivity depends on ownership, and that foreign firms benefit more than domestic firms do from imported inputs.

¹⁴ We have also estimated this model using the within estimator, and system GMM. Results, which are available on request, are qualitatively similar to the OLS results in Table 5. In particular, in both cases we obtain a positive and significant effect the interaction term between foreign ownership and imported inputs.

Table 2.5: Covariates of GNR productivity

<i>Variables</i>	<i>Dependent variable: GNR Productivity</i>
Import intensity	0.028* (0.016)
Foreign	0.016 (0.018)
Import Intensity $\times$ Foreign	0.075** (0.030)
Ln(Firm_age)	0.014* (0.008)
Skill Intensity	-0.002*** (0.002)
Capital City (dummy)	0.023 (0.016)
Industry Specific Effects	Yes
Year Specific Effects	Yes
Observations	10,526
R-squared	0.19

*Notes: For the GNR-based productivity the dependent variable is log of Total Factor Productivity (“productivity”). Standard errors in parentheses estimated using the bootstrap with 200 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Foreign denotes a dummy variable equal to 1 for foreign-owned firms and 0 for domestically owned firms.*

As discussed above, these results should be interpreted with some caution. We now consider system GMM results. Column 1 in Table 2.6 shows average elasticities based on a translog specification. The skill intensity variable is treated as predetermined, while the other productivity determinants are assumed exogenous. The average translog output elasticities are positive and statistically significant. The highest output elasticity is that of intermediate input (0.53), followed by labor (0.28) and capital (0.10). Imported intermediates increases productivity. Increasing the share of imported intermediates from zero to 100% is associated with an increase in productivity of 4%, and 13%, for domestically owned and foreign-owned firms, respectively. These results are consistent with foreign ownership enhancing learning by importing.

We now turn to the specification tests. According to the Hansen test, we do not reject the null hypothesis that the overidentifying restrictions are valid. We find strong evidence of first-order serial correlation in the differenced error term but do not reject the null hypothesis that there is

no second-order serial correlation. These findings are consistent with the assumption that the error term in (8) is serially uncorrelated, which is an important assumption that underlies our identification strategy.

To shed some light on whether our instruments are strong or weak, we test for underidentification. Since there is no reason to assume that the instruments for the differenced equation are stronger or weaker than those for the levels equation, we test for underidentification for the both equations separately. Both equations are just identified, which implies that the GMM estimator coincides with two-stage least squares. We can thus use the underidentification test proposed by Kleibergen and Paap (2006) for two-stage least squares. The evidence clearly shows that the identification of the translog levels equation is very weak, but for the translog-differenced equation, we reject the null hypothesis that the equation is under identified at the 5% level of significance. Moreover, the estimation results for the differenced equation (not reported) are similar to the system GMM estimates.¹⁵ Importantly, the effect from the interaction term between foreign ownership and imported inputs remains positive and statistically significant (at the 5% level) for the translog differenced equation.

Given that some of the instruments in the translog model are weak, we also consider results from the simpler Cobb-Douglas specification. Since the Cobb-Douglas model contains six fewer predetermined and endogenous variables than the translog model, we expect stronger evidence against underidentification for the Cobb-Douglas model. The results for the Cobb-Douglas model, which are shown in column 2 of Table 6, imply that we can reject the hypothesis of underidentification at the 1% level for both the levels specification and the differenced equation. In both cases, the coefficient on the interaction term between foreign ownership and imported inputs remains positive and statistically significant at the 5% level. Based on an F-test, we do not reject the null hypothesis that the parameters on the nonlinear terms in the translog specification are equal to zero (p-value = 0.11; Table 6, col. 1). This finding suggests that the Cobb-Douglas results may not be severely biased by the omission of the nonlinear translog terms, which is reassuring.¹⁶ We thus conclude that our main empirical result, i.e., that the effect of imported

¹⁵ This is as expected, since the system GMM estimator will assign higher weights to low-variance moments.

¹⁶ It follows that there is little evidence of complementarities between intermediate inputs and other inputs. Of course, given that the instruments underlying the estimation of the translog model appear quite weak, the result from the F-test should be interpreted with some caution.

inputs varies with ownership, is not a spurious outcome driven by weak instruments. It can also be noted that our key results differ little across the two empirical methods considered in this paper, which is reassuring.

Overall, our results corroborate existing evidence from other countries. A 10-percentage-point rise in the share of imported intermediates increased firm productivity by 1.5% for Spanish firms (Augier et al., 2013) and 1.8% for Hungarian firms (Halpern et al., 2015). For manufacturing firms in Ecuador, a 100% increase in the share of imported inputs boosts firm productivity by 7% (Pinzón & Carrillo-Maldonado, 2020). In general, imported inputs may affect productivity growth in many ways. Firstly, the imported inputs expand the variety of intermediate inputs. In this regard, Elliott et al. (2016) claimed that imported inputs allow domestic firms to produce various products that enhance domestic productivity growth. Secondly, the productivity of firms increases due to the quality effect that can arise because of the better quality of imported inputs (Halpern et al., 2015; Zhong, 2023). Thirdly, the accumulation of knowledge results from "learning by doing" and the extraction of technology embodied in imported inputs from the frontier of knowledge (Pane and Patunru, 2023; Mo et al., 2021; Zhong, 2023). Imported inputs help increase the efficiency of the division of labor and thus the firm's overall productivity (Feng et al., 2016; Mo et al., 2021).

The results also imply that foreign-owned importing firms do have a higher premium in terms of productivity gains from importing as compared to domestically owned firms. This may be because foreign-owned firms use high-quality foreign inputs, have better know-how about foreign markets, and can access cheap suppliers abroad as compared to domestically owned firms. (Halpern et al., 2015). Thus, foreign ownership magnifies the effect of trade on firm productivity, which is consistent with previous work (Halpern et al., 2015; Bykova & Lopez-Iturriaga, 2018).

Table 2.6: System GMM estimates of the gross output production function

Variables	(1) Translog	(2) Cobb-Douglas
(a) Average elasticities		
Ln(Capital)	0.101** (0.024)	0.106** (0.017)
Ln(Labor)	0.282** (0.051)	0.225** (0.048)
Ln(intermediates)	0.533** (0.086)	0.553** (0.082)
(b) Productivity determinants ⁽¹⁾		
Import Intensity	0.040* (0.023)	0.009 (0.022)
Foreign	-0.016 (0.027)	-0.024 (0.026)
Import intensity x Foreign	0.086** (0.041)	0.106** (0.043)
Ln(Firm_age)	0.015 (0.022)	0.018 (0.017)
Lagged output	0.118** (0.034)	0.115** (0.032)
Skill Intensity	-0.000 (0.001)	0.000 (0.001)
Capital City (dummy)	-0.015 (0.028)	-0.007 (0.020)
AR1 (p-value)	0.00	0.00
AR2 (p-value)	0.40	0.65
F-test: Translog vs. Cobb-Douglas (p-value)	0.11	
Hansen-statistic (p-value)	0.34	0.21
Underidentification levels equation(p-value)	0.87	0.00
Underidentification differenced equation(p-value)	0.046	0.00
Number of firms	1884	1886
Number of instruments	49	37
Observations	6,371	6,393

Notes: The dependent variable is log gross value of production ("output"). Capital, Labor, Intermediates are in their respective log form. Robust standard errors in parentheses in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of overidentifying restrictions for the translog specification is 13 and for the Cobb-Douglas specification it is 7. Instruments as follows. Differenced equation: L2.y L.k L.l L2.m L.ll L.kk L2.mm L.lk L2.lm L2.km L2. wateshare D.L.importrate D.L.importrate_foreign D.foreign. Levels equation: L.D.y D.k D.l D.L.m D.ll D.kk D.L.mm D.lk D.L.lm D.L.km D.L2.wateshare, L.importrate L.importrate_foreign foreign log_age, addis, year dummies. L is the first lag operator (t-1), L2 is the second lag operator (t-2), and D is the time difference operator. y = log output, k = log capital, l = log labor, m = log intermediate inputs; ll, kk, mm denote squared terms, lk, lm, ki denote interaction terms. For Cobb-Douglas specification, squared and interaction terms are excluded from the instrument set.

(1) The productivity determinants correspond to the term $x_{it}\theta$ in equation (8).

2.5. Conclusion

In this paper, we examine the role of foreign ownership in shaping the relationship between import intensity and firm productivity. Using a long census-based panel dataset covering the period 1996–2016, we employ two complementary empirical approaches: the Gandhi–Navarro–Rivers (GNR) method to estimate the gross output production function, and the System GMM estimator to analyze a translog specification of the production function. We find that foreign ownership magnifies the effect of importing on the productivity of firms, a result that is robust across the two estimators used in this paper.

Our findings bear relevance to ongoing policy discussions concerning the significance of trade for economic development in low-income countries. Our results contribute to a growing body of literature emphasizing input tariff liberalization and imports of intermediate inputs as potential channels for technology transfer and technology adoption by domestic firms.¹⁷ Our findings also shed light on the significance of exchange rate policies for growth. The work by Moller and Wacker (2017) suggests that an overvalued exchange rate helped to boost economic growth in Ethiopia, since it made imported inputs relatively cheaper. Our results confirm that imported inputs are a key determinant of firm-level productivity, implying that an undervalued exchange rate could constrain industrial growth by raising the effective cost of imports.

While these findings provide valuable insights, the study has several limitations that suggest avenues for future research. First, the dataset does not distinguish between imported capital goods and intermediate inputs, nor capture their source countries, preventing assessment of whether productivity gains are driven more by capital goods or by inputs from technologically advanced nations. Addressing these distinctions in future work would provide a deeper understanding of the mechanisms through which imported inputs affect productivity. Second, foreign ownership is treated as a binary variable, yet foreign-owned firms are highly heterogeneous. Differences between joint ventures and wholly foreign-owned firms, or between majority and minority stakes, may shape how imports are utilized and the resulting productivity effects. Disaggregating ownership categories in future research could uncover more nuanced patterns. Third, while

¹⁷ See for example Aberha (2019); Amity and Konings (2007); Dosis and Milgram-Baleix (2009); Forlani (2017); Halpern et al. (2015); Kasahara and Rodrigue (2008); Luqman and Murtaza (2023); Lööf and Andersson (2010); Pane and Patunru (2023); and Smeets and Warzynski (2013).

Ethiopia provides a valuable low-income context, the findings may not fully generalize to other developing economies, where institutional and policy environments differ; comparative studies are needed to test whether the observed dynamics hold more broadly. Finally, although the empirical strategy addresses endogeneity arising from simultaneity and unobserved heterogeneity, some longer-term dynamic processes such as cumulative learning-by-importing or broader path dependence in technology adoption may not be fully captured. Future research could explore these mechanisms using complementary approaches.

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Chapter Three

3. Estimating Labor Demand Using Dynamic Framework: Evidence from Manufacturing Firms in Ethiopia

Abstract

This paper investigates firm-level labor demand in Ethiopia's manufacturing sector, distinguishing between production and non-production tasks. Using a nationally representative unbalanced panel dataset from 1996 to 2016 and applying System-GMM estimation, we estimate short and long-run labor demand elasticities while capturing labor heterogeneity and capital–labor interactions. Results indicate that firms adjust employment relatively quickly, suggesting moderate adjustment costs. Own-wage elasticities are larger for production than for non-production tasks, consistent with substitutability and labor flexibility theory, while positive cross-wage elasticities reveal substantial interdependence between labor types. Increases in capital stock augment labor demand, particularly for production workers. The findings are robust across alternative specifications and offer critical insights for designing labor market policies and minimum wage reforms in Ethiopia.

Keywords: Labor demand, dynamic framework, wage elasticity, adjustment costs, panel data, manufacturing firms, Ethiopia.

JEL Classification: J23; J30; C10; O55

3.1. Introduction

Firm-level labor demand refers to the quantity and types of workers a firm employs, shaped by production needs, wages, input costs, and broader market conditions. Accurately estimating labor demand is crucial for labor market analysis and policy formulation, as it reveals how employment responds to changes in wages, output, and other economic drivers. Such evidence informs targeted interventions, training programs, wage regulations, and employment incentives that align with labor market dynamics (Hamermesh, 1993, 2021; Popp, 2023). In Ethiopia, where job creation is a central development objective, insights on wage elasticity and adjustment costs are particularly important, as hiring, training, and firing costs can delay labor demand responses (Bossler & Popp, 2022; Popp, 2023). Understanding these dynamics is therefore vital for designing effective labor market policies.

Empirical evidence indicates that static labor demand models, particularly translog specifications, are widely used to estimate labor demand (Roberts & Skoufias, 1997; Nasir, 2019; Jia & López, 2021), often assuming instantaneous adjustment to changes in wages or output prices. In reality, firms adjust inputs more gradually due to adjustment costs, expenses incurred when changing labor usage, which slow their response to shocks (Oi, 1962; Hamermesh & Pfann, 1996). The responsiveness of labor demand to wages has also been extensively studied (Rauch & Trindade, 2003; Riedel, 2011; Boeters & Savard, 2013; Jacquet et al., 2014; Behar, 2025), yet no consensus exists on its magnitude. Over 80% of variation in estimates arises from differences in theoretical frameworks, model specifications, data types, and sectoral or national contexts (Lichter et al., 2015). Much of the literature relies on aggregate data, neglecting firm-level dynamics and labor heterogeneity. Even when disaggregated analyses are attempted, labor is often treated as homogeneous or restrictive assumptions are imposed on adjustment costs, limiting understanding of how firms adjust demand across labor types, a question central to both labor economics and development policy (Hamermesh, 1986; Chen, 2019; Popp, 2023). Moreover, Identification strategies in labor demand studies often assume that wages are unaffected by labor demand (Hamermesh, 1986; Chen, 2019). However, this assumption may not hold in all settings.

To address these gaps, this paper employs a dynamic labor demand framework that distinguishes between production and non-production workers. The framework allows for analyzing short-run adjustment dynamics of heterogeneous labor, which is particularly relevant in Ethiopia's

manufacturing sector where rapid population growth, a young labor force, and industrialization policies make job creation a national priority. At the same time, firms operate in a labor market characterized by high turnover, skill mismatches, and relatively high wage-productivity growth gap (Gebreeyesus et al., 2020; Gelb et al., 2020; Halvorsen, 2021; Fox & Sohnesen, 2012), creating conditions that static models cannot adequately capture.

By addressing these limitations, this study makes the following key contributions. First, it provides firm-level evidence on labor demand in a low-income country, addressing gaps left by static and aggregate analyses. Second, it applies a dynamic framework that captures adjustment costs and labor heterogeneity—particularly relevant in a setting characterized by turnover and wage-productivity mismatches. Third, it builds on Haile et al. (2017), who studied imported technology and employment in Ethiopian manufacturing (1996–2004), by expanding the scope to estimate both short- and long-run elasticities, incorporating a richer set of covariates, and testing wage treatment as predetermined or exogenous. Fourth, by distinguishing between production and non-production workers, it provides more precise elasticity estimates, crucial for targeted labor market policies aligned with development goals. Fifth, it explores capital-labor interactions, an under examined area in low-income countries, shedding light on how investment in physical capital influences employment patterns. Sixth, by exploiting a unique panel dataset covering 1996–2016 and employing System-GMM approach, the study produces robust elasticity estimates and new insights into how adjustment costs, labor heterogeneity, and capital-labor interactions shape employment dynamics.

The empirical analysis highlights three main findings. First, Ethiopian firms adjust employment relatively quickly, suggesting moderate adjustment costs for both production and non-production workers. Second, own-wage elasticities are larger for production than non-production tasks, consistent with theory on substitutability and labor flexibility (Hamermesh, 2021). Third, positive cross-wage elasticities indicate substantial interdependence between labor types. The findings also point to capital-labor complementarity, suggesting that capital deepening through investments in machinery and technology fosters employment growth. As expected, labor demand is less elastic in the short run than in the long run (Popp, 2023). These insights are valuable for policymakers designing training programs, minimum wage policies, and employment incentives that reflect actual labor market dynamics. The robustness of these findings is confirmed across alternative

model specifications.

The remainder of the paper is structured as follows. Section 2 outlines the theoretical framework and empirical strategy. Section 3 describes the dataset and presents descriptive statistics. Section 4 presents and discusses the estimation results, while Section 5 conducts robustness checks. Section 6 concludes with key findings, policy implications, and directions for future research.

3.2. Theoretical Framework and Empirical Approach

3.2.1. Theoretical Framework

A large body of research on firm behavior assumes that firms seek to either maximize profits or minimize production costs, both of which lead to the determination of optimal input quantities (Bognanno et al., 1987). Labor demand is typically derived within cost or production function frameworks. One commonly used approach is the static translog cost function, which enables the derivation of long-run factor demand equations under the assumption of cost-minimizing behavior (Falk & Koebel, 2001; Kölling, 2018). This static framework assumes that firms operate at their long-run equilibrium and can adjust input factors instantaneously (Hamermesh, 1993; Lichter et al., 2015). As such, it implicitly assumes full adjustment of all inputs within a single period. Although cost minimization in the long run necessitates price homogeneity and symmetry, these conditions may not be behaviorally justified in the short run.

To account for potential short-run deviations from long-run optimal behavior, we adopt a dynamic specification in our estimation (Anderson and Blundell, 1984). Dynamic models allow for varying short-run responses to changes in factor prices and other variables. In this framework, all factors are treated as variable, each exhibiting distinct short-run adjustment behaviors (John et al., 2014).

3.2.2. Empirical Approach

This study utilizes the two-step System GMM estimator developed by Arellano and Bover (1995), Blundell, and Bond (1998) to estimate dynamic labor demand models. This estimation technique effectively addresses endogeneity concern and accounts for time-invariant, firm-specific unobserved heterogeneity (Blundell and Bond, 2000). In these models, current employment is influenced by its own lagged values as well as other explanatory variables (Hamermesh, 1993).

The approach captures temporal changes in labor demand for different occupational categories.¹⁸. A dynamic specification is employed to account for adjustment costs (Lachenmaier & Rottmann, 2011; Conte & Vivarelli, 2011).

3.2.2.1. Empirical Model Specification

Our empirical strategy builds on the models developed by Conte & Vivarelli (2011), Meschi et al. (2016) and Haile et al. (2017). Dynamic approaches explicitly capture short-run adjustment processes (Nickell, 1981). In the absence of theoretical complexity, reduced-form models can more easily incorporate dynamics by including lagged versions of the dependent variable (Tinsley, 1971). These models provide greater flexibility in variable selection, and their coefficients can be directly interpreted as elasticities (Lichter et al., 2015). The basic dynamic labor demand models for the two labor categories are expressed as follows:

Demand Equation for Production (P) Workers

$$lP_{ijt} = \alpha_0 + \alpha_1 lP_{ijt-1} + \alpha_2 lN_{ijt-1} + \alpha_3 lW_{P,ijt} + \alpha_4 lW_{N,ijt} + \alpha_5 lK_{jit-1} + \alpha_6 lTFP_{ijt-1} \\ + \alpha_7 l\text{age}_{ijt} + \alpha_8 l\text{export}_{ijt-1} + \alpha_9 \text{Location}_i + D_t + D_i + \varepsilon_{ijt}$$

Demand Equation for Non-production (N) Workers

$$lN_{ijt} = \beta_0 + \beta_1 lP_{ijt-1} + \beta_2 lN_{ijt-1} + \beta_3 lW_{P,ijt} + \beta_4 lW_{N,ijt} + \beta_5 lK_{jit-1} + \beta_6 lTFP_{ijt-1} \\ + \beta_7 l\text{age}_{ijt} + \beta_8 l\text{export}_{ijt-1} + \beta_9 \text{Location}_i + D_t + D_i + \varepsilon_{ijt}$$

Where: ijt is firm i in industry j at time t . All variables except location and time dummies are expressed in natural logarithms. We model the total number of production workers (P) and non-production workers (N) as functions of labor costs per worker in each category. The labor cost per production worker (W_p) is calculated by dividing the total wage bill for non-production workers by their total number, and the labor cost per non-production worker (W_n) is obtained similarly for production workers. Each equation includes lags of total number of employees and wage costs for both occupational categories which influences firms' hiring decisions. The empirical model also controls for observable firm heterogeneity due to variations in capital stock, Total Factor Productivity (TFP), firm age, firm location, and export value among other.

¹⁸ Empirically, the dynamics of labor demand based on symmetric adjustment costs are in general at odds with the data. The rejection is stronger as the level of data disaggregation rises _e.g. from industry to firm. (Alonso-Borrego.)

Capital stock (K) is included to assess whether an increase in a firm's physical capital augments or substitutes labor across different worker categories (Berlingieri et al., 2024). Following Hsieh and Klenow (2009), Söderbom (2012) and Gebreeyesus et al. (2020), the book value of fixed assets at the end of the year is used as the measure of capital stock.

TFP is estimated non-parametrically using the method developed by Gandhi et al., (2020). Higher productivity can improve profitability, motivating firms to expand output and increase hiring (Foster et al., 2008; Syverson, 2011; Bloom et al., 2012).

Firm age is determined by subtracting the firm's year of establishment or reported birth year from the survey year. It reflects 'vintage effects,' as older and newer firms tend to use different generations of technology and production methods, which influence their labor composition needs (Roberts & Skoufias, 1997; Haltiwanger et al., 1999)

Export: represents the firm's real export value and is included to evaluate the employment impacts of trade integration (Shiferaw & Hailu, 2016; Helpman, 2006).

Location is a dummy variable that takes the value of 1 if the firm is located in the capital city, Addis Ababa, and 0 if the firm is located in other regions. This location dummy is expected to capture differences in firms' access to resources, markets, and better infrastructure, all of which influence labor demand (Roberts & Skoufias, 1997; Bigsten & Gebreeyesus, 2007; Haile et al., 2017). A set of time dummies (D_t) is included to control for time-period-specific shocks that are common across all firms in the industries (Roberts & Skoufias, 1997). Finally, standard to panel data analysis, the error term is composed by the idiosyncratic error component (ε_{ijt}) and the time invariant firm fixed effect component (D_i). With longitudinal data on firms, the inclusion of firm fixed effects will capture time-invariant unobserved differences between employers. In such a case, the respective elasticity estimates stem from pure variation within firms (Popp, 2023).

In these models, the parameters α_1 and β_2 are directly linked to the magnitude of adjustment costs for production and non-production workers, from which the adjustment speed of employment or firms' inertia in adjusting towards their static equilibrium can be computed (Bresson et al, 1992; Hamermesh, 1993). The expected range for α_1 and β_2 is between 0 and 1. To account for adjustment costs, previous studies use proxy indicators such as labor intensity, employment

protection legislation, or skill levels (Anderson et al., 2003; Banker et al., 2013; Ghaly et al., 2017). Despite these efforts, identifying reliable proxies for adjustment costs remain a persistent empirical challenge, limiting the generalizability of the findings (Banker et al., 2013; Golden et al., 2020). The parameter α_3 and β_4 represents the own-wage elasticity of labor demand for production and non-production workers respectively. The parameter α_4 and β_3 shows the cross-wage elasticity of demand, indicating substitution or complementarity between the two labor categories (Teal, 2000). The parameter α_2 and β_1 also shows the possibility of substitution or complementarity between the two labor categories. The parameters α_5 and β_5 reflects capital-labor complementarity or substitutability for each category of workers. An increase in capital stock is likely to augment labor demand (Bergstrom & Panas, 1992; Krusell et al., 2000). From theory and empirical findings of labor demand literature, we expect positive and significant coefficients (α_6 to α_9 and β_6 to β_9). Negative and significant coefficients (α_3 to β_4) either positive or negative significant coefficients for (α_2 and α_4 ; β_1 and β_3). The long-run elasticities are expected to be numerically greater than the short-run elasticities (Lichter et al., 2015). Empirical studies on labor demand typically assume that wages are exogenously determined for each individual establishment, or that wages are unaffected by demand (Hamermesh, 1986; Chen, 2019). A single firm faces an exogenously given wage rate when labor markets are perfectly competitive. However, this assumption may be violated when the model is applied to real data (Popp, 2023).

3.3. Data and Descriptive Statistics

3.3.1. Data Description

This paper utilizes firm-level data from the Large and Medium Manufacturing Industries Survey (LMMIS), an annual census conducted by the Ethiopian Statistical Services (ESS), covering the period 1996–2016. The census encompasses both public and private establishments across all regions of Ethiopia, limited to large and medium-scale firms employing at least ten workers and using electricity in production. Firms included in the survey account for approximately 50% of total manufacturing employment and over 70% of sectoral value added, including informal manufacturing activities (Asturias et al., 2021).

In this study, we focus on industries with ISIC Revision 3.1 codes from 1511 to 3610, which correspond to the manufacturing sector. The panel includes both continuous incumbent firms as

well as those that entered or exited during the census period. The dataset provides detailed information on establishment-level output, sales, employment, location, inputs (local and imported), wages, and other firm characteristics. We combine data on employment, capital stock, and material inputs to estimate firm-level measures of (TFP) using the approach developed by Gandhi et al., (2020).¹⁹

The dataset provides detailed firm-level data on wages and occupation for both production and non-production workers²⁰. These classifications align with previous studies that categorize non-production workers as skilled and production workers as unskilled, as defined by, Bresson et al. (1992) for France, Akay & Yuksel (2009) and Teal (2000) for Ghana, and Meschi et al. (2016) for Turkey; Haile et al. (2017) for Ethiopia . In this study, we use the production and non-production labor classification instead of the unskilled and skilled labor classification, since information on the educational level of workers is not available in the dataset. All financial variables are expressed in real terms using sector-specific deflators from the FAO database (2021). We also trim the 1% tails of each series to make the results robust to outliers. These criteria result in a final sample of approximately 13,886 plant-year observations.

This dataset has been widely used in studies on Ethiopia's manufacturing sector. Applications include analyses of firm performance (Bigsten & Gebreeyesus, 2007; Söderbom, 2012; Bigsten et al., 2016; Siba & Gebreeyesus, 2016; Haile et al., 2017; Shiferaw & Söderbom, 2018; Aberha, 2019; Erena et al., 2021; Fiorini et al., 2021; Tsaedu & Chen, 2021), firm entry and survival (Shiferaw, 2006), Africa's manufacturing puzzle (Diao et al., 2024), and Ethiopia's productivity report (Gebreeyesus et al., 2020).

¹⁹ Following Gandhi et al., (2020), we estimate the Total Factor Productivity using firm level data non-parametrically

²⁰ According to CSA (2018) definition the non-production workers (Admin and technical employees) category consists of salaried directors and managers, technicians, superintendents, research workers, draftsmen and designers, engineers, chemists, architects, accountants, bookkeepers, office machine operators, receptionists, salesmen, delivery personnel, guards and other office staff who are not directly engaged in the production of new products. As for the production workers, they include workers directly engaged in production i.e., persons engaged in fabricating, processing, assembling, maintenance, repair, janitorial, record keeping and other associated activities.

3.3.2. Descriptive Analysis

Table 3.1A presents summary statistics for key variables, including the total number of workers, the breakdown between production and non-production workers, their average wage growth, and other variables relevant to the model. Over the study period, the total labor force and nominal labor cost per employee grew by 3.8% and 12.6%, respectively, while the average real labor cost per employee increased by 4.8%. Between 1996 and 2016, nominal labor costs in the manufacturing sector increased by an average of 15.4%, while nominal labor cost per employee rose at an average annual rate of 10.3% (Gebreeyesus et al., 2020). The table also indicates that wage cost growth for non-production and production workers was 4.9% and 4.7%, respectively. Average employment growth for production and non-production labor was 3.3% and 2.6%, respectively, reflecting typically slower growth in managerial and administrative roles compared to production roles. The higher growth rate of production labor relative to non-production labor is consistent with patterns observed in labor-intensive manufacturing firms (Bigsten and Söderbom, 2006).

The average capital stock growth rate of 9.9% suggests relatively strong investment across firms, although the high variance indicates substantial heterogeneity in capital access and allocation. Higher capital stock growth is often associated with increased productivity, as recent studies emphasize the importance of capital intensity in shaping labor demand (Syverson, 2011). Total Factor Productivity (TFP) grew at an average rate of 2.0%, with wide variation across firms, potentially reflecting operational inefficiencies that result in negative productivity for some.

Between 1997 and 2016, TFP in the manufacturing sector increased at an average annual rate of approximately 2.5% (Gebreeyesus et al., 2020). Export growth is 0.64%, indicating limited export activity among firms. While export participation is rising in Ethiopia's manufacturing sector, most industries are largely absent from international markets (Bigsten et al., 2016). Firm age averaged 15.5 years, with a standard deviation of 15.3, highlighting a diverse mix of both young and mature firms. Firm size also varied widely, with a mean of 89 employees and a standard deviation of 140.6, ranging from small to large enterprises. Prior research suggests that older and larger firms are more likely to benefit from established market positions and economies of scale (Evans, 1987).

Table 3.1: Summary statistics and wage shares

	N	Mean	Median	SD	Min	Max
Panel A: Summary statistics						
Ln(Labor)	13886	3.76	3.56	1.13	1.10	7.39
Ln(Production Labor)	13886	3.24	3.09	1.19	.69	6.64
Ln(Non-Production Labor)	13886	2.6	2.39	1.27	0	6.84
Ln(Nominal Wage)	13886	12.59	12.46	1.60	8.80	17.02
Ln(Real Wage per Labor)	13886	4.76	4.78	.84	-.47	9.11
Ln(Real Wage per Production Labor)	13886	4.67	4.67	.90	-.28	9.75
Ln(Real Wage per Nonproduction Lab)	13886	4.88	4.96	1.11	-1.22	10.17
Ln(Capital Stock)	13886	9.96	10.11	2.11	5.08	14.78
Ln(TFP)	13781	1.94	1.99	.69	-.77	6.05
Ln(export)	13886	.64	0.00	2.64	0	13.65
Firm Age	13886	15.44	10.00	15.17	0	101
Firm Size	13886	89.48	35.00	140.6	10	1615
Panel B: Labor and wage Shares						
Labor share of production workers	13886	.63	0.65	.19	0	1
Labor share of non-production workers	13886	.37	0.34	.19	0	1
Share of production labor wage from total wage	13886	.59	0.60	.21	0	1
Share of nonproduction labor wage from total wage	13886	.42	0.40	.21	0	1
Share of wage from Value added	12754	.32	0.23	.27	0	1
Share of wage of production labor from value added	12754	.19	0.12	.19	0	1
Share of Wage of Non-Production labor from value add	12754	.12	0.08	.14	0	1
Share of wage from sales	13664	.16	0.09	.21	0	1
Share of Wage of Prod. from sales	13664	.10	0.05	.14	0	1
Share of Wage of Non- Prod. from sales	13664	.06	0.03	.10	0	1

Notes: All variables reported in logs are natural logarithms. Labor refers to the total number of employees, which is the sum of production and non-production workers. Firm age is measured in years since establishment, and firm size is measured as the total number of employees. Total factor productivity (TFP) is computed using the GNR method. Labor share refers to the proportion of production or non-production workers in total employment. Wage shares are computed relative to total wage bill, value added, and sales.

As shown in Table 3.1B, the labor share is divided between production and non-production workers at 63% and 37%, respectively, indicating a workforce composition skewed toward production-intensive operations, a common trend in many developing economies. This distribution aligns with findings that in developing economies manufacturing firms exhibit a labor composition that leans heavily toward production roles attributed to slower adoption of automation technologies and structural economic characteristics (Das, 2018). On average, production workers account for 59% of total labor costs, while non-production workers represent 41%. Consequently, a relative change in production worker wages has a greater impact on overall labor costs than an equivalent change in non-production wages (Bognanno et al., 1987).

The wage structure reveals notable disparities: production workers receive a higher share of both value-added (19%) and total sales (9.6%) compared to non-production workers, who receive 12% and 6.3%, respectively. These differences exhibit significant variability across firms. Such patterns

are consistent with Teal's (2000) analysis of Ghanaian manufacturing firms, where unskilled labor received a larger share of value-added (29%) compared to skilled labor (11%). These findings underscore potential areas for policy intervention, particularly in addressing wage disparities and rebalancing workforce composition in the face of evolving labor market dynamics.

Table 3.2A highlights systematic differences in employment and wages between medium and large firms in Ethiopian manufacturing. Large firms employ substantially more workers than medium firms across both production and non-production categories. Total employment in large firms is approximately 1.5 times that of medium firms for production workers and nearly twice as high for non-production workers, reflecting the greater organizational scale and complexity in larger establishments (Tybout, 2000; Bigsten & Söderbom, 2006).

The data confirm a firm-size wage premium. On average, workers in large firms earn about 23% more than they earn those in medium firms, consistent with higher productivity, better access to resources, and more structured wage-setting mechanisms (Oi & Idson, 1999; Söderbom & Teal, 2004). The wage gap between production and non-production workers increases with firm size. In large firms, non-production workers earn approximately 53% more than production workers, compared to a 41% gap in medium firms do. This indicates that larger firms not only offer higher wages overall but also reward skill and responsibility differentials more strongly, reflecting internal labor market structures and the value of specialized skills in larger organizations (Berman, Bound, & Griliches, 1994; Van Biesebroeck, 2005).

These patterns suggest that firm expansion is associated with both more workers and higher wages, greater skill differentiation labor market effects. For policy, this underscores the importance of supporting medium firms to scale up, as transitioning to larger firm size is associated with higher productivity, better wages, and more structured labor markets.

Table 3.2: Employment and shares by firm size

Panel A: Employment and wages by firm size						
Firm size	<i>Labor</i>	<i>Prod.</i>	<i>Non-Prod</i>	<i>Wage</i>	<i>Wage_prod</i>	<i>Wage_NonProd</i>
Large firms	5.445	4.883	4.303	4.996	4.831	5.258
Medium firms	3.684	3.192	2.464	4.792	4.645	4.991

Panel B: Wage shares, labor shares, and value-added distribution							
	Share of Production Labor	Share of Non-prod Labor	Wage share of prod. labor	Wage share of Non- prod. Labor	Wage share from Value Added	Wage share of Prod Lab from VA	Wage share of Non-prod Lab from VA
Large firms	.613	.387	.534	.466	.268	.147	.121
Medium firms	.649	.351	.577	.423	.305	.182	.123

Notes: Labor natural logarithm of total employment; Prod and Non-Prod are natural logarithms of production and non-production workers, respectively; Wage is natural logarithm of average wage across all workers; Wage_Prod and Wage_NonProd natural logarithms of average wages for production and non-production workers, respectively. Large firms are defined as establishments employing more than 100 workers; medium firms employ 20–99 workers as per World Bank Enterprise Surveys (WBES) criteria. Share of Production/Non-Production Labor = proportion of total employment in production or non-production roles. Wage Share of Production/Non-Production Labor = proportion of total wages paid to production or non-production workers. Wage Share from Value Added = total wages as a fraction of firm value added. Wage Share of Prod/Non-Prod Labor from VA = wages paid to production or non-production workers as a fraction of firm value added. Large firms are defined as establishments employing more than 100 workers; medium firms employ 20–99 workers as per World Bank Enterprise Surveys (WBES) criteria.

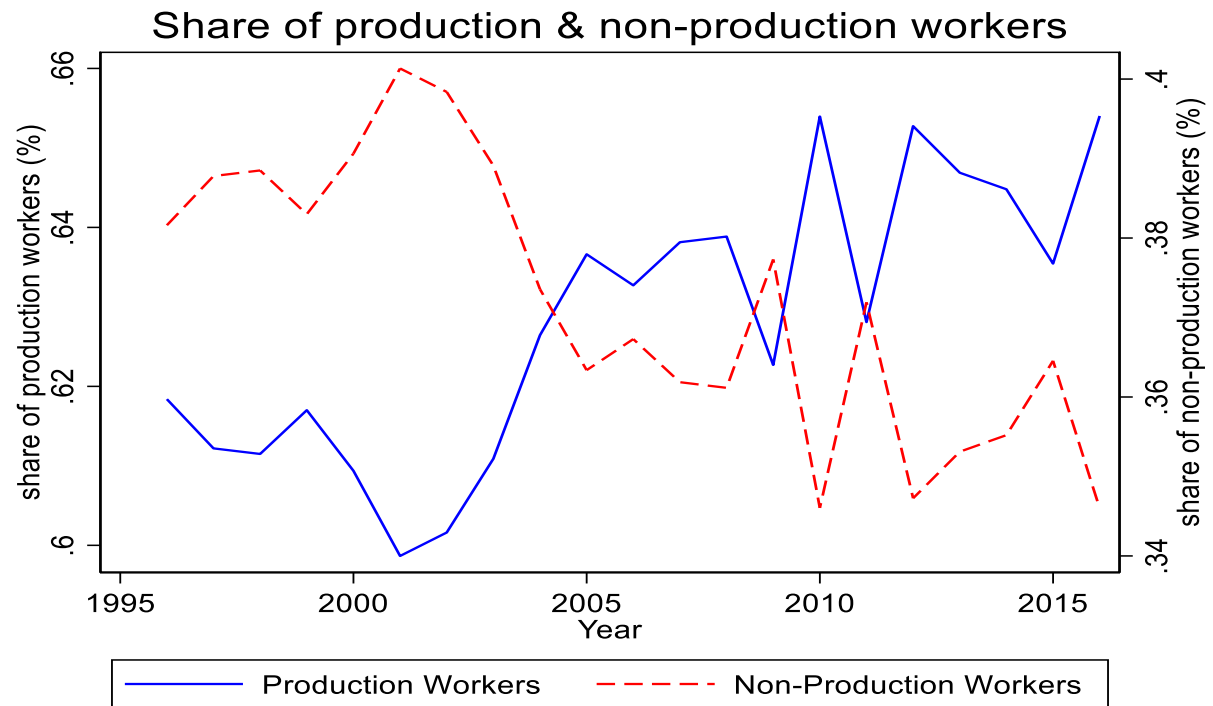
Table 3.2B highlights differences in labor composition, wage allocation, and the share of wages from value added between medium and large manufacturing firms in Ethiopia. Production workers remain the majority in both firm categories, accounting for 65% of employment in medium firms and 61% in large firms, while non-production workers constitute 35–39% of the workforce. This indicates that larger firms employ a relatively more balanced mix of skilled and unskilled labor, reflecting greater organizational complexity and specialization (Bigsten & Söderbom, 2006; Tybout, 2000). In terms of wages, medium firms allocate a larger share to production workers (58%) compared to large firms (53%), whereas large firms devote a higher proportion of total wages to non-production workers (47% vs. 42%), highlighting the emergence of a skill premium.

The share of wages in total value added declines with firm size, from 31% in medium firms to 27% in large firms, suggesting that larger firms retain a greater portion of value added for reinvestment or capital accumulation, consistent with higher productivity and capital intensity (Oi & Idson, 1999; Van Biesebroeck, 2005). Within value-added allocations, production workers in large firms receive a slightly smaller share (15%) compared to medium firms (18%), while non-production workers' share remains similar (~12%). Overall, these patterns indicate that firm size

significantly shapes labor composition, wage structures, and the distribution of value added, emphasizing the role of firm growth in promoting more efficient labor utilization, skill differentiation, and investment capacity.

Figure 3.1 illustrates the evolution of employment shares between production and non-production workers in manufacturing firms from 1996 to 2016, revealing minimal structural shifts over the two decades. The diverging growth patterns suggest a degree of substitutability between the two labor categories. Specifically, the data show a declining share of non-production workers alongside a rise in production worker employment, indicating increased reliance on labor-intensive roles. This trend contrasts with findings from Berman et al. (1998), who argue that technological advancements and efficiency gains typically reduce the demand for routine manual labor while increasing the need for skilled, non-production roles. The observed pattern in this context may reflect delayed technological adoption or structural constraints in the manufacturing sector of developing economies. Overall, the findings underscore a labor-intensive production environment and highlight the need for targeted policies and management strategies to support balanced and sustainable industrial growth.

Fig 3.1: Evolution of employment share of production and non-production workers.



3.4. Results and Discussions

The regression results in Table 3.3 highlight the significance of the lagged dependent variable, underscoring the appropriateness of a dynamic model specification (Wilkins, 2018)). The OLS and fixed effects (FE) estimations indicate that most explanatory variables are statistically significant, with coefficient signs aligning with theoretical expectations. However, these estimates may be biased due to endogeneity concerns. As noted by Bond (2002), OLS estimates tend to be upward-biased, while FE estimates are generally downward-biased. Consequently, the consistent GMM estimates are expected to lie between the OLS and FE results, offering a more reliable representation of the underlying causal relationships.

The GMM estimates for the labor demand system (Column 3) were evaluated using a series of diagnostic tests to assess instrument validity and strength. The Kleibergen-Paap (2006) under-identification test, typically used in two-stage least squares frameworks, was employed to examine the relevance of the instruments in the labor demand equation. The results suggest that both the level and differenced equations are just identified. Additionally, the weak identification test indicates that the instruments are sufficiently strong, enhancing the reliability of the parameter estimates (see Annex). The Hansen test of over-identifying restrictions fails to reject the null hypothesis, supporting the validity of the instruments and confirming that they are uncorrelated with the error term. Moreover, the Arellano and Bond tests for serial correlation show no evidence of second-order autocorrelation, further validating the consistency of the GMM estimators. Together, these results affirm the robustness and credibility of the model specification.

The estimation results reveal an adjustment cost coefficient of 0.5, indicating that 50% of the disequilibrium is employment corrected instantaneously in the long run.²¹ This suggests moderate adjustment costs, which impede immediate changes in employment levels in response to economic shocks. The wage elasticity of -0.13 implies that firms exhibit relatively low sensitivity to wage fluctuations in the short run, likely due to factors such as limited substitutability between labor and capital, or need to maintain a certain workforce size for operational continuity. The combination of moderate adjustment costs and a relatively inelastic wage elasticity highlights the importance

²¹ The adjustment speed toward long-run equilibrium employment is captured by one minus the adjustment cost (Popp, 2023)

of considering both factors when designing labor market policies aimed at stabilizing employment levels. Hamermesh (1976) summarized own-wage elasticities from reduced-form models that incorporate dynamic adjustments, concluding that the likeliest value for the short-run conditional wage elasticity of labor demand is approximately -0.15 (Lichter et al., 2015; Popp, 2023). Moreover, the results suggest that capital is labor-augmenting, as increases in TFP and greater firm experience are associated with higher labor demand.

In a dynamic setting, the wage coefficient reflects the short-run elasticity of labor demand, while the long-run elasticity is derived by incorporating the coefficient of the lagged dependent variable. This study estimates the long-run wage elasticity at -0.26 , suggest that firms are more responsive to wage changes over time, likely due to the increased substitutability between labor and capital. As theory predict, long-run elasticities are typically more negative than short-run estimates. In his review of international evidence, Hamermesh (1986) find that aggregate conditional long-run wage elasticities typically range from -0.50 to -0.15 .

Since labor varies across multiple dimensions, understanding the demand for heterogeneous worker types is a central concern in labor economics (Popp, 2023). Consequently, adjustment costs, wage elasticities, and capital-labor complementarities are likely to differ across occupational categories. The literature suggests that labor classes with higher levels of human capital tend to exhibit lower wage elasticities. Disaggregating labor into different categories is essential when estimating adjustment costs and wage elasticities, as these groups often experience different labor market dynamics, cost structures, and responsiveness to shocks.

Table 3.3: Estimates of total labor demand*Dependent variable: log of total number of workers*

	<i>Capital, TFP and Export dated at t-1</i>		
<i>Variables</i>	<i>(1)</i> <i>OLS</i>	<i>(2)</i> <i>FE</i>	<i>(3)</i> <i>GMM</i>
$Ln(Labor)_{t-1}$	0.864*** (0.008)	0.385*** (0.023)	0.483*** (0.032)
$Ln(wage_cost)_t$	-0.070*** (0.007)	-0.101*** (0.010)	-0.126*** (0.013)
$Ln(capital)_{t-1}$	0.053*** (0.004)	0.038*** (0.007)	0.037*** (0.010)
$Ln(TFP)_{t-1}$	0.035*** (0.007)	0.080*** (0.011)	0.064*** (0.020)
$Ln(Export)_{t-1}$	0.004*** (0.001)	-0.002 (0.003)	0.004 (0.005)
$Ln(age)_t$	0.030*** (0.009)	0.136*** (0.023)	0.212*** (0.022)
<i>Location</i>	0.030*** (0.009)	0.092 (0.127)	0.024 (0.033)
<i>Constant</i>	0.166*** (0.040)	2.007*** (0.144)	1.564*** (0.182)
<i>Year Fixed Effects</i>	Yes	Yes	Yes
<i>Observations</i>	10,595	10,595	7,987
<i>R-squared</i>	0.859	0.228	
<i>F_Statistics</i>	2224	27.33	3599
<i>Number of Groups</i>		2,137	1,986
<i>Instrument Count</i>			31
<i>AR(1)</i>			0
<i>AR(2)</i>			0.248
<i>Hansen Statistics</i>			0.114

Note: In the equations presented in columns (1) - (6) the dependent variable is log of total number of employees. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All estimates include time dummies that are not reported. OLS refers to Ordinary Least Squares Estimation, FE refers to Fixed Effects Estimation and GMM represents two step system Generalized Method of Moments estimator. The instruments are as follows. Columns (3): For Endogenous variable; for the differenced equations, total number of labor($llabor$), ,capital TFP and export variables lagged 2 periods; for the levels equation, the first differenced of these variables lagged 1 period used as instruments for the level equation . For predetermined variable: for the differenced equations, wage cost of labor ($wage_cost$) lagged 1 period; for the levels equation the first difference of $wage_cost$ used as an instrument

Table 3.4 presents the benchmark results from the OLS and Fixed Effects (FE) estimations for both production and non-production labor demand models, shown in columns (1) and (2), and (4) and (5), respectively. The results indicate that most explanatory variables are statistically significant, with coefficient signs aligned with theoretical expectation. However, due to potential endogeneity, OLS and FE estimates may be biased and fail to capture causal effects. To address this issue, the System Generalized Method of Moments (SYS-GMM) estimator, developed by Blundell and Bond (1998), is employed using lagged regressors as instruments. All relevant specification tests

are conducted to validate the model and ensure the robustness of the results

A Wald test is conducted to assess the overall joint significance of the independent variables, and the null hypothesis of insignificant coefficients is rejected. The Hansen test for over-identifying restrictions confirms that we fail to reject the null hypothesis, indicating that the over-identifying restrictions are valid. This implies that the instruments used are uncorrelated with the error term and correctly excluded from the estimated equation. The standard Arellano and Bond (AR) tests for autocorrelation support the consistency of the adopted GMM estimators, as we fail to reject the null hypothesis of no second-order serial correlation an essential assumption for our identification strategy. Additionally, all estimates are obtained using the two-step procedure, with standard errors corrected following Windmeijer (2005). Given that our panel is unbalanced with gaps, we apply orthogonal deviations as recommended by Arellano and Bover (1995) to correct the estimator. Overall, these statistical tests indicate that the system GMM model is well specified.

To evaluate the validity and strength of the instruments used in our model, we conducted under-identification and weak identification tests. Specifically, we applied the under-identification test proposed by Kleibergen and Paap (2006) for two-stage least squares to assess instrument validity in both labor demand equations. The results indicate that both the level and differenced equations are just identified at the 1% significance level, confirming that the GMM estimator aligns with two-stage least squares. Additionally, we tested for weak identification in both level and difference equations separately. The results demonstrate that the instruments are sufficiently strong at the 1% significance level, ensuring precise and reliable estimates for both labor demand equations. Additionally, the number of groups exceeds the number of instruments, indicating that we did not use excessive instruments (Roodman, 2009; Okafor et al., 2017). Thus, well-conjectured inferences can be made from the results.

An examination of the labor demand estimates in columns (3) and (6) of Table 7 reveals that the positive and highly significant lagged employment coefficients for both production and non-production workers indicate strong persistence in employment dynamics over time (Haile et al., 2017). Consistent with theoretical expectations, the demand for each labor category is negatively associated with its own wage rate, while positively associated with the wage rate of the alternative category, suggesting potential substitutability between the two categories of labor (Meschi et al.,

2016). Additionally, firm-level total factor productivity (TFP) and capital stock exert a positive influence on the demand for both types of workers. The estimated adjustment cost coefficients, 0.35 for production workers and 0.34 for non-production workers—are in line with previous findings by Haile et al. (2019), who report comparable values of 0.30 and 0.28, respectively.

A lower adjustment cost, reflected in a higher speed of adjustment, indicates that firms can more rapidly align their workforce with changing market conditions. The findings show that 72% of the deviation from long-run equilibrium employment for production workers and 69% for non-production workers is adjusted instantaneously²². This gradual response suggests that labor demand remains out of equilibrium in the short run. Adjustment costs for both worker categories tend to be similar due to overlapping job roles and uniform labor policies (Porto & Hoekman, 2010). Furthermore, lower labor adjustment costs stem from weak labor law enforcement and widespread informal employment (Hasan & Jandoc, 2013; Artuç & McLaren, 2015).

The wage elasticity of labor demand is a key indicator of how firms respond to changes in labor costs. The estimated own-wage elasticity coefficients for production and non-production workers are -0.29 and -0.25, respectively, suggesting that the demand for production labor is more sensitive to wage change. These results are consistent with both theoretical expectations and prior empirical research, indicating that labor demand for blue-collar workers tends to be more elastic than for white-collar workers (Hamermesh, 1993).

In his seminal review, Hamermesh (1993) analyzed studies on labor demand and concluded that the constant-output own-wage elasticity typically ranges from [-0.75, -0.15]. A widely cited interpretation of this relationship, known as the “3 for 10” rule, suggests that a 10% increase in labor costs results in a 3% reduction in employment (Lichter et al., 2015; Hamermesh, 2021). When considering the responses of both unskilled and skilled labor, the observed elasticity tends to align closely with this 3 for 10 rule on average (Hamermesh, 2021). Our estimate falls within the middle of this range and is consistent with the estimates provided by both Hamermesh (1993) and Lichter et al. (2015). Ethiopia’s industrial sector, which remains highly labor-intensive, shows that production labor demand is particularly sensitive to wage changes. In such contexts, higher

²² The speed of adjustment toward long-run equilibrium employment is reflected in the ratio of short-run to long-run wage elasticity coefficients. For production workers, this ratio is approximately 0.69 (-0.285/-0.4111), and for non-production workers, it is about 0.72 (-0.25/-0.345) (see Table 7 and Table 8).

wage elasticity reflects the ability of firms to adjust production roles in response to shifting labor market conditions (Fafchamps & Söderbom, 2006).

The coefficients for lagged non-production labor in the production labor demand equation (0.11) and lagged production labor in the non-production labor demand equation (0.15) suggest a complementary relationship between the two roles. In labor-intensive firms, these roles often reinforce each other as workforce structuring adapts to production expansion (Goldberg & Pavcnik, 2007). Consequently, both labor categories tend to grow simultaneously, regardless of wage fluctuations (Almeida & Carneiro, 2009). Ethiopia's manufacturing sector remains heavily dependent on production labor, while non-production labor primarily serves a supportive role to enhance efficiency (Bigsten & Gebreeyesus, 2007). Similar patterns of complementarity have been observed in Brazilian and Mexican manufacturing firms, where both labor categories tend to expand together in response to operational needs (Almeida & Carneiro, 2009). Additionally, Teal (2000) finds that in Ghanaian manufacturing firms, cross-price elasticities between skilled and unskilled labor indicate that the two labor categories are complementary in the production process.

Recognizing labor heterogeneity requires understanding how changes in the cost of one type of labor affect the demand for other types (Alonso-Borrego, 1998). Our findings indicate that the cross-wage elasticity coefficients for non-production workers in the production labor demand equation (0.14) and for production workers in the non-production labor demand equation (0.17) suggest some degree of substitutability between the two labor categories. Specifically, production labor demand is more sensitive to changes in the wages of non-production workers than the reverse. This pattern aligns with studies on Korean manufacturing firms, where production and non-production labor are viewed as substitute (Bognanno et al., 1987). In Ethiopian manufacturing firms, the demand for unskilled labor is more elastic, as these workers can often be substituted for skilled workers more easily (Haile et al., 2017). In response to rising wages, firms often reallocate tasks to preserve cost efficiency, assigning non-production responsibilities to production workers (Acemoglu, 1999; Aaronson & Phelan, 2024). This strategic task redistribution reflects how firms adapt to labor cost pressures by optimizing their workforce across different skill levels. Similar patterns are observed in Kölling's (2018) study of German manufacturing firms, which finds that low- and medium-skilled workers can substitute for high-skilled workers, especially when the wages of lower-skilled employees increase.

The results indicate that increases in capital stock are associated with higher employment for both production and non-production workers. However, the labor-augmenting effect is slightly stronger for production workers (0.04) than for non-production workers (0.03), and this difference is statistically significant. This finding suggests a complementary relationship between capital and production labor in modern manufacturing settings (Curtis et al., 2021). In contrast, the demand for non-production labor appears less responsive to capital accumulation, likely because such roles are less directly affected by production-focused investments (Tekleselassie et al., 2018; Abreha et al., 2021). The findings highlight the sector's reliance on capital to enhance, rather than replace, manual labor, reflecting a labor-augmenting approach to capital investment (Tekleselassie et al., 2018; Aghion et al., 2022). These results align with broader research indicating strong capital–labor complementarity, particularly in labor-intensive manufacturing sectors (Chen et al., 2020; Curtis, 2021). For example, Curtis et al. (2021), using U.S. Census data on manufacturing establishments, find that subsidized investment in physical capital leads to a greater increase in production labor demand than in non-production labor.

As anticipated, total factor productivity (TFP) has a positive effect on both production and non-production labor, indicating that productivity improvements drive higher demand for both categories of workers. Specifically, the findings show that a rise in TFP increases demand for production workers by 0.08 and for non-production workers by 0.05, with the difference between these coefficients being statistically significant. Firms with higher TFP typically expand their production workforce to fully exploit productivity gains (Foster et al., 2008; Bartelsman et al., 2013). In contrast, the demand for non-production roles grows more gradually, as these positions are less directly tied to the production process and therefore less responsive to productivity improvements (Tekleselassie et al., 2018; Kebede & Heshmati, 2020). The study by Shiferaw & Söderbom (2018) provide further insights into TFP and employment dynamics across different firm sizes in Ethiopian, showing that larger firms experience higher productivity, which is more strongly associated with increased demand for production labor. Similarly, Dai et al. (2022), in their study of China's labor-intensive manufacturing sector, found that TFP gains primarily benefit production workers due to their direct involvement in output generation.

The results indicate that an increase in firm age raises the demand for non-production workers slightly more than for production workers, with estimated increases of 0.24 and 0.20, respectively.

However, the difference between these coefficients is not statistically significant. As firms mature, they often diversify workforce, placing greater emphasis on strategic roles such as management, marketing, and research, which typically require non-production labor (Fox & Smeets, 2011). Additionally, the results show that firms located in the capital city exhibit higher demand for production workers compared to those based outside the capital. Operating in urban centers often leads firms to prioritize production roles due to the need for higher output and operational efficiency (Elvery & Dunn, 2021; Aghion et al., 2023). Together, these findings suggest that the advantages of capital city environments, such as superior infrastructure, access to skilled labor, and productivity gains, favor increased employment in production roles.

Table 3.4: Labor demand estimates for production and non-production workers*Dependent Variable: Number of production workers and number of non-production workers*

Variables	Production Labor			Non-Production Labor		
	(1) <i>OLS</i>	(2) <i>FE</i>	(3) <i>GMM</i>	(1) <i>OLS</i>	(2) <i>FE</i>	(3) <i>GMM</i>
$Ln(prod)_{t-1}$	0.670*** (0.012)	0.248*** (0.020)	0.350*** (0.028)	0.211*** (0.009)	0.162*** (0.016)	0.152*** (0.024)
$Ln(nonprod)_{t-1}$	0.177*** (0.008)	0.131*** (0.014)	0.113*** (0.020)	0.661*** (0.010)	0.210*** (0.018)	0.342*** (0.024)
$Ln(wage_prod)_t$	-0.240*** (0.010)	-0.257*** (0.013)	-0.285*** (0.016)	0.168*** (0.009)	0.163*** (0.011)	0.166*** (0.014)
$Ln(wage_nonprod)_t$	0.141*** (0.007)	0.137*** (0.009)	0.137*** (0.012)	-0.187*** (0.009)	-0.224*** (0.011)	-0.250*** (0.014)
$Ln(capital)_{t-1}$	0.040*** (0.005)	0.045*** (0.008)	0.039*** (0.013)	0.068*** (0.004)	0.031*** (0.007)	0.030*** (0.012)
$Ln(TFP)_{t-1}$	0.016*** (0.009)	0.096*** (0.015)	0.078*** (0.025)	0.058*** (0.010)	0.065*** (0.015)	0.054*** (0.024)
$Ln(Export)_{t-1}$	0.006*** (0.002)	-0.001 (0.004)	0.004 (0.006)	0.001 (0.002)	-0.005 (0.004)	0.001 (0.006)
$Ln(age)_t$	0.027*** (0.007)	0.137*** (0.026)	0.202*** (0.025)	0.037*** (0.007)	0.137*** (0.029)	0.238*** (0.026)
<i>Location</i>	0.039* (0.013)	0.054 (0.123)	0.066* (0.037)	0.013 (0.014)	0.205 (0.145)	-0.033 (0.041)
<i>Constant</i>	0.522*** (0.057)	1.759*** (0.153)	1.397*** (0.168)	-0.502*** (0.057)	1.154*** (0.159)	0.738*** (0.167)
<i>Year Fixed Effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	10,595	10,595	7,987	10,595	10,595	7,987
<i>R-squared</i>	0.800	0.232		0.799	0.209	
<i>F_Statistics</i>	1142	33.60	2094	1193	33.06	1156
<i>Number of Groups</i>		2,137	1,986		2,137	1,986
<i>Instrument Count</i>			35			35
<i>AR(1)</i>			0			0
<i>AR(2)</i>			0.698			0.675
<i>Hansen Statistics</i>			0.123			0.229

Note: In the equations presented in columns (1) - (3) the dependent variable is log of total number of production employees and the estimates presented in columns (3) - (6) is log of total number of non-production employees. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All estimates include time dummies and a constant that are not reported. The standard errors are in Parentheses. OLS refers to Ordinary Least Squares Estimation, FE refers to Fixed Effects Estimation and GMM represents two-step system Generalized Method of Moments estimator. The instruments are as follows. Columns (3)–(6): For Endogenous variable; for the differenced equations, total number of production labor(prod), total number of non-production labor(nonprod), capital TFP and export variables lagged 2 periods; for the levels equation, the first differenced of these variables lagged 1 period used as instruments for the level equation. For predetermined variable: for the differenced equations, wage cost for production labor (wage_prod), wage cost for non-production labor (wage_nonprod) variables lagged 1 period; for the levels equation the first difference of these variables are used as an instrument.

Specification tests: AR (1) – first order serial correlation in the differenced error term; AR (2) – second order serial correlation in the differenced error term; Hansen test/statistics – validity of the over-identifying restrictions.

Long Run Estimates

We compute and summarize the long-run elasticity estimates of the key variables in Table 3.5²³. The own-wage elasticity estimates for production workers and non-production workers are -0.41 and -0.34, respectively, indicating that the demand for production labor is more responsive to wage rate changes than the demand for non-production labor. The results show a higher absolute value for the wage elasticity of production labor compared to non-production labor. As anticipated by theory, long-run elasticities are more negative than their short-run counterparts (Popp, 2023). Our empirical findings support this theoretical expectation, demonstrating that labor demand is less elastic in the short run than in the long run (Lichter et al., 2015).

Teal (2000) reports that unskilled labor in Ghanaian manufacturing firms exhibits a higher absolute own-wage elasticity (-0.52) than skilled labor (-0.44), a pattern consistent with findings by Roberts & Skoufias (1997) for Colombian manufacturing, where own-wage elasticities are -0.65 for unskilled and -0.42 for skilled labor. Similarly, in the context of German manufacturing industries, Falk & Koebel (2001) find that, in the long run, the demand for unskilled labor (-0.21) is more sensitive to wage changes than that for skilled labor (-0.10). Reviewing various empirical evidence, Hamermesh (1986) concluded that long-run conditional own-wage elasticity of labor demand typically falls within the range of -0.50 to -0.15.

The cross-wage elasticity coefficients suggest that production and non-production workers function as substitutes in the production process. The long-run cross-wage elasticity between these worker categories is estimated at 0.15, indicating a modest degree of substitutability even over extended periods. Additionally, an increase in capital stock raises the demand for production and non-production workers by 0.07 and 0.06, respectively, implying that capital is labor augmenting in the long run. This capital-labor complementarity is a key factor in explaining long-term patterns of wage inequality (Krusell et al., 2000; Lindquist, 2004). Furthermore, improvements in total factor productivity (TFP) lead to increased demand for production and non-production labor by 0.11 and 0.14, respectively.

²³ The long-run effects are calculated after deriving long-run equations for production and non-production workers from the system of dynamic equations (see Appendix I).

Notably, employment demand in manufacturing firms is more responsive to changes in TFP in the long run compared to the short run. Overall, the findings confirm that, as theory suggests, short-run elasticities are smaller in absolute terms than their corresponding long-run elasticities.

Table 3.5: Long-run estimates of production and non-production labor demand

Variables	Production Workers	Non-Production Workers
<i>Ln(wage_prod)</i>	-0.411*** (0.031)	0.158*** (0.030)
<i>Ln(wage_nonprod)</i>	0.151*** (0.025)	-0.345*** (0.027)
<i>Ln(capital)</i>	0.071*** (0.021)	0.061*** (0.020)
<i>Ln(TFP)</i>	0.141*** (0.041)	0.113** (0.040)

Robust standard errors in the parenthesis *** p<0.01, ** p<0.05, * p<0.1

Own-Wage Elasticities of Labor Demand: Empirical Evidence and Literature Comparison

The constant-output own-wage elasticity of labor demand is a key parameter for understanding employment behavior. Numerous estimates of this elasticity have been produced using a variety of methods and data sources (Hamermesh, 1993). Firm-level studies, in particular, have helped mitigate aggregation bias, leading to estimates that are more precise. Table 3.6 summarizes findings from these studies, which typically model employment as a function of wages and output to estimate this parameter directly. While results differ across studies due in part to methodological choices and data characteristics some of the variation likely reflects genuine cross-country differences in production technologies. Nonetheless, a consistent pattern emerges in most empirical findings: over the long run, production workers tend to exhibit greater wage elasticity than non-production workers.

Table 3.6: Long-run own-wage elasticity estimates by country and worker category

			Estimated Own-wage elasticity	
Country/Study	Data	Frequency /Time Period	Non- production (White-collar)/ Skilled Labor	Production (Blue-collar)/ unskilled Labor
Colombia/ Roberts & Skoufias (1997)	Firms	Annual/1981–86	-0.42	-0.65
Ghana/ Teal(2000)	Firms	Annual/1969–94	-0.44	-0.52
Chile/Fajnzylber & Maloney(2005)	Firms	Annual/1981–86	-0.32	-0.48
Mexico/ Fajnzylber & Maloney(2005)	Firms	Annual/1986–90	-0.42	-0.44
Colombia/ Cárdenas & Bernal (2003)	industry	Annual/1992–96	-0.35	-0.40
Egypt/ Nasir(2019)	Firms	Monthly/Aug-Oct.2008	-0.68	-0.16
Colombia/ Arango et al. (2019)	Firms	Annual/ 2000-2013	-0.59	-0.42

3.5. Robustness Checks

To further validate the main results presented in Table 3.6, we conduct a series of robustness checks. Specifically, we examine whether the estimates are sensitive to: (1) using contemporaneous values of the control variables (capital, TFP, and exports) instead of lagged values; (2) re-estimating the model without control variables; and estimating the level and first-differenced equations separately using instrumental variables or Two-Stage Least Squares (2SLS) estimators. In all cases, the coefficients of our key variables remain stable, confirming the robustness of our results.

Contemporaneous Control Variables

Table 3.7 reports estimates from both labor demand models using control variables measured at time t rather than $t-1$. The Hansen test for over-identifying restrictions does not reject the null hypothesis, confirming the validity of the instruments, and the Arellano-Bond (AR) test finds no evidence of second-order serial correlation, supporting a key identification assumption.

Table 3.7: Estimates of labor demand for production and non-production workers with contemporaneous control variables

Variables	Production Labor			Non-Production Labor		
	(1) <i>OLS</i>	(2) <i>FE</i>	(3) <i>GMM</i>	(1) <i>OLS</i>	(2) <i>FE</i>	(3) <i>GMM</i>
$Ln(prod)_{t-1}$	0.659*** (0.012)	0.252*** (0.019)	0.356*** (0.027)	0.198*** (0.009)	0.163*** (0.015)	0.156*** (0.023)
$Ln(nonprod)_{t-1}$	0.164*** (0.009)	0.129*** (0.014)	0.112*** (0.020)	0.645*** (0.011)	0.206*** (0.017)	0.336*** (0.023)
$Ln(wage_prod)_t$	-0.245*** (0.010)	-0.257*** (0.013)	-0.296*** (0.016)	0.163*** (0.009)	0.155*** (0.011)	0.150*** (0.015)
$Ln(wage_nonprod)_t$	0.130*** (0.007)	0.130*** (0.009)	0.130*** (0.012)	-0.201*** (0.009)	-0.232*** (0.011)	-0.257*** (0.014)
$Ln(capital)_t$	0.060*** (0.005)	0.071*** (0.008)	0.042*** (0.013)	0.094*** (0.005)	0.076*** (0.008)	0.061*** (0.013)
$Ln(TFP)_t$	0.001 (0.009)	0.048*** (0.017)	-0.047* (0.026)	0.036*** (0.009)	-0.001 (0.015)	-0.058** (0.020)
$Ln(Export)_t$	0.009*** (0.002)	0.006 (0.004)	0.009 (0.006)	0.005** (0.008)	0.006 (0.005)	0.016** (0.007)
$Ln(age)_t$	0.037*** (0.007)	0.151*** (0.026)	0.193*** (0.025)	0.050*** (0.008)	0.157*** (0.028)	0.232*** (0.025)
<i>Location</i>	0.043*** (0.013)	0.076 (0.123)	0.054 (0.036)	0.015 (0.014)	0.265* (0.141)	-0.036 (0.039)
<i>Constant</i>	0.471*** (0.057)	1.571*** (0.160)	1.710*** (0.206)	-0.572*** (0.059)	0.836*** (0.157)	0.757*** (0.194)
<i>Year Specific Effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	10,588	10,588	7,964	10,935	10,935	7,964
<i>R-squared</i>	0.804	0.240		0.818	0.227	
<i>F_Statistics</i>	1162	34.40	2144	1387	35.74	1207
<i>Number of Groups</i>		2,141	1,982		2,215	1,982
<i>Instrument Count</i>			35			35
<i>AR(1)</i>			0			0
<i>AR(2)</i>			0.600			0.686
<i>Hansen Statistics</i>			0.302			0.162

Note: In the equations presented in columns (1) - (3) the dependent variable is log of total number of production employees and the equations presented in columns (3) - (6) is log of total number of non-production employees. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All estimates include time dummies and a constant that are not reported. OLS refers to Ordinary Least Squares Estimation, FE refers to Fixed Effects Estimation and GMM represents two-step system Generalized Method of Moments estimator. The instruments are as follows. Columns (3)–(6): For Endogenous variable; for the differenced equations, total number of production labor (*prod*), total number of non-production labor (*nonprod*) variables lagged 2 periods and capital, TFP, export variables lagged 1 periods used as an instrument; for the levels equation, the first differenced of *prod* and *nonprod* variables lagged 1 period and capital, TFP, export variables first differenced as instruments for the level equations. For predetermined variable: for differenced equations, wage cost for production labor (*wage_prod*) and wage cost for non-production labor (*wage_nonprod*) variables lagged 1 period is used as an instrument; for the levels equation, first differenced of *wage_prod* and *wage_nonprod* variables are used as an instrument.

Specification tests: AR (1) – first order serial correlation in the differenced error term; AR (2) – second order serial correlation in the differenced error term; Hansen test/statistics – validity of the over-identifying restrictions.

The adjustment cost coefficients for production and non-production workers are similar, at 0.36 and 0.34, respectively. The own-wage elasticity for production labor (-0.30) is larger in magnitude than that for non-production labor (-0.26). Positive and statistically significant coefficients on lagged production workers (0.11) in the non-production labor demand equation, and lagged non-production workers (0.16) in the production labor demand equation, indicate conditional complementarity between the two labor categories. At the same time, cross-wage elasticity coefficients suggest a degree of substitutability. Increases in capital stock raise the demand for both labor types, highlighting that capital is labor augmenting and particularly complementary to production labor. Except for the TFP coefficients, these results are consistent with the baseline model using lagged control variables, reinforcing the robustness of the estimates.

Alternative Estimation Techniques (2SLS Estimators) and GMM estimates without Control

Table 3.8 shows that our model estimates remain robust when alternative estimation methods are applied. Specifically, we estimated the level and first-differenced equations for the production labor demand model using Two-Stage Least Squares (2SLS). Traditional goodness-of-fit measures, such as R-squared, are not appropriate in this context; instead, we rely on specialized diagnostic tests. The underidentification test confirms proper model identification ($P < 0.05$), the weak identification test verifies the relevance of the instruments, and the Cragg-Donald F-statistic indicates that the instruments are sufficiently strong ($F > 10$).

The own-wage elasticity for production workers is consistent across both level and differenced estimations. Positive and statistically significant coefficients on lagged production workers indicate conditional complementarity with non-production labor, while positive cross-wage elasticities suggest partial substitutability. Increases in TFP and capital stock raise production labor demand, though the capital coefficient in the differenced equation is not statistically significant. These results align closely with System GMM estimates using control variables measured at both t and $t-1$.

We also re-estimated the System GMM model without control variables. Diagnostic tests for the two-step System GMM were successfully passed, and the results remain consistent with the baseline model in both coefficient signs and statistical significance. Overall, the findings demonstrate robustness across alternative estimation methods and specifications.

Table 3.8: Production labor demand estimates – 2SLS with controls and GMM excluding controls

Level Equation	Coefficients	First Difference Equation	Coefficients	GMM-Excluding controls	Coefficients
<i>Variables</i>	<i>Ln(Prod)</i>	<i>Variables</i>	<i>Ln(DProd)</i>	<i>Variables</i>	<i>Ln(Prod)</i>
<i>Ln(Prod)_{t-1}</i>	0.333*** (0.029)	<i>Ln(DProd)_{t-1}</i>	0.253*** (0.038)	<i>Ln(Prod)_{t-1}</i>	0.343*** (0.029)
<i>Ln(NonProd)_{t-1}</i>	0.130*** (0.024)	<i>Ln(DNonProd)_{t-1}</i>	0.067** (0.028)	<i>Ln(NonProd)_{t-1}</i>	0.116*** (0.020)
<i>Ln(wageprod)_t</i>	-0.296*** (0.018)	<i>Ln(Dwageprod)_t</i>	-0.289*** (0.019)	<i>Ln(wageprod)_t</i>	-0.288*** (0.016)
<i>Ln(wagenonprod)_t</i>	0.135*** (0.014)	<i>Ln(Dwagenonprod)_t</i>	0.143*** (0.015)	<i>Ln(wagenonprod)_t</i>	0.124*** (0.013)
<i>Ln(Capital)_{t-1}</i>	0.046*** (0.013)	<i>Ln(DCapital)_{t-1}</i>	0.004 (0.021)		
<i>Ln(TFP)_{t-1}</i>	0.080*** (0.027)	<i>Ln(DTFP)_{t-1}</i>	0.065** (0.026)		
<i>Ln(export)_{t-1}</i>	0.005 (0.006)	<i>Ln(Dexport)_{t-1}</i>	-0.004 (0.009)		
<i>Ln(age)_t</i>	0.199*** (0.025)	<i>Ln(Dage)_t</i>	0.051 (0.04)		
Location	0.078** (0.037)				
Constant	1.448*** (0.190)	Constant	-0.054* (0.034)	Constant	2.580*** (0.157)
Year specific eff.	Yes		Yes		Yes
Observations	7,987	Observations	7,974	Observations	8,073
Number of Groups	1986	Number of Groups	1985	Number of gr.	2,002
Underidentification test (P_value)	0.00		0.00	Instr. count	27
Weak identification test(F statistic)	52.4		30.6	AR(1)	0
				AR(2)	0.388
				Hansen Stat.	0.336
F(27, 1985)	48.13	F(26, 1984)	13.77	F (22, 2058)	

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

Table 3.9 presents results for non-production labor demand, focusing on instrument validity and model robustness. The under-identification test confirms that the model is properly identified ($P < 0.05$), while the weak identification test and the Cragg-Donald F-statistic ($F > 10$) indicate that the instruments are relevant and sufficiently strong

Table 3.9: Non-Production Labor Demand Estimates – 2SLS with Controls and GMM Excluding Controls

Level Equation	Coefficient	First Difference Equation	Coefficient	GMM_Excluding controls	Coefficient
Variables	<i>Ln(NonProd)</i>	Variables	<i>Ln(DNonProd)</i>	Variables	<i>Ln(NonProd)</i>
<i>Ln(NonProd)_{t-1}</i>	0.332*** (0.026)	<i>Ln(DnonProd)_{t-1}</i>	0.288*** (0.034)	<i>Ln(NonProd)_{t-1}</i>	0.347*** (0.024)
<i>Ln(Prod)_{t-1}</i>	0.165*** (0.025)	<i>Ln(DProd)_{t-1}</i>	0.143*** (0.037)	<i>Ln(Prod)_{t-1}</i>	0.148*** (0.024)
<i>Ln(wagenonprod)_t</i>	-0.258*** (0.015)	<i>Ln(Dwagenonprod)_t</i>	-0.245*** (0.017)	<i>Ln(wagenonprod)_t</i>	-0.259*** (0.014)
<i>Ln(wageprod)_t</i>	0.162*** (0.017)	<i>Ln(Dwageprod)_t</i>	0.174*** (0.018)	<i>Ln(wageprod)_t</i>	0.157*** (0.015)
<i>Ln(Capital)_{t-1}</i>	0.040*** (0.013)	<i>Ln(DCapital)_{t-1}</i>	0.023 (0.022)		
<i>Ln(TFP)_{t-1}</i>	0.058** (0.027)	<i>Ln(DTFP)_{t-1}</i>	0.065** (0.033)		
<i>Ln(export)_{t-1}</i>	0.001 (0.008)	<i>Ln(Dexport)_{t-1}</i>	0.002 (0.008)		
<i>Ln(age)_t</i>	0.236*** (0.027)	<i>Ln(Dage)_t</i>	0.044 (0.04)		
Location	-0.033 (0.041)				
Constant	0.812*** (0.191)	Constant	-0.03 (0.030)	Constant	1.798*** (0.149)
Observations	7,987	Observations	7,974	Observations	8,073
Year Specific Eff.	Yes		Yes		Yes
Number of Groups	1986	Number of Groups	1985	Number of Groups	2002
Underidentification test (P_value)	0.00		0.00	Instrument Count	27
Weak identification test(F statistic)	52.448		30.557	AR(1)	0
				AR(2)	0.383
				Hansen Stat.	0.097
F(27, 1985)	43.74	F(26, 1984)		F(22, 2058)	981.7

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

The own-wage elasticity of non-production workers remains consistent across both level and first-differenced equations. Positive and statistically significant coefficients for lagged production workers and cross-wage elasticities indicate conditional complementarity and partial substitutability between labor categories. Increases in TFP and capital stock are associated with higher production labor demand, although the capital coefficient in the differenced equation is not statistically significant. These results align with System GMM estimates using control variables at both t and $t-1$.

We also re-estimated the System GMM model for non-production labor demand without control variables. All diagnostic tests for the two-step System GMM were successfully passed, and the estimates remain consistent with the baseline results in both sign and significance. Overall, the findings confirm robustness across estimation methods, specifications, and labor categories.

3.6. Conclusion

In recent years, there has been a growing body of labor demand studies utilizing panel data. In this study, we estimated dynamic labor demand models using a two-system GMM approach and census data from Ethiopian manufacturing firms. Our findings indicate that adjustment costs for both production and non-production workers are low and nearly identical, with the majority of employment disequilibrium being adjusted instantaneously in the long run. We also find that the demand for production labor is more responsive to wage changes compared to non-production labor. The coefficients for lagged production and non-production workers suggest that these two worker categories complement each other in the production process, with the complementarity between capital and production labor slightly stronger than that between capital and non-production labor. Additionally, increases in total factor productivity (TFP) boost the demand for both types of labor, with a greater impact on production workers.

These findings offer important insights for policymakers by highlighting how increases in labor costs may affect different categories of employment. It is essential to consider the potential adverse effects of policies that raise labor costs, such as minimum wage hikes. A deeper understanding of labor adjustment costs can also inform the design of more effective policy measures, including employment protection regulations and workforce training programs, to mitigate potential negative effects on firm behavior and employment.

While these results provide valuable insights, the study has several limitations that suggest avenues for future research. First, it focuses on medium and large manufacturing firms, excluding micro and small enterprises (SMEs), which constitute a substantial portion of Ethiopia's private sector. Labor demand in SMEs is likely more sensitive to economic fluctuations and policy changes, so the results may underestimate overall labor market responsiveness. Incorporating SMEs in future studies would provide a more comprehensive understanding of employment dynamics across firm sizes. Second, although the study estimates labor demand elasticities and adjustment costs, it cannot fully capture alternative firm responses to rising labor costs, such as automation, price adjustments or market exit. Additionally, the current classification of labor into production and non-production categories may overlook heterogeneity by skill level, tenure, or contract type, which could influence substitution and complementarity patterns. Finally, the study does not

incorporate informal sector employment, a significant component of the Ethiopian labor market, nor does it directly simulate the effects of minimum wage or other labor policies. Future research integrating informal employment, more detailed labor categories, and policy simulations would provide a richer and more representative understanding of labor demand and adjustment in developing-country manufacturing contexts.

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Appendix I: Deriving Long-Run Effects from System of Dynamic Equations

To **derive the long-run effects** from our system of **dynamic labor demand equations** for production (P) and non-production (N) workers, we follow a standard approach using **steady-state analysis** of the equations. Here's a breakdown of the process:

System of Dynamic Labor Demand Equations

- **Equation for production workers (1):**

$$lP_{ijt} = \alpha_1 lP_{ijt-1} + \alpha_2 lN_{ijt-1} + \alpha_3 lW_{P,ijt} + \alpha_4 lW_{N,ijt} + \alpha_5 lK_{ijt-1} + \alpha_6 lTFP_{ijt-1}$$

- **Equation for non-production workers (2):**

$$lN_{ijt} = \beta_1 lP_{ijt-1} + \beta_2 lN_{ijt-1} + \beta_3 lW_{P,ijt} + \beta_4 lW_{N,ijt} + \beta_5 lK_{ijt-1} + \beta_6 lTFP_{ijt-1}$$

Where:

- P: Production workers
- N: Non-production workers
- W_P : Wage cost for production labor
- W_N : Wage cost for non-production labor
- K : Capital
- TFP : Total Factor Productivity
- Firm i in industry j at time t

Step 1. Steady-State Assumption

Assume the system reaches a long-run steady state, where:

$$lP_{ijt} = lP_{ijt-1} = \bar{P}$$

$$lN_{ijt} = lN_{ijt-1} = \bar{N}$$

$$K_{ijt} = K_{ijt-1} = \bar{K}$$

$$W_{P,ijt} = W_P$$

$$W_{N,ijt} = W_N$$

Step 2: Rewrite Equations at SteadyState

Equation for production workers (3):

$$\bar{P} = \alpha_1 \bar{P} + \alpha_2 \bar{N} + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \bar{TFP}$$

Equation for non-production workers (4):

$$\bar{N} = \beta_1 \bar{P} + \beta_2 \bar{N} + \beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \bar{TFP}$$

Step 3: Rewrite Equations (3) and (4)

Move terms with $\bar{P}$ to the left-hand side and solve for $\bar{P}$

$$\bar{P}(1 - \alpha_1) = \alpha_2 \bar{N} + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \bar{TFP}$$

$$\bar{P} = \frac{1}{1 - \alpha_1} (\alpha_2 \bar{N} + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \bar{TFP}) \text{-----Equation (5)}$$

Move terms with $\bar{N}$ to the left-hand side and solve for $\bar{N}$

$$\bar{N}(1 - \beta_2) = \beta_1 \bar{P} + \beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \bar{TFP}$$

$$\bar{N} = \frac{1}{1 - \beta_2} (\beta_1 \bar{P} + \beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \bar{TFP}) \text{-----Equation (6)}$$

Step 4: Deriving Long-Run Equation for Production Workers (P)

Substitute equation (6)'s expression for $\bar{N}$ into equation (5) and solve for $\bar{P}$. This gives the long-run labor demand equation for production workers in terms of $\bar{W}_P$, $\bar{W}_N$, $\bar{K}$, $\bar{TFP}$, short-run elasticity coefficients.

$$\bar{P} = \frac{1}{1 - \alpha_1} \left\{ (\alpha_2 \left[\frac{1}{1 - \beta_2} (\beta_1 \bar{P} + \beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \bar{TFP}) \right] + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \bar{TFP}) \right\}$$

$$\bar{P} \left(1 - \frac{\alpha_1 \beta_1}{(1 - \alpha_1)(1 - \beta_2)} \right) = \frac{1}{1 - \alpha_1} \left\{ (\alpha_2 \left[\frac{1}{1 - \beta_2} (\beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \bar{TFP}) \right] + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \bar{TFP}) \right\}$$

$$\begin{aligned}
\bar{P} \left(1 - \frac{\alpha_2 \beta_1}{(1 - \alpha_1)(1 - \beta_2)} \right) &= \frac{(\alpha_2 \beta_3 \bar{W}_P + \alpha_2 \beta_4 \bar{W}_N + \alpha_2 \beta_5 \bar{K} + \alpha_2 \beta_6 \overline{TFP})}{(1 - \alpha_1)(1 - \beta_2)} \\
&\quad + \frac{\alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \overline{TFP}}{(1 - \alpha_1)} \\
\bar{P} \left(\frac{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1}{(1 - \alpha_1)(1 - \beta_2)} \right) &= \left[\frac{\alpha_2 \beta_3}{(1 - \alpha_1)(1 - \beta_2)} + \frac{\alpha_3}{(1 - \alpha_1)} \right] \bar{W}_P + \left[\frac{\alpha_2 \beta_4}{(1 - \alpha_1)(1 - \beta_2)} + \frac{\alpha_4}{(1 - \alpha_1)} \right] \bar{W}_N \\
&\quad + \left[\frac{\alpha_2 \beta_5}{(1 - \alpha_1)(1 - \beta_2)} + \frac{\alpha_5}{(1 - \alpha_1)} \right] \bar{K} + \left[\frac{\alpha_2 \beta_6}{(1 - \alpha_1)(1 - \beta_2)} + \frac{\alpha_6}{(1 - \alpha_1)} \right] \overline{TFP} \\
\bar{P} \left(\frac{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1}{(1 - \alpha_1)(1 - \beta_2)} \right) &= \left[\frac{\alpha_2 \beta_3 + \alpha_3(1 - \beta_2)}{(1 - \alpha_1)(1 - \beta_2)} \right] \bar{W}_P + \left[\frac{\alpha_2 \beta_4 + \alpha_4(1 - \beta_2)}{(1 - \alpha_1)(1 - \beta_2)} \right] \bar{W}_N + \left[\frac{\alpha_2 \beta_5 + \alpha_5(1 - \beta_2)}{(1 - \alpha_1)(1 - \beta_2)} \right] \bar{K} \\
&\quad + \left[\frac{\alpha_2 \beta_6 + \alpha_6(1 - \beta_2)}{(1 - \alpha_1)(1 - \beta_2)} \right] \overline{TFP} \\
\bar{P} &= \left[\frac{\alpha_2 \beta_3 + \alpha_3(1 - \beta_2)}{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1} \right] \bar{W}_P + \left[\frac{\alpha_2 \beta_4 + \alpha_4(1 - \beta_2)}{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1} \right] \bar{W}_N \\
&\quad + \left[\frac{\alpha_2 \beta_5 + \alpha_5(1 - \beta_2)}{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1} \right] \bar{K} + \left[\frac{\alpha_2 \beta_6 + \alpha_6(1 - \beta_2)}{1 - \alpha_1 - \beta_2 + \alpha_1 \beta_2 - \alpha_2 \beta_1} \right] \overline{TFP}
\end{aligned}$$

Where $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are short-run elasticity estimates

Step 5. Deriving Long-Run Equation for Non-Production Workers (N)

Likewise, Substitute equation (5)'s expression for $\bar{P}$ into equation (5) and solve for $\bar{N}$. This gives the long-run labor demand equation for non-production workers in terms of $\bar{W}_P, \bar{W}_N, \bar{K}, \overline{TFP}$, short-run elasticity coefficients.

$$\bar{N} = \frac{1}{1 - \beta_2} \left\{ \beta_1 \left[\frac{1}{1 - \alpha_1} (\alpha_2 \bar{N} + \alpha_3 \bar{W}_P + \alpha_4 \bar{W}_N + \alpha_5 \bar{K} + \alpha_6 \overline{TFP}) \right] + \beta_3 \bar{W}_P + \beta_4 \bar{W}_N + \beta_5 \bar{K} + \beta_6 \overline{TFP} \right\}$$

$$\begin{aligned}\bar{N}\left(1 - \frac{\alpha_2\beta_1}{(1-\alpha_1)(1-\beta_2)}\right) &= \frac{1}{1-\beta_2} \left\{ (\beta_1 \left[\frac{1}{1-\alpha_1} (\alpha_3\bar{W}_P + \alpha_4\bar{W}_N + \alpha_5\bar{K} + \alpha_6\overline{TFP}) \right] \right. \\ &\quad \left. + \beta_3\bar{W}_P + \beta_4\bar{W}_N + \beta_5\bar{K} + \beta_6\overline{TFP} \right\}\end{aligned}$$

$$\begin{aligned}\bar{N}\left(1 - \frac{\alpha_2\beta_1}{(1-\alpha_1)(1-\beta_2)}\right) &= \frac{(\alpha_3\beta_1\bar{W}_P + \alpha_4\beta_1\bar{W}_N + \alpha_5\beta_1\bar{K} + \alpha_6\beta_1\overline{TFP})}{(1-\alpha_1)(1-\beta_2)} \\ &\quad + \frac{\beta_3\bar{W}_P + \beta_4\bar{W}_N + \beta_5\bar{K} + \beta_6\overline{TFP}}{(1-\beta_2)}\end{aligned}$$

$$\begin{aligned}\bar{N}\left(\frac{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1}{(1-\alpha_1)(1-\beta_2)}\right) &= \left[\frac{\alpha_4\beta_1}{(1-\alpha_1)(1-\beta_2)} + \frac{\beta_4}{(1-\beta_2)} \right] \bar{W}_N + \left[\frac{\alpha_3\beta_1}{(1-\alpha_1)(1-\beta_2)} + \frac{\beta_3}{(1-\beta_2)} \right] \bar{W}_P \\ &\quad + \left[\frac{\alpha_5\beta_1}{(1-\alpha_1)(1-\beta_2)} + \frac{\beta_5}{(1-\beta_2)} \right] \bar{K} + \left[\frac{\alpha_6\beta_1}{(1-\alpha_1)(1-\beta_2)} + \frac{\beta_6}{(1-\beta_2)} \right] \overline{TFP}\end{aligned}$$

$$\begin{aligned}\bar{N}\left(\frac{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1}{(1-\alpha_1)(1-\beta_2)}\right) &= \left[\frac{\alpha_4\beta_1 + \beta_4(1-\alpha_1)}{(1-\alpha_1)(1-\beta_2)} \right] \bar{W}_N + \left[\frac{\alpha_3\beta_1 + \beta_3(1-\alpha_1)}{(1-\alpha_1)(1-\beta_2)} \right] \bar{W}_P + \left[\frac{\alpha_5\beta_1 + \beta_5(1-\alpha_1)}{(1-\alpha_1)(1-\beta_2)} \right] \bar{K} \\ &\quad + \left[\frac{\alpha_6\beta_1 + \beta_6(1-\alpha_1)}{(1-\alpha_1)(1-\beta_2)} \right] \overline{TFP}\end{aligned}$$

$$\begin{aligned}\bar{N} &= \left[\frac{\alpha_4\beta_1 + \beta_4(1-\alpha_1)}{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1} \right] \bar{W}_N + \left[\frac{\alpha_3\beta_1 + \beta_3(1-\alpha_1)}{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1} \right] \bar{W}_P \\ &\quad + \left[\frac{\alpha_5\beta_1 + \beta_5(1-\alpha_1)}{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1} \right] \bar{K} + \left[\frac{\alpha_6\beta_1 + \beta_6(1-\alpha_1)}{1-\alpha_1-\beta_2+\alpha_1\beta_2-\alpha_2\beta_1} \right] \overline{TFP}\end{aligned}$$

Appendix II: Descriptive Statistics of Labor, Wage Shares, TFP, and Capital Intensity by Manufacturing Industry

Industry Category	Share of Prod. Labor	Share of non-prod. Labor	Wage share-Prod-lab	Wage share-Non-prod. labor	Log TFP	Cap./Lab
Manufacture of soft drink & Water	0.51	0.49	0.43	0.57	1.63	1582.7
Manufacture of meat, fruit and veg	0.48	0.52	0.40	0.60	1.70	2327.9
Manufacture of wearing apparel	0.72	0.28	0.66	0.34	1.59	998.65
Manufacture of footwear	0.73	0.27	0.62	0.38	1.78	2390.9
Manufacture of Paints & Varnishes	0.51	0.49	0.43	0.57	2.38	1539.9
Manufacture of Pharmaceuticals	0.62	0.38	0.48	0.52	1.66	2630.7
Manufacture of soap & detergent	0.64	0.36	0.52	0.48	2.19	1533.9
Manufacture of Chemical products	0.60	0.40	0.51	0.49	2.00	2532.3
Manufacture of plastic products	0.71	0.29	0.57	0.43	2.03	2155.1
Manufacture of basic iron and steel	0.60	0.40	0.52	0.48	2.49	3192.9
Manufacture of metal product	0.69	0.31	0.66	0.34	1.92	1223.3
Manufacture of cutlery and tools	0.67	0.33	0.71	0.29	1.39	1162.3
Manufacture of other metal products	0.69	0.32	0.68	0.32	1.93	1264.7
Manufacture of other fabricated product	0.62	0.38	0.59	0.41	1.77	2726.8
Manufacture of machinery for food Processing	0.58	0.42	0.53	0.47	2.04	3160.7
Manufacture of furniture	0.57	0.43	0.57	0.43	2.53	3869.4
Manufacture of parts and accessories	0.58	0.42	0.60	0.40	1.88	1987.9
All Firms	0.63	0.37	0.59	0.41	1.94	1475.6

Notes: *Share of production (non-production) labor refers to the proportion of total employees engaged in production (non-production) activities. Wage share is the ratio of total wages paid to production (non-production) labor relative to the total wage bill. Log TFP is the natural logarithm of total factor productivity, computed using the GNR method. Capital per labor (Cap./Lab) is measured in Ethiopian birr*

Chapter Four

4. Idiosyncratic Uncertainty and Capital Accumulation: Evidence from Manufacturing Firms in Ethiopia

Abstract

This paper examines whether firm-specific uncertainty affects capital accumulation in a nonlinear manner among Ethiopian manufacturing firms. Using firm-level panel data (1996–2016), we construct a cross-sectional dataset by averaging observations over time. To address endogeneity concerns, uncertainty is measured ex-ante and capital accumulation ex-post. We estimate several OLS models with different backward-looking proxies for idiosyncratic uncertainty, including high-dimensional fixed effects to control for sectoral and regional heterogeneity. The results indicate a nonlinear relationship: capital accumulation initially increases with uncertainty but declines beyond a threshold. The positive coefficient on the linear term suggests that moderate uncertainty may encourage capital investment, while the negative coefficient on the squared term reflects a dampening effect at higher levels. This pattern aligns with real options theory, which suggests that firms defer irreversible investments under heightened uncertainty. These findings are robust across alternative uncertainty measures and specifications.

Keywords: idiosyncratic uncertainty, capital accumulation, nonlinear relationship, backward-looking measures of uncertainty, manufacturing firms, Ethiopia

JEL Classification: D24, D81, E22, L60, O12

4.2. Introduction

Studying the effect of uncertainty on economic and firm-level outcomes is crucial, as uncertainty, whether economic, political, or policy-related, shapes decision-making and resource allocation (Arellano, 2019; Alfaro et al., 2024). At the macro level, heightened uncertainty is associated with reductions in investment, consumption, and output growth (Baker et al., 2016; Bloom et al., 2018; Kellogg, 2014; Gilchrist et al., 2014). At the firm level, uncertainty distorts investment decisions, delays innovation, and affects capital allocation (Guiso & Parigi, 1999; Gulen & Ion, 2016; Nguyen & Trinh, 2023). While the uncertainty–investment relationship has been well studied—emphasizing mechanisms such as investment irreversibility, market power and firms’ risk preferences (Anh et al., 2024; Bloom et al., 2007; Chortareas et al., 2021; Guiso & Parigi, 1999; Koetse et al., 2011; Pindyck, 1990; Rashid & Saeed, 2017; Schauer, 2019), most evidence comes from advanced economies, with limited empirical work on low-income contexts characterized by macroeconomic volatility, weak institutions, and underdeveloped financial systems (Ahmad et al., 2022; Bigsten et al., 2005; Rashid et al., 2022; Shiferaw, 2009).

This paper contributes by examining how firm-specific uncertainty affects capital accumulation in Ethiopia’s manufacturing sector. Unlike short-term investment flows, capital accumulation captures firms’ cumulative responses to persistent uncertainty, offering a more comprehensive measure of productive transformation (Bond et al., 2008; Chirinko, 1993; Jorgenson, 1963; McMillan et al., 2014; Rodrik, 2013). Ethiopian firms operate under persistent macroeconomic and political instability, credit constraints, and policy unpredictability (Dinh et al., 2012; Shiferaw, 2009). These conditions amplify firm-specific uncertainty, particularly for medium and large manufacturing firms, which account for about half of sectoral employment and over 70% of value added (Asturias et al., 2021). Their high capital intensity and limited access to secondary markets make them especially vulnerable to the irreversibility of capital investments (Diao et al., 2024; Shiferaw, 2009). Yet, empirical evidence on how idiosyncratic uncertainty shapes long-run capital accumulation in such environments remains scarce.

Theoretically, the long-run relationship between uncertainty and capital accumulation is ambiguous. Real options models predict that uncertainty can encourage investment under low levels but increase incentives to delay under high levels, potentially yielding an inverted U-shaped relationship (Abel & Eberly, 1999). Linear models may thus obscure important nonlinearities.

Building on Bo and Lensink (2005), this paper explicitly tests whether capital accumulation responds nonlinearly to firm-specific uncertainty.

Using a cross-sectional dataset constructed from panel data of Ethiopian manufacturing firms (1996–2016), we apply OLS estimation to assess the effect of firm-specific uncertainty on capital accumulation. Uncertainty is measured using multiple backward-looking proxies, moving beyond reliance on sales volatility, while capital accumulation is captured over later periods to reflect long-run effects.

This paper advances the literature in the following ways. First, it addresses a critical empirical gap by focusing on Ethiopia, where structural and institutional weaknesses magnify the role of uncertainty. Second, it shifts attention from short-term investment to long-term capital accumulation, central to productivity growth and structural transformation. Third, it emphasizes medium and large manufacturing firms, which play a pivotal role in industrialization but are particularly exposed to investment irreversibility. Fourth, it tests for nonlinearities, identifying potential threshold effects overlooked in linear models. Finally, it leverages a rare panel dataset with broad sectoral and firm-size coverage in a low-income country setting.

Our findings reveal a nonlinear relationship: capital accumulation rises with uncertainty up to a threshold, after which it declines. This inverted U-shaped pattern suggests moderate uncertainty may encourage risk-taking, while elevated uncertainty deters investment due to irreversibility and risk aversion, consistent with real options theory (Abel & Eberly, 1999). The results remain robust across alternative measures of uncertainty and specifications, reinforcing the need to account for nonlinear effects when studying uncertainty in developing-country contexts.

This paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework and presents the empirical model. Section 4 describes the data and provides descriptive statistics. Section 5 presents the empirical results and discusses the key findings. Section 6 conducts robustness checks to validate the results. Finally, Section 7 concludes with a summary of the findings, policy implications, and directions for future research

4.3. Literature Review

Understanding and measuring uncertainty at the firm level is crucial due to its significant influence on key firm behaviors, particularly investment, employment, capital accumulation, and innovation. Firm-specific uncertainty affects decision-making through channels such as investment irreversibility, adjustment costs, and risk aversion (Bloom, 2009; Dixit & Pindyck, 1994). Empirical evidence consistently shows that heightened uncertainty tends to reduce investment (Bloom et al., 2007; Ghosal & Loungani, 2000), employment (Bloom, 2009), and innovation activity (Aghion et al., 2005). For instance, Guiso and Parigi (1999) demonstrate that the adverse effects of uncertainty extend beyond macroeconomic shocks to include firm-level uncertainty: Italian firms facing higher perceived uncertainty invest significantly less. This underscores the importance of quantifying firm-specific uncertainty using appropriate proxies to better diagnose barriers to private investment and inform policy design.

Measuring Firm-Level Uncertainty

Various approaches have been developed to capture uncertainty, including news-based, survey-based, and econometric methods (Bloom et al., 2020; Bontempi et al., 2010; García-Gómez et al., 2022). Typically, studies rely on second moments of firm-level outcomes, such as stock return volatility, profit fluctuations, or forecast errors, as proxies for economic uncertainty (Jurado et al., 2015). The most conventional measure remains the standard deviation of daily stock returns, which captures financial uncertainty at the firm level (Bloom et al., 2007; Bloom, 2009). These measures consistently show that firms become more cautious and tend to curtail investment in uncertain business environments (Bloom et al., 2007; Bo, 2002). However, firm-level uncertainty is not static; it varies both cross-sectionally and over time (Bachmann et al., 2017; Senga, 2018), highlighting the need for dynamic, firm-specific indicators. Notably, Rashid (2011) and Rashid and Saeed (2017) show that, in private manufacturing firms in the UK and Pakistan respectively, firm-specific uncertainty has a stronger dampening effect on investment than aggregate market uncertainty.

Effect of Uncertainty on Investment and Other Outcomes

There is broad consensus that firm-specific uncertainty negatively affects capital investment. For instance, Shiferaw (2009) finds that demand uncertainty and electricity blackouts significantly reduce firm-level investment in Ethiopia. This aligns with evidence from Bo (2002) on Dutch firms and Tran (2014) on Australian non-financial firms, both of whom emphasize the dominant role of idiosyncratic uncertainty relative to macroeconomic uncertainty in shaping investment behavior. Similarly, Baum et al. (2008) and Handley and Li (2020) document significant negative effects of firm-specific uncertainty on investment and employment, highlighting the consistency of these relationships across countries and time periods.

While these studies generally support a negative association, the literature also reveals important heterogeneity in firm responses. For example, Anh et al. (2024) suggest that firms' risk preferences moderate the impact of uncertainty, with risk-seeking firms being less likely to reduce investment under uncertainty compared to risk-averse ones. Panousi et al. (2012) further argue that managerial risk aversion intensifies the negative link between idiosyncratic uncertainty and investment. Moreover, competition and market power appear to condition the uncertainty–investment relationship: firms with greater market power experience stronger negative effects (Bulan, 2005; Shima, 2016), while competitive pressures tend to mitigate these effects.

Channels and Amplifiers of Uncertainty Effects

The literature identifies several key mechanisms explaining how uncertainty dampens investment. Investment irreversibility plays a central role: firms facing high sunk costs tend to delay or reduce investments when future payoffs are uncertain (Dixit & Pindyck, 1994; Guiso & Parigi, 1999). Guiso and Parigi (1999) find this effect to be more pronounced among Italian firms with greater capital irreversibility, suggesting that heterogeneity in investment flexibility matters. Financial constraints also amplify the negative effect of uncertainty. For example, Baum et al. (2010) report that highly leveraged U.S. manufacturing firms cut investment more sharply in response to increased uncertainty. Choi et al. (2018), who show that industries reliant on external financing are disproportionately affected, support this pattern. These findings suggest that capital market imperfections intensify the adverse impact of uncertainty (Lakdawala & Moreland, 2024).

Short-Run vs. Long-Run Effects on Capital Accumulation

Although uncertainty tends to reduce short-run investment, its long-run effects on capital stock are more ambiguous and less studied. Abel and Eberly (1999) show theoretically that in dynamic models with irreversible investment, demand uncertainty can have ambiguous effects on expected long-run capital levels. Empirically, Bond et al. (2011) find consistently negative effects of uncertainty on long-run capital accumulation under quadratic adjustment costs—often larger than those predicted by real options theory. Similarly, Bond et al. (2007) demonstrate that reducing uncertainty leads to modest increases in short-run investment but substantial gains in long-run capital stock across firms in China, India, Morocco, and Ghana. These findings suggest that the full impact of uncertainty on firm behavior unfolds over longer horizons—a point that remains underexplored in empirical research.

Synthesis and Gaps

While most empirical studies find that firm-specific uncertainty negatively affects investment, several important nuances and gaps remain. Firm-level heterogeneity such as differences in risk preferences and managerial attitudes can moderate this relationship (Anh et al., 2024; Panousi et al., 2012), highlighting the need to incorporate behavioral and strategic considerations into investment models. Industry characteristics, including the degree of competition and market power, also shape how firms respond to uncertainty (Bulan, 2005; Shima, 2016). The likelihood of a negative relationship between uncertainty and investment increases with the degree of irreversibility (Dixit & Pindyck, 1994; Guiso & Parigi, 1999). Moreover, financial constraints amplify the adverse effects of uncertainty on investment (Ghosal & Loungani, 2000; Baum et al., 2010).

Measurement remains a key challenge in the uncertainty–investment literature. Common proxies, such as financial volatility or survey-based expectations, often fail to capture the operational uncertainties faced by firms in developing countries. Moreover, the long-term effects of uncertainty on capital accumulation remain understudied, particularly in contexts characterized by capital irreversibility and high adjustment costs. This is especially relevant in low-income economies like Ethiopia, where macroeconomic instability compounds firm-level uncertainty, and

large firms contend with capital intensity and a lack of secondary markets. Despite theoretical support for nonlinear effects as suggested by real options theory most empirical studies assume linearity and focus on short-run investment. Although some theoretical studies suggest a nonlinear relationship, empirical studies documenting an inverted U-shaped relationship are scant—Bo and Lensink (2005) being a notable exception. This study addresses this gap by investigating whether a nonlinear relationship exists between firm-specific uncertainty and capital accumulation, using data from Ethiopian manufacturing firms. In doing so, it contributes new empirical evidence from a low-income country, under-researched context and challenges the dominant linear assumptions in the literature.

4.4. Theoretical Framework and Empirical Approach

4.4.1. Theoretical Framework

The nonlinear relationship between firm-specific uncertainty and capital accumulation can be explained through a theoretical framework that integrates risk aversion and investment irreversibility. Risk-averse managers are more sensitive to potential losses as uncertainty rises. At low to moderate levels, they may still pursue profitable opportunities, but beyond a certain threshold, they reduce investment to avoid unfavorable outcomes (Eeckhoudt et al., 2005; Guiso & Parigi, 1999). Simultaneously, the irreversibility and lumpy nature of capital investments increase the option value of waiting, further discouraging investment under high uncertainty (Dixit & Pindyck, 1994; Abel & Eberly, 1996; Bond et al., 2007). Together, these mechanisms give rise to an inverted U-shaped investment response: investment initially rises with uncertainty due to potential upside gains and then falls as uncertainty heightens the risks and costs of irreversible decisions (Abel & Eberly, 1999).

This conceptual framework is supported by both theoretical and empirical studies (e.g., Bertola & Caballero, 1994; Caballero, 1991; Bloom et al., 2007), which show that risk aversion and irreversibility reinforce each other in shaping firms' nonlinear investment behavior. Recent dynamic models incorporating firm heterogeneity and adjustment frictions (Bachmann & Bayer, 2013) further predict such non-monotonic responses, emphasizing that the marginal effect of uncertainty on investment depends on a firm's proximity to its adjustment thresholds.

At low uncertainty levels, a marginal increase can even stimulate investment by enhancing the value of upside opportunities (Hartman, 1972; Abel, 1983). However, as uncertainty continues to rise, firms adopt a “wait-and-see” strategy to avoid costly mistakes, consistent with real options theory (Bernanke, 1983; Dixit & Pindyck, 1994). Thus, the peak of the inverted U reflects a theoretical “sweet spot” where the trade-off between risk and opportunity is most favorable, beyond which, rising uncertainty suppresses capital accumulation.

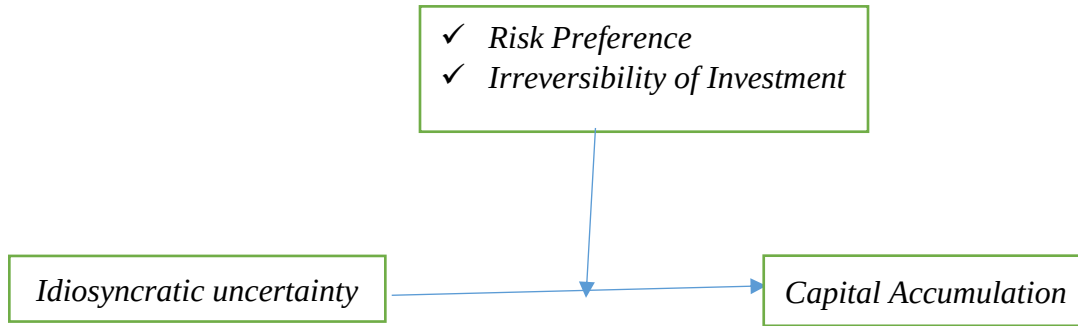


Figure 4.1: Theoretical framework: Nonlinear capital accumulation response to firm specific uncertainty

4.4.2. Empirical Approach

We estimate our model using Ordinary Least Squares (OLS) on a cross-sectional dataset derived from firm-level panel data, incorporating high-dimensional fixed effects (HDFE) to control for unobserved heterogeneity across industries and locations. The cross-sectional dataset is constructed by averaging firm-level observations over time. We leverage the panel's temporal structure by measuring firm-level uncertainty using averages from earlier years (ex-ante) and capital accumulation using averages from later years (ex-post)²⁴. This temporal sequencing helps to mitigate endogeneity concerns, particularly those related to simultaneity and reverse causality. Our regressions also control for key firm characteristics such as firm-size, firm-age, trade status,

²⁴ . We employ varying thresholds to classify uncertainty measures (ex-ante) and capital accumulation (ex-post). Specifically, for each firm, we divide the panel data into two segments: one consisting of the first or most recent 30%, 40%, or 50% of observations (used to compute capital accumulation, i.e., ex-post), and the other consisting of the remaining 70%, 60%, or 50% of earlier-period observations (used to compute uncertainty measures, i.e., ex-ante). This variation in thresholds enables us to assess the robustness of our results. We then construct a cross-sectional dataset by collapsing the panel data, averaging both the uncertainty measures and capital accumulation over time for each firm.

and market concentration for the entire periods²⁵. The inclusion of HDFE for industry and location further absorbs persistent structural differences across sectors and regions. Absorbing fixed effects provides unbiased estimates of the other variables' coefficients while controlling for omitted variable bias from unobserved group effects. Moreover, errors may be correlated within each of these groups, violating the assumption of i.i.d. errors. As a result, we use standard errors clustered by industry and location. While we cannot fully eliminate bias from time-varying unobservables, our approach provides a reasonably strong identification strategy for cross-sectional analysis. Therefore, the results should be interpreted with appropriate caution.

We estimate multiple model specifications, each using a different backward-looking proxy for uncertainty, primarily the standard deviations of sales, output, value added, total factor productivity, wage cost, material costs, number of employees, profits and Principal Component Analysis (PCA) based composite index²⁶. This approach allows for a robust assessment of the relationship between capital accumulation and firm-specific uncertainty across diverse measures of idiosyncratic uncertainty. The robustness of our results are checked for alternative uncertainty measures (variance and coefficient of variation), and the exclusion of firms with short panel histories.

4.4.2.1. Empirical Model Specification

The model builds on the framework developed by Bo and Lensink (2005). Firms are assumed to produce output using capital and flexible inputs within constant returns to scale Cobb-Douglas production function (Bond et al., 2008; 2011). To capture potential nonlinearity, the specification includes both linear and quadratic terms of the firm-specific uncertainty measures:

²⁵A potential concern is the inclusion of controls such as market concentration and firm size, which may be endogenous. To assess the robustness of our results, we re-estimate the model with and without these variables. The findings remain qualitatively similar, except in a few specifications where excluding firm size leads to unstable or undefined standard errors when clustering by both industry and location. This suggests that firm size plays a central role in explaining capital accumulation and contributes significantly to within-cluster variation, supporting its inclusion in the baseline specification.

²⁶ Our measures capture related aspects of firm-specific uncertainty. While no single measure provides a complete picture, their consistency supports the robustness of our main findings across alternative proxies. Given the moderate to high correlations among them, we argue that these variables are reasonable proxies for the same underlying construct. Therefore, using them individually, or constructing a composite index (e.g., via Principal Component Analysis or a standardized average), is justifiable.

$$\log(\text{Capital})_i = \beta_0 + \beta_1 \log(\text{Uncert})_i + \beta_2 [\log(\text{Uncert})_i]^2 + \beta_3 X_i + \varepsilon_i$$

Where: i denotes the firm; $\log(\text{Capital})$ represents logarithm of capital stock; $\log(\text{uncert})$ and $\log(\text{uncert})^2$ represent the linear and squared terms of the firm-specific uncertainty measure, respectively; and X_i is a vector of control variables, including firm age, firm size, use of imported inputs, export activity, market concentration, location, and industry fixed effects. All control variables, except dummy variables, are expressed in logarithmic form.

The standard capital accumulation equation from investment theory is given by: Capital stock (K_{it}) = $(1 - \delta)K_{it-1} + I_{it}$ (Bond et al., 2008; Ding et al., 2016). New investment (I_t) and productive capital depreciates at the known, constant rate δ at the end of each period (Bond et al., 2008). Following Hsieh and Klenow (2009), Söderbom (2012) and Gebreeyesus et al. (2020), the book value of fixed assets at the end of the year is used as the measure of capital stock. In the dataset, capital stock is reported as the net value at the beginning of the year, adjusted for new capital expenditures, and subtracting assets that have been sold, disposed of, or depreciated.

Most empirical studies proxy for firm-specific uncertainty using volatility-based measures, with the standard deviation of firm sales in particular widely used as a backward-looking indicator of firm-specific uncertainty (Bond et al., 2008; Castro et al., 2009; Comin & Mulani, 2006; Rashid, 2011; Rashid & Saeed, 2017; Shima, 2016). While simple and effective, this measure cannot fully separate idiosyncratic uncertainty from aggregate shocks (Bo, 2002). To address this, other studies employ alternative firm-level variables such as standard deviations of wages and material costs (Huizinga, 1993), the number of employees (Bo & Lensink, 2005), cash flow (Beladi et al., 2021), profit growth (Bloom, 2009), productivity shocks (Bloom et al., 2012).

Other commonly used proxies include the coefficient of variation of output (Shiferaw, 2009), and the variance of returns (Ferderer, 1993). In this study, we construct multiple backward-looking proxies of firm-specific uncertainty using the within-firm standard deviation of sales, TFP, wages, material costs, employment, and profits. To capture shared variation, we also develop composite uncertainty index using Principal Component Analysis (PCA)²⁷. Using multiple proxies enhances

²⁷ We analyze the details of the PCA procedure, including the firm-level uncertainty proxies used as inputs, the proportion of total variance explained by each principal component, and—crucially—the factor loadings for the first principal component, which is the one used in the empirical analysis.

the robustness of our analysis. As an additional robustness check, we also estimate the model using the variance and coefficient of variation of each proxy instead of standard deviations.

The coefficient β_1 captures the linear effect of uncertainty and β_2 captures the nonlinear effect. A positive β_1 ($\beta_1 > 0$) suggests that at low levels of uncertainty, capital accumulation increases, albeit with diminishing returns. A negative β_2 ($\beta_2 < 0$) implies that beyond a certain threshold, higher uncertainty reduces capital stock, indicating an inverted U-shaped relationship. A larger absolute value of β_2 implies a sharper decline in capital accumulation at high uncertainty (Abel and Eberly, 1999).

X_i : represent the set of firm specific variables that may influence capital stock.

Firm size: the size of the firm in terms of the total number of employments. Larger firms are generally expected to accumulate more capital due to better access to finance, economies of scale, and stronger internal resource generation (Fazzari et al., 1988; Rajan and Zingales, 1995).

Firm age: denotes how long a firm has been in operation. Older firms may have accumulated intangible assets, gained operational efficiency, and rely less on physical capital. In contrast, younger firms are more volatile and often experience higher capital intensity during early growth phases (Evans, 1987).

Imported Inputs- represents the value of imported inputs. Firms that import intermediates tend to engage in more advanced and potentially capital-intensive production processes. Such firms may hold higher levels of capital stock as part of upgrading and expanding production capabilities (Amiti & Konings, 2007; Bas and Strauss-Kahn, 2014).

Export – represents the value of export. Exporting firms tend to be more productive and larger, and they often invest more in capital to meet international standards. Exporters are more productive and more capital-intensive than non-exporters (Melitz, 2003 and Bernard et al., 2007).

Market Concentration: We use the Herfindahl-Hirschman Index (HHI) to measure industry concentration, calculated as the sum of squared market shares within an industry (Shiferaw, 2009). To assess the role of market power, we construct a dummy variable equal to 1 if a firm's HHI exceeds the median, and 0 otherwise. Prior studies suggest that firms in more concentrated

industries may accumulate more capital due to higher profitability (Schmalensee, 1989).

Industry and location fixed effects: Industry and location fixed effects are included in the regression model to control for unobserved heterogeneity across sectors and regions, such as differences in capital intensity, technology adoption, infrastructure quality, and market conditions that may influence firms' capital accumulation decisions. Controlling for these fixed effects helps mitigate omitted variable bias and ensures that the estimated relationship between firm-specific uncertainty and capital accumulation captures within-industry and within-location variation

4.5. Data and Descriptive Statistics

4.5.1. Data Description

This study uses establishment-level data from the Large and Medium Scale Manufacturing Industries (LMSMI) surveys conducted annually by the Ethiopian Statistical Service (ESS) between 1996 and 2016. The census covers both public and private manufacturing establishments across all regions, including firms that employ at least 10 workers and use electricity in production. These firms account for approximately 50% of total manufacturing employment and over 70% of value added in the sector (Diao et al., 2024; Asturias et al., 2021).

In this study, we focus on industries classified under ISIC codes 1511–3610, which correspond to manufacturing activities under the ISIC Revision 4.1 classification. The dataset provides detailed information on establishment-level book values of fixed assets, output, sales, employment, wages, material costs, and other firm characteristics relevant for analyzing backward-looking measures of uncertainty and capital accumulation. To obtain a cross-sectional dataset, we average firm-level observations over time. All financial variables are converted to real terms using sector-specific deflators from the FAO (2021) database. To reduce the influence of outliers, we trim the top and bottom 1% of each variable.

The dataset has been widely used in empirical studies on Ethiopian manufacturing, including research on firm performance (Aberha, 2019; Bigsten et al., 2016; Erena et al., 2021; Fiorini et al., 2021; Haile et al., 2017; Shiferaw & Söderbom, 2018; Siba & Gebreeyesus, 2016; Söderbom, 2012; Tsaedu & Chen, 2021), firm entry and survival (Shiferaw, 2006), Africa's manufacturing puzzle (Diao et al., 2024), and Ethiopia's productivity performance (Gebreeyesus et al., 2020).

4.5.2. Descriptive Statistics

Table 4.1 presents descriptive statistics for variables commonly associated with firm capital stock. Uncertainty proxies are measured as the standard deviation of log-transformed firm-level variables. Profit exhibits the highest mean variability, followed by total cost and output, highlighting significant operational uncertainty. This supports Bloom (2009), who emphasizes that volatility in profits and sales has a strong influence on firm investment behavior. In contrast, employment and TFP display lower variability, suggesting greater stability while still capturing meaningful firm-level shocks.

Among the control variables, import activity has a high mean and wide dispersion, reflecting uneven integration into global value chains. This aligns with the findings of Bas and Strauss-Kahn (2014), who showed that importing firms tend to be more productive and capital-intensive. Exports are less common, with a mean of 0.582 and a median of zero. Firm size varies widely, highlighting disparities between medium and large firms. Firm age ranges from 1 to 99 years, with a mean of 12.3, suggesting a diverse sample across different growth stages. The Herfindahl-Hirschman Index (HHI) has a mean of 0.301, indicating moderate industry concentration (Schmalensee, 1989). Additionally, over half of the firms are located in the capital city, suggesting potential advantages in infrastructure and financial access (Duranton and Puga, 2004). Overall, the statistics reveal considerable heterogeneity in both uncertainty exposure and firm characteristics. High variability in profits, costs, and output reflects significant operational uncertainty (Bloom, 2009), while differences in trade participation, firm size, and location suggest context-specific influences on capital accumulation (Melitz, 2003; Bernard et al., 2007).

Table 4.1: Summary statistics of firm-level variables used to construct uncertainty proxies

	N	Mean	Median	SD	Min	Max
Log(sales)	2124	.569	0.427	.551	0	5.733
Log(wage)	2162	.489	0.357	.445	0	3.038
Log(employment)	2162	.258	0.177	.288	0	2.605
Log(output)	2161	.558	0.408	.551	0	5.733
Log(total_cost)	2161	.628	0.465	.6	0	5.696
Log(profit)	1877	.714	0.566	.654	.001	5.797
Log(TFP)	2139	.327	0.254	.299	0	2.16
Log(export)	2162	.582	0.000	2.215	0	15.052
Log(import)	2107	6.373	6.571	3.921	0	15.391
HHI_index	2162	.301	0.276	.17	0	1
Labor	2162	75.306	31.000	116.323	10	1147
Firm_age	2162	12.344	8.000	13.04	1	99
Location	2162	.535	1.000	.494	0	1

Notes: Log-transformed variables (sales, wage, employment, output, total cost, profit, TFP) are used as inputs to construct firm-level uncertainty proxies. HI Index measures market concentration, Labor refers to the number of workers in the firm. Firm Age is measured in years, Location is a dummy variable indicating the firm's location.

Table 4.2 presents summary statistics of key variables disaggregated by firm size (large and medium) to explore how firm size influences capital accumulation. Medium firms display somewhat higher variation in sales and output, suggesting operational fluctuations at their scale. In contrast, large firms demonstrate lower volatility in TFP and profits, consistent with evidence that they benefit from economies of scale, diversification, and more effective risk management (Melitz, 2003; Syverson, 2011). These results highlight that capital accumulation strategies are shaped by firm characteristics such as age, market exposure, and volatility. Medium-sized firms, while dynamic, may face greater uncertainty in revenues and costs that can constrain long-term investment, whereas larger firms enjoy relative stability and are more likely to expand capital to sustain competitiveness (Fort et al., 2013; Ghosal & Loungani, 2000).

Labor scales sharply with size: large firms average 254 employees compared to 44 for medium firms. Large firms also report higher average import demand growth (9.226) than medium firms (6.362), reflecting deeper integration into global supply chains. Bernard et al. (2007) argue that such firms often require more capital to meet complex production needs. Export growth follows a similar pattern (1.817) for large firms versus (0.411) for medium firms, supporting Melitz (2003), who links exporting with firm size, productivity, and capital intensity. Firm age also increases with size: large firms average 19.7 years compared to 10.7 years for medium firms. While older firms may benefit from accumulated experience and more stable capital structures, they may also face diminishing returns on capital (Evans, 1987). Location advantages are evident as well, with more

than half of both large and medium firms located in the capital city, where infrastructure and financial access are stronger.

Table 4.2: Summary statistics of firm-level variables by firm size

Large firms	N	Mean	Median	SD	Min	Max
Log(sales)	413	.533	0.354	.585	.008	5.104
Log(wage)	422	.53	0.309	.533	.003	3.038
Log(employment)	422	.26	0.160	.331	0	2.605
Log(output)	422	.505	0.340	.541	.005	5.219
Log(total cost)	422	.557	0.368	.65	.001	5.696
Log(profit)	369	.646	0.460	.632	.003	4.736
Log(TFP)	418	.283	0.224	.263	0	1.69
Labor	422	253.874	194.000	166.537	100	1147
Firm_Age	422	19.664	10.000	19.601	1	99
Log(export)	422	1.817	0.000	3.836	0	15.052
Log(import)	418	9.226	10.449	3.782	0	15.391
HHI_Index	422	.263	0.255	.17	.058	1
Location	422	.545	1.000	.489	0	1
Medium firms						
Log(sales)	1036	.597	0.462	.562	0	5.733
Log(wage)	1053	.498	0.389	.431	.001	3.019
Log(employment)	1053	.289	0.203	.312	0	2.059
Log(output)	1052	.589	0.438	.565	0	5.733
Log(total cost)	1052	.66	0.512	.587	.001	4.486
Log(profit)	902	.724	0.578	.647	.001	5.797
Log(TFP)	1041	.335	0.256	.304	0	2.16
Labor	1053	43.691	37.000	21.242	20	99
Firm_Age	1053	10.723	7.000	10.681	1	67
Log(export)	1053	.411	0.000	1.762	0	14.773
Log(import)	1034	6.362	6.615	3.685	0	15.073
HHI_Index	1053	.291	0.264	.163	0	1
Location	1053	.564	1.000	.491	0	1

Notes: Size classification are based on World Bank, 2015. The definitions adopted by the enterprise surveys with small firms having five to 19 employees, medium-sized firms having 20 to 99 employees and large firms having over 100 employee.

4.6. Estimation Results

4.6.1. Main Regression Results

This section presents the results of multiple regression models that examine the effect of firm-specific uncertainty on capital accumulation, with a particular focus on testing whether the relationship is nonlinear. Each model includes a consistent set of control variables—firm size, firm age, trade activity, market concentration, firm location, and industry fixed effects—while varying the proxy used to measure uncertainty. The firm-specific uncertainty proxies include the standard deviation of log-transformed sales, output, value added, total factor productivity, wage costs, , number of employees, profit, and a composite index derived from Principal Component Analysis. This approach enables a robust evaluation of the relationship across a range of idiosyncratic uncertainty measures.

The results in Table 4.3 show consistently high R-squared values across all models (~ 0.65 – 0.67), indicating strong explanatory power. The F-tests are statistically significant across all models, confirming the joint significance and overall relevance of the explanatory variables. Moreover, a separate joint hypothesis test assessing whether uncertainty and its squared term jointly have no effect shows that both terms are statistically significant across all specifications. This supports the inclusion of both terms to capture a potential nonlinear relationship.

In some models (Model 7), although the squared term is not individually significant, the joint significance of both the linear and squared terms suggests that the nonlinear specification meaningfully captures the underlying dynamics. The inclusion of high dimensional fixed effects (location and industry fixed effects) accounts for unobserved heterogeneity in capital structure across regions and sectors. Standard errors are clustered both at the industry and location level. Clustering on both dimensions provides standard errors that are more robust by accounting for Within-industry and region correlation.

Model 1 uses the standard deviation of the log of sales as the proxy for uncertainty. The linear term is positive and statistically significant coefficient (0.271), while the squared term is negative (-0.063) and marginally significant. This suggests a nonlinear relationship: at lower levels, increased uncertainty is associated with higher capital stock, but beyond a certain point, further

increases in uncertainty reduce capital accumulation.

Model 2 uses the standard deviation of the log of output as the proxy for uncertainty. The coefficient on the linear term is 0.315, while the squared term is -0.072 , both are statistically significant. This again supports the inverted-U pattern. Output variability may motivate firms to build capital buffers or automate processes, but beyond certain threshold, it may discourage further investment.

Model 3 uses the standard deviation of the log of value added as the proxy for uncertainty. Value added filters out input cost volatility driven by external shocks, offering a clearer view of firm-specific performance. The coefficient on the linear term is 0.371, while the squared term is -0.089 , both are statistically significant. This again supports the inverted-U pattern.

Model 4 uses the standard deviation of the log of total factor productivity (TFP) as the proxy for uncertainty. The linear term is strongly positive (0.702), while the squared term is negative (-0.434); both are statistically significant. This again supports the inverted U-shaped relationship, but with a larger magnitude, suggesting that TFP uncertainty may have a stronger initial positive effect on capital accumulation before turning negative at higher levels. The results indicate that productivity-related uncertainty can initially encourage firms to invest possibly to enhance efficiency but that excessive unpredictability ultimately hinders such investment.

Model 5 uses the standard deviation of log wage costs as the proxy for uncertainty. The coefficient on the linear term is 0.441, while the squared term is -0.251 , both are statistically significant. This continues the pattern of nonlinear relationship, suggesting that wage volatility initially encourages investment, perhaps to stabilize production or reduce reliance on labor, but that high wage uncertainty ultimately dampens capital accumulation.

Model 6 uses the standard deviation of the log of total employment as the proxy for uncertainty. The coefficient on the linear term is strongly positive (0.599) and the squared term is negative (-0.276) and statistically significant. This also confirms the nonlinear relationship, suggesting that at lower level of uncertainty labor-related uncertainty may encourage capital deepening but that high employment uncertainty ultimately dampens capital accumulation.

Model 7 uses the standard deviation of the log of profit as the proxy for uncertainty. The coefficient on the linear term is positive (0.624), while the squared term is negative (−0.284) but statistically insignificant. However, the joint significance test indicates that the two terms are jointly significant, providing evidence in favor of a nonlinear specification. This suggests that profit related uncertainty may encourage capital deepening, although the shape of the relationship should be interpreted with caution given the insignificance of the squared term.

Model 8 employs a PCA-based composite index as the proxy for uncertainty. The linear term is positive (0.139), while the squared term is significantly negative (−0.024), reaffirming the inverted U-shaped pattern. The relatively small magnitudes of the coefficients likely reflect the index's aggregation of multiple sources of uncertainty. By capturing a more holistic uncertainty environment, the PCA-based index strengthens robustness of the observed nonlinear relationship. Moreover, the control variables mainly firm size, firm age, trade activity, market concentration, and firm location generally display the expected signs and levels of statistical significance.

4.6.2. Interpretation and Discussion

Across all models, the results consistently reveal a nonlinear (inverted U-shaped) relationship between uncertainty and capital accumulation. The positive coefficient on the linear term reflects risk-taking behavior under moderate levels of uncertainty, below a certain threshold, while the negative squared term indicates that capital stock increases with uncertainty up to a point, but begins to decline once that threshold is exceeded. This effect is most pronounced in Model 4 (TFP-based uncertainty), where both the linear and squared terms are larger and statistically significant, highlighting a stronger nonlinear effect. Similarly strong patterns are observed in models using wage cost, output, and PCA-based uncertainty measures. These findings suggest that the influence of uncertainty depends not only on its magnitude but also on its form and source.

These results provide robust evidence of a nonlinear relationship between firm-specific uncertainty and capital accumulation. This nuanced pattern suggests that moderate levels of uncertainty may stimulate investment by encouraging risk-taking, while high levels of uncertainty deter capital accumulation due to heightened caution and investment delay. This behavior is consistent with the real options framework of Abel and Eberly (1999), which posits that under conditions of uncertainty and capital irreversibility, firms may initially increase investment in response to

moderate uncertainty, but become more cautious as uncertainty rises. In this framework, higher uncertainty increases the value of waiting, making firms reluctant to invest, even in the face of positive demand shocks due to the risk of being left with excess capital if adverse conditions materialize. Similarly, Bond et al. (2007) find that lower levels of uncertainty are associated with firms holding higher capital stocks, underscoring the sensitivity of investment decisions to the degree of uncertainty.

The observed nonlinear relationship is consistent with empirical findings by Bo and Lensink (2005), who also document a nonlinear relationship between uncertainty and investment. These studies suggest that while moderate levels of uncertainty may stimulate investment due to precautionary motives, higher levels of uncertainty tend to deter investment. This decline is often attributed to increased risk aversion, investment delays, and the irreversibility of capital expenditures. Such behavior may reflect firms' strategic responses to volatility, including building capital buffers to maintain flexibility and resilience in uncertain environments. Additionally, findings from Arellano et al. (2019) and Gilchrist et al. (2014) highlight that the effect of uncertainty on investment is context-specific, shaped by factors such as access to finance, market competition, and internal firm capabilities.

Regarding the control variables, firm size is consistently positive and significant across all models, indicating that larger firms accumulate more capital due to greater capital intensity and better access to financial resources. This finding aligns with Beck et al. (2005) and Rajan and Zingales (1995), who identify firm size as a key determinant of investment capacity and capital structure. Conversely, firm age is negatively associated with capital, reflecting greater efficiency and lower capital intensity in older firms. This may result from improved capital utilization or reduced expansion over time. Evans (1987) supports this interpretation, showing that younger firms tend to invest more aggressively, consistent with the negative coefficient on firm age.

Trade variables are significantly positive across all models. Import activity, in particular, shows a strong positive association with capital, likely because firms engaged in importing invest in infrastructure and technology to manage imported inputs. Bernard et al. (2007) highlight importing as a key driver of firm structure and investment pattern.

Export activity also has a positive and significant effect in some of the models, reflecting the capital investment required for firms to compete internationally and enhance productivity. Melitz (2003) and Bernard et al. (2007) find that exporters tend to be more productive and capital-intensive. Bernard and Jensen (1999) show that U.S. exporters are generally larger, more productive, and more capital-intensive than non-exporters. Additionally, Alfaro and Charlton (2007) link participation in global value chains, particularly through exports, with greater capital accumulation.

A positive and significant coefficient on the market concentration dummy (HHI) suggests that firms operating in markets that are more concentrated accumulate more capital than those in less concentrated ones. This implies that greater market power facilitates investment, as dominant firms benefit from stable profits, reduced risk, and enhanced long-term planning. Gutiérrez and Philippon (2017) show that rising industry concentration in the U.S. has been accompanied by increased investment among leading firms, supporting the link between market power and capital accumulation.

Table 4.3: The effect of firm-specific uncertainty on capital stock (standard deviation-based proxies)

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)	(Model 8)
Uncertainty	0.271*** (0.066)	0.315*** (0.086)	0.371*** (0.081)	0.702*** (0.201)	0.441*** (0.094)	0.599** (0.216)	0.182** (0.061)	0.139*** (0.022)
Uncertainty2	-0.063* (0.031)	-0.072** (0.032)	-0.089*** (0.025)	-0.434*** (0.135)	-0.251*** (0.016)	-0.276** (0.109)	-0.032 (0.031)	-0.024** (0.008)
Ln(Firm_Size)	1.137*** (0.059)	1.152*** (0.057)	1.126*** (0.052)	1.147*** (0.058)	1.153*** (0.058)	1.147*** (0.057)	1.108*** (0.054)	1.112*** (0.052)
Ln(Firm_Age)	-0.239*** (0.016)	0.238*** (0.015)	-0.246*** (0.022)	-0.241*** (0.015)	-0.240*** (0.021)	-0.235*** (0.022)	-0.240*** (0.019)	-0.240*** (0.021)
Ln(Export)	0.035 (0.021)	0.038 (0.021)	0.043 (0.025)	0.037* (0.020)	0.038 (0.022)	0.042* (0.021)	0.038 (0.022)	0.038* (0.020)
Ln(Import)	0.059*** (0.016)	0.057*** (0.014)	0.057*** (0.016)	0.059*** (0.014)	0.056*** (0.015)	0.055*** (0.014)	0.064*** (0.018)	0.066*** (0.018)
HHI_Dummy	0.092* (0.049)	0.110** (0.041)	0.107*** (0.026)	0.127** (0.041)	0.128** (0.044)	0.117** (0.047)	0.869** (0.036)	0.101** (0.033)
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.537*** (0.225)	5.462*** (0.227)	5.521*** (0.258)	5.446*** (0.213)	5.477*** (0.204)	5.490*** (0.220)	5.604*** (0.260)	5.688*** (0.240)
Observations	2062	2088	2048	2071	2089	2089	1888	1838
AdjR-squared	0.66	0.65	0.66	0.65	0.65	0.66	0.67	0.67
F_Statistics	128.69	302.84	674.21	212.31	188.13	134.12	309.96	283.06

Notes: The dependent variable is log of capital stock. All regressions control for high-dimensional fixed effects (location and industry) and use clustered standard errors. We apply two-way clustering, as both industry and location may introduce independent sources of correlation in the residuals. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The proxy for firm-specific uncertainty varies across specifications: **Model 1**: SD of log sales; **Model 2**: SD of log output; **Model 3**: SD of log value added; **Model 4**: SD of log TFP; **Model 5**: SD of log wage cost; **Model 6**: SD of log total employees; **Model 7**: SD of log profit; **Model 8**: SD of log of a PCA-based composite index.

4.6.3. Percentile Based Analysis

To further explore this nonlinear dynamic, the relationship between uncertainty and capital stock is examined across percentiles of the uncertainty distribution. Table 4.4 presents the uncertainty range from the 1st to the 99th percentile and identifies an optimal level for capital accumulation. The results confirm that at low to moderate uncertainty levels, capital stock steadily increases, suggesting that manageable risk may encourage capital investment. Capital peaks at the optimal uncertainty level, representing the most favorable balance between risk and expected return. Beyond this point, higher uncertainty corresponds with declining capital stock, likely due to increased risk aversion and investment delays. The sharp decline observed at the 99th percentile underscores the detrimental effect of extreme uncertainty. These findings emphasize the importance of modeling nonlinear effects by including both linear and squared terms in uncertainty measures.

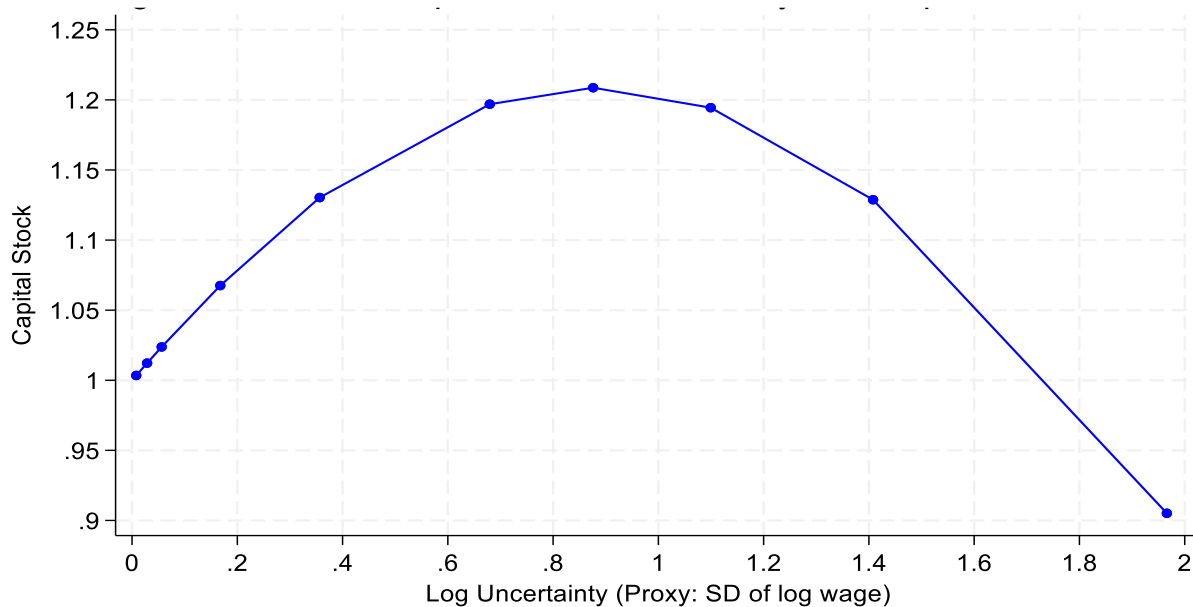
Table 4.4: The relationship between firm-specific uncertainty and capital stock across percentiles

<i>Percentiles</i>	<i>log_uncertainty</i>	<i>log_capital</i>	<i>capital</i>
1	0.008	0.003	1.003
5	0.029	0.012	1.012
10	0.056	0.024	1.024
25	0.168	0.065	1.068
50	0.357	0.123	1.130
75	0.680	0.180	1.197
	0.876	0.190	1.209
90	1.100	0.178	1.194
95	1.408	0.121	1.129
99	1.966	-0.100	0.905

NB: SD of log of wage is used as a proxy to measure uncertainty.

Figure 4.2 illustrates the relationship between uncertainty and capital stock across the percentiles of the uncertainty distribution. Capital stock is low at minimal uncertainty, rises steadily through the lower percentiles, and peaks near the 75th percentile. Beyond this point (90th–99th percentile), capital stock declines sharply, highlighting the adverse effects of excessive uncertainty on capital investment. The peak occurs at an uncertainty level of where capital stock reaches at its optimal, representing the optimal balance between risk and investment. The subsequent decline reflects increased caution among firms as uncertainty intensifies, leading to delayed or reduced investment. This observed pattern is consistent with existing empirical findings.

Figure 4.2: The Relationship between Uncertainty and Capital Accumulation



4.7. Robustness Checks

We conduct several robustness checks to validate the relationship between firm-specific uncertainty and capital accumulation. First, we re-estimate the capital stock equation using an alternative uncertainty measure—specifically, the variance of the original measures (Table 4.5). Second, we use another alternative: the coefficient of variation of the original measures (Table 4.6). In both cases, the results remain consistent, confirming the robustness of our findings across different specifications. Third, we restrict the sample to firms with more than six observations to address concerns related to data quality and firm longevity (Table 4.7). The results remain robust, with both the linear and squared terms of uncertainty generally retaining their expected signs and statistical significance in most cases. These findings indicate that our conclusions are not driven by early-stage firms or by sensitivity to changes in the data structure. Overall, the robustness checks reinforce the validity of our results and confirm that the observed nonlinear relationship is not an artifact of specific modeling assumptions or sample selection.

Use of variance of the variables as a measure of uncertainty

Table 4.5: The effect of firm-specific uncertainty on capital stock (variance-based proxies)

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)
Uncertainty	0.0507*** (0.0130)	0.0608* (0.0287)	0.0651* (0.0323)	0.0553** (0.0199)	-0.00983 (0.0517)	0.389** (0.123)	0.0553** (0.0199)
Uncertainty ²	-0.00202*** (0.000467)	-0.00230** (0.000988)	-0.00277** (0.00114)	-0.00226*** (0.000613)	-0.00533 (0.00776)	-0.0886*** (0.0238)	-0.00226*** (0.000613)
Log(Firm_Size)	1.135*** (0.0592)	1.149*** (0.0571)	1.122*** (0.0491)	1.107*** (0.0527)	1.149*** (0.0591)	1.145*** (0.0578)	1.107*** (0.0527)
Log(Firm_Age)	-0.240*** (0.0164)	-0.239*** (0.0150)	-0.248*** (0.0209)	-0.239*** (0.0187)	-0.243*** (0.0184)	-0.240*** (0.0176)	-0.239*** (0.0187)
Log(Export)	0.0343 (0.0206)	0.0371 (0.0211)	0.0411 (0.0238)	0.0371 (0.0220)	0.0367 (0.0219)	0.0402* (0.0210)	0.0371 (0.0220)
Log(Import)	0.0583*** (0.0158)	0.0566*** (0.0147)	0.0575*** (0.0156)	0.0636*** (0.0182)	0.0561*** (0.0150)	0.0556*** (0.0148)	0.0636*** (0.0182)
HHI_Dummy	0.0748 (0.0474)	0.0883* (0.0440)	0.0749** (0.0271)	0.0693* (0.0327)	0.0949* (0.0443)	0.0944* (0.0465)	0.0693* (0.0327)
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.651*** (0.216)	5.593*** (0.217)	5.690*** (0.235)	5.684*** (0.253)	5.636*** (0.211)	5.596*** (0.219)	5.684*** (0.253)
Adju.R-squared	0.64	0.65	0.65	0.66	0.64	0.65	0.65
F_Statistics	673.55	2255.40	527.91	354.15	102.23	138.50	354.15
Observations	2062	2088	1927	2071	2089	2106	1838

Notes: The dependent variable is log of capital stock. All regressions control for high-dimensional fixed effects (location and industry) and use clustered standard errors. We apply two-way clustering, as both industry and location may introduce independent sources of correlation in the residuals. Standard errors are reported in parentheses. $p < 0.10$, $p < 0.05$, $p < 0.01$. The proxy for firm-specific uncertainty varies across specifications: **Model 1**: Variance of log sales; **Model 2**: Variance of log output; **Model 3**: Variance of log value added; **Model 4**: Variance of log FFP; **Model 5**: Variance of log wage cost; **Model 6**: Variance of log total employees; **Model 7**: Variance of log profit.

Use of coefficient of variation of the variables as a measure of uncertainty

Table 4.6: The effect of firm-specific uncertainty on capital stock (coefficient of variation – based proxies)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Uncertainty	2.682*** (0.799)	2.770** (0.915)	3.252* (0.035)	0.216*** (0.061)	3.835** (1.288)	1.849** (0.680)	-0.122 (0.709)
Uncertainty ²	-9.515** (3.949)	-8.641* (4.293)	-4.477** (0.001)	0.00442 (0.006)	-19.46*** (3.694)	-2.898** (0.947)	2.015 (2.842)
Log(Firm Size)	1.141*** (0.060)	1.156*** (0.058)	1.122*** (0.049)	1.135*** (0.060)	1.156*** (0.057)	1.163*** (0.054)	1.110*** (0.055)
Log(Firm Age)	-0.241*** (0.015)	-0.241*** (0.015)	-0.248*** (0.021)	-0.239*** (0.022)	-0.240*** (0.017)	-0.236*** (0.019)	-0.242*** (0.021)
Log(Export)	0.036 (0.022)	0.038 (0.023)	0.041 (0.024)	0.038 (0.021)	0.037 (0.022)	0.0403* (0.021)	0.0362 (0.023)
Log(Import)	0.059*** (0.016)	0.057*** (0.014)	0.058*** (0.016)	0.061*** (0.016)	0.056*** (0.015)	0.056*** (0.014)	0.064*** (0.018)
HHI Dummy	0.0967* (0.049)	0.110** (0.042)	0.0749** (0.027)	0.0857 (0.047)	0.128** (0.050)	0.114** (0.045)	0.0680* (0.036)
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.543*** (0.232)	5.480*** (0.234)	5.690*** (0.235)	5.598*** (0.211)	5.470*** (0.207)	5.446*** (0.215)	5.705*** (0.269)
AdjR-Squared	0.64	0.65	0.66	0.65	0.64	0.65	0.65
F_Statistics	89.64	144.13	421.91	124.55	223.28	129.98	411.22
Observations	2062	2088	1927	2071	2089	2106	1838

Notes: The dependent variable is log of capital stock. All regressions control for high-dimensional fixed effects (location and industry) and use clustered standard errors. We apply two-way clustering, as both industry and location may introduce independent sources of correlation in the residuals. Standard errors are reported in parentheses. $p < 0.10$, $p < 0.05$, $p < 0.01$. The proxy for firm-specific uncertainty varies across specifications: **Model 1:** Coefficient of variation CV of log sales; **Model 2:** CV of log output; **Model 3:** CV of log value added; **Model 4:** CV of log TFP; **Model 5:** CV of log wage cost; **Model 6:** CV of log total employees; **Model 7:** CV of log profit.

Use of panel observations (firm-year observation ≥ 6)

Table 4.7: The effect of firm-specific uncertainty on capital stock: sensitivity to data structure

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Uncertainty	1.113*** (0.176)	1.146*** (0.264)	1.371*** (0.041)	0.509 (0.382)	0.745*** (0.214)	0.673 (0.490)	0.173 (0.240)
Uncertainty ²	-0.458*** (0.109)	-0.467*** (0.096)	-0.397*** (0.025)	-0.283 (0.320)	-0.415*** (0.126)	-0.130 (0.396)	-0.0421 (0.097)
Log(Firm_Size)	1.021*** (0.044)	1.030*** (0.039)	1.126*** (0.052)	1.025*** (0.086)	1.038*** (0.083)	1.016*** (0.083)	1.020*** (0.089)
Log(Firm_Age)	-0.255*** (0.033)	-0.256*** (0.033)	-0.246*** (0.022)	-0.270*** (0.059)	-0.254*** (0.059)	-0.244*** (0.067)	-0.269*** (0.059)
Log(Export)	0.038* (0.019)	0.037 (0.022)	0.043 (0.025)	0.042 (0.035)	0.047 (0.034)	0.046 (0.037)	0.055* (0.030)
Log(Import)	0.116*** (0.024)	0.111*** (0.020)	0.0571*** (0.016)	0.108*** (0.023)	0.105*** (0.022)	0.111*** (0.026)	0.113*** (0.025)
HHI_Dummy	-0.029 (0.069)	-0.007 (0.060)	0.107*** (0.026)	0.009 (0.088)	0.028 (0.088)	0.015 (0.089)	0.008 (0.081)
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.355*** (0.243)	5.331*** (0.288)	5.521*** (0.258)	5.711*** (0.423)	5.532*** (0.391)	5.611*** (0.468)	5.719*** (0.410)
AdjR-Squared	0.70	0.69	0.71	0.68	0.69	0.69	0.68
F-Statistics	177.88	312.78	113.3	82.26	50.58	76.65	87.58
Observations	837	844	1844	844	844	844	834

Notes: The dependent variable is log of capital stock. All regressions control for high-dimensional fixed effects (location and industry) and use clustered standard errors. We apply two-way clustering, as both industry and location may introduce independent sources of correlation in the residuals. Standard errors are reported in parentheses. $p < 0.10$, $p < 0.05$, $p < 0.01$. The proxy for firm-specific uncertainty varies across specifications: **Model 1:** Standard deviation (SD) of log sales; **Model 2:** SD of log output; **Model 3:** SD of log value added; **Model 4:** SD of log TFP; **Model 5:** SD of log wage cost; **Model 6:** SD of log total employees; **Model 7:** SD of log profit; **Model 8:** SD of log of a PCA-based composite index.

4.8. Conclusion

This study finds robust evidence of a nonlinear (inverted U-shaped) relationship between firm-specific uncertainty and capital accumulation. Across multiple model specifications, using distinct backward-looking proxies for uncertainty and estimated via OLS, the results consistently show a positive linear term and a negative squared term. This pattern is especially strong when uncertainty is measured using TFP- and output-based proxies, suggesting that capital investment is most responsive at moderate levels of uncertainty. These findings are consistent with real options theory, which predicts that moderate uncertainty can stimulate investment, while excessive uncertainty discourages it.

The results highlight important implications for both policymakers and managers. While moderate uncertainty may reward risk-taking and encourage investment, high levels of uncertainty can deter firms from committing resources. Policy measures that reduce extreme or unmanaged uncertainty can therefore help sustain capital accumulation. Targeted interventions to improve market forecasting, stabilize input and output markets, and expand firms' access to credit and insurance products can support investment decisions under uncertain conditions. At the same time, promoting innovation and technological upgrading can enhance firms' resilience to shocks, especially when uncertainty is linked to productivity fluctuations. By addressing uncertainty in these ways, policymakers can help create a more conducive environment for sustainable investment and long-term industrial transformation.

Despite these contributions, the study has several limitations that suggest promising avenues for future research. First, it relies on backward-looking, ex-ante proxies for uncertainty and does not incorporate subjective or forward-looking measures, such as managers' expectations, which could provide richer insights into investment behavior. Second, although the analysis separates ex-ante uncertainty from ex-post capital accumulation and controls for high-dimensional fixed effects to mitigate endogeneity concerns, potential reverse causality or omitted variable bias may still influence the estimates. Third, the relatively short time span and averaging of the panel data limit the ability to capture long-term investment dynamics and delayed responses to uncertainty.

In addition, the focus on manufacturing firms in Ethiopia may restrict the generalizability of the findings to other sectors or countries with different institutional and economic contexts. Finally, firm heterogeneity in size, ownership, and access to finance is also not explicitly addressed, leaving open questions about which types of firms are most sensitive to uncertainty. Addressing these limitations in future research would provide a more comprehensive understanding of how uncertainty shapes capital accumulation in developing-country firms.

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Chapter Five

5. General Conclusion and Policy Implications

5.1. Conclusion

This dissertation has examined firm behavior in Ethiopia's manufacturing sector through three interrelated studies on imported inputs and productivity, labor demand, and firm-specific uncertainty and capital accumulation. Taken together, these papers provide a comprehensive picture of how firms in a low-income, volatile economy allocate resources, respond to incentives, and adapt to shocks. By combining firm-level microdata with dynamic econometric techniques, the dissertation contributes to ongoing debates on industrialization, trade, and structural transformation in developing countries.

The first study demonstrated that imported intermediate inputs significantly raise firm productivity, with the gains being strongest among foreign-owned firms. This finding highlights the dual role of trade and ownership structure in facilitating technology transfer and knowledge spillovers. Imported inputs serve not only as production enhancers but also as conduits for learning, technology adoption, and upgrading. The Ethiopian case underscores the critical role of exchange rate and trade policy in shaping access to these inputs. Policies that raise the cost of imported intermediates, whether through overvalued exchange rates, tariffs, or foreign exchange shortages, can inadvertently weaken firm productivity and undermine industrial competitiveness. In this respect, the study provides new evidence that in economies seeking structural transformation, trade openness in inputs is not simply a matter of market integration but a foundation for domestic capability building.

The second study turned to the labor market, showing that labor demand in Ethiopian manufacturing firms is highly dynamic, with moderate costs for both production and non-production workers implying that firms adjust rapidly to disequilibria. Own-wage elasticities are larger for production than for non-production tasks, consistent with theory about substitutability and labor flexibility, and both are complemented by capital. Third, we find positive cross-wage elasticities: higher wages for one task category are associated with greater demand for the other, implying substantial interdependence between labor types. These results highlight the importance of distinguishing between types of labor in both empirical analysis and policy design. They suggest

that blanket labor policies such as uniform minimum wages may have uneven impacts across worker categories, potentially influencing firms' employment strategies, output decisions, and investment in technology. The findings also indicate that productivity gains from imported inputs and foreign ownership (as identified in the first paper) may interact with labor dynamics, as firms integrate imported technologies with human capital to enhance competitiveness. By showing that labor markets are flexible but heterogeneous, the study provides new evidence for designing more nuanced labor and industrial skills policies in developing countries.

The third study introduced the dimension of uncertainty, focusing on its effect on capital accumulation. The analysis revealed that firm-specific uncertainty has a nonlinear (inverted U-shaped) effect on capital accumulation: moderate uncertainty encourages risk-taking and capital expansion, while excessive uncertainty deters long-term commitments. This finding, consistent with real options theory, underscores the complex role of uncertainty in shaping firm behavior in volatile environments. In Ethiopia, where firms face macroeconomic instability, policy unpredictability, and structural bottlenecks, the results highlight the need to distinguish between manageable levels of uncertainty that promote dynamism and excessive uncertainty that paralyzes investment. Importantly, this study connects to the other two papers by showing that the productivity-enhancing effects of imports and the flexibility of labor markets will only translate into sustained industrial growth if uncertainty is kept within manageable bounds.

Taken together, the three studies point to a broader conclusion: firm performance and investment behavior in Ethiopia's manufacturing sector are shaped not by isolated factors but by the interaction of trade openness, labor market dynamics, and uncertainty management. Imported inputs and foreign ownership enhance productivity, but their potential is conditioned by the macroeconomic and institutional environment. Labor demand is flexible, but heterogeneous across worker categories, with employment outcomes tied closely to capital dynamics and productivity shocks. Uncertainty is not uniformly harmful but exerts a nonlinear effect, making stabilization policies essential for creating an environment where firms can invest and grow.

The dissertation's central contribution lies in showing that firm behavior in a low-income, volatile context cannot be understood through single-factor explanations. Instead, it requires an integrated approach that combines insights from trade theory, labor economics, and investment under

uncertainty. The findings extend existing literature by providing micro-level evidence from Ethiopia, a country undergoing structural transformation under conditions of rapid population growth, recurrent macroeconomic shocks, and institutional constraints. More broadly, the results highlight that industrial policy in developing countries must go beyond static prescriptions of protection or liberalization and instead recognize the interplay between openness, flexibility, and stability.

In conclusion, this dissertation provides both theoretical insights and empirical evidence on how firms in low-income economies adapt to global integration, shifting labor markets, and volatile environments. It shows that imported inputs and foreign ownership can serve as engines of productivity growth, that labor demand is more flexible than commonly assumed, and that firm-specific uncertainty shapes investment in complex, nonlinear ways. By linking these dimensions together, the dissertation contributes to a more nuanced understanding of firm dynamics in developing countries and offers a foundation for policies that seek to enable firms not only to survive but also to invest, innovate, and drive long-term structural transformation

5.2. Policy Implications

The empirical findings of this dissertation carry several important implications for industrial and economic policy in Ethiopia and other low-income economies pursuing structural transformation. A central message is that firm behavior is shaped by the interaction of trade openness, labor market dynamics, and the broader macroeconomic environment. Policies that address these dimensions in an integrated manner are more likely to foster sustained productivity growth, investment, and industrial upgrading.

One of the most consistent findings across the studies is the productivity-enhancing role of imported intermediate inputs. These inputs should not be viewed as ordinary consumption goods but as strategic assets that underpin learning, upgrading, and competitiveness. Policies that restrict access, through tariffs, foreign exchange shortages, or overvalued exchange rates, risk constraining productivity growth and weakening industrial competitiveness. Exchange rate management, therefore, should balance the objective of export promotion with the equally important goal of ensuring affordable access to productivity-enhancing inputs. In this way, trade and exchange rate policies can serve as enablers rather than barriers to structural transformation.

The findings also highlight the importance of foreign ownership as a channel for knowledge transfer and capability building. The complementarity observed between imported inputs and foreign-owned firms suggests that foreign direct investment (FDI) contributes not only financial resources but also managerial expertise and technological spillovers. Industrial policy should therefore move beyond an emphasis on attracting capital inflows and actively promote linkages between foreign and domestic firms. Joint ventures, supplier development programs, and initiatives that facilitate technology transfer can help embed foreign presence within the domestic industrial fabric, allowing local firms to enhance their productivity and integrate into global value chains.

Labor market policies also require careful calibration to reflect firm-level heterogeneity. The evidence that production and non-production workers respond differently to wage changes, yet complement each other in the production process, indicates that uniform labor policies may produce uneven or unintended effects. For instance, blanket minimum wage increases may improve welfare for one group of workers while reducing employment opportunities for another. More nuanced approaches that account for differences in labor demand across occupations and sectors are therefore needed. At the same time, policies to expand sector-specific skills training can ensure that workers are equipped with the capabilities required by firms adopting new technologies, reinforcing the complementarities between capital, labor, and productivity growth.

Finally, the nonlinear relationship between uncertainty and capital accumulation underscores the need for stabilization policies. While moderate uncertainty can encourage innovation and dynamism, excessive uncertainty stemming from macroeconomic volatility, unpredictable regulations, or institutional weakness—discourages long-term investment. Policies that improve transparency, reduce policy unpredictability, and strengthen institutional credibility are therefore essential. Complementary measures such as better access to credit and insurance, stronger market forecasting, and support for innovation can also help firms manage risk more effectively and sustain investment even in the face of shocks.

Taken together, these insights suggest that industrial policy in developing economies must move beyond static debates over protection versus liberalization. Instead, it should integrate openness to productivity-enhancing imports, policies that facilitate knowledge transfer through foreign

investment, labor market interventions that reflect firm-level realities, and macroeconomic frameworks that reduce excessive uncertainty. By addressing these areas in concert, governments can create an environment in which firms are able not only to withstand volatility but also to invest, innovate, and drive long-term structural transformation.

Overall, the dissertation underscores that industrial policy in developing economies must move beyond static debates over protection versus liberalization. Effective strategies will integrate three pillars: openness to productivity-enhancing imports, labor market flexibility supported by skill development and targeted regulation, and macroeconomic stability that keeps uncertainty within manageable bounds. By addressing these dimensions in concert, policymakers can create an environment in which firms are able not only to survive volatility but also to invest, innovate, and contribute to long-term structural transformation.

5.3. Venues for Future Research

Building on the limitations of the three studies, future research could further deepen our understanding of firm behavior in low-income economies. First, differentiating between imported capital goods and intermediate inputs, and identifying their source countries, would clarify which imports yield the highest productivity gains. Second, disaggregating foreign ownership by joint ventures, wholly foreign-owned, or majority/minority stakes would provide more nuanced insights into how ownership structure affects technology adoption and productivity. Third, extending analysis to include micro and small enterprises, informal sector employment, and broader labor heterogeneity would yield a more representative view of labor dynamics. Fourth, incorporating forward-looking measures of uncertainty, firm-level heterogeneity in size, ownership, and access to finance, could enrich understanding of capital accumulation and investment responses. Finally, comparative studies across developing economies would help test the generalizability of these findings and inform the design of context-specific industrial and labor policies. Together, these avenues offer a roadmap for future research aimed at supporting more inclusive and resilient industrial development in low-income countries.