

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

Eyayu Tesfaye Mulugeta ¹| Måns Söderbom ²

¹ Department of Economics, Addis Ababa University, Addis Ababa, Ethiopia
Email: eyayu.tesfaye@aau.edu.et; tesfaye.mulu@gmail.com
ORCID: <https://orcid.org/0000-0002-9620-3210>

² Department of Economics, University of Gothenburg, Gothenburg, Sweden
Email: mans.soderbom@economics.gu.se
ORCID: <https://orcid.org/0000-0001-9310-093X>

Declarations

Ethical Approval and Consent to Participate

This research does not involve human participants or animals and is an original study based on publicly available data. This paper is based on firm-level census data on Large and Medium-Scale Manufacturing collected by the Ethiopian Statistical Services, which is available upon institutional request. There is no need for ethical approval or consent.

Consent for Publication

We, the authors, give our consent for the publication of identifiable details in the manuscript to be published in the Journal of..... No further institutional approval is needed.

Data Availability

The data that has been used is available for researchers and academicians up on the institutional request to the Ethiopian Statistical Services. As restrictions apply to the availability of these data, the authors of this study are not at liberty to share the data.

Declaration of Competing Interests

We, the authors, hereby declare that this submission is entirely our own work, in our own words, and that all sources used in researching it are fully acknowledged and all quotations are properly identified. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This research received no specific grant from any funding agency.

CRediT authorship contribution statement

The authors are responsible for study conception and design, data analysis, and interpretation of results. **Eyayu Tesfaye Mulugeta:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Måns Söderbom:** Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Acknowledgements

The authors are grateful to the Ethiopian Statistical Services and to Tadele Ferede and Tsegaye Gebrekidan for providing access to the dataset. We also thank Adrian Poignant for his valuable feedback, as well as participants at the conferences and seminars where this paper was presented. Special thanks go to Alemu Lambamo and Zerayehu Semie for their helpful comments. Mulugeta gratefully acknowledges financial support from the Swedish International Development Cooperation Agency (Sida), and Söderbom acknowledges support from the Bromanska Foundation. The authors are solely responsible for any remaining errors..

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

1. 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 presents the empirical approach. Section 3 describes the data and provides descriptive statistics. Section 4 presents the empirical results and discusses the key findings. Section 5 conducts robustness checks to validate the results. Finally, Section 6 concludes with a summary of the findings, policy implications, and directions for future research

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)³. 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, and market concentration for the entire periods⁴. 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

³ 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.

⁴A 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.

Analysis (PCA) based composite index⁵. 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.

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:

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

Where: i denotes the firm; $\log(Capital)$ represents logarithm of capital stock; $\log(uncert)$ and $\log(uncert)^2$ 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.

⁵ 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.

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 (Ferdeger, 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)⁶. Using multiple proxies enhances 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

⁶ 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.

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

3. Data and Summary Statistics

3.1. 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 & Gebreeyesus, 2007; 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).

3.2. Summary Statistics

Table 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 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. HHI 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 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 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. Estimation Results

4.1. 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 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.

4.2. 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 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. $p < 0.10$, $p < 0.05$, $p < 0.01$. 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.

4.3. 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 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.

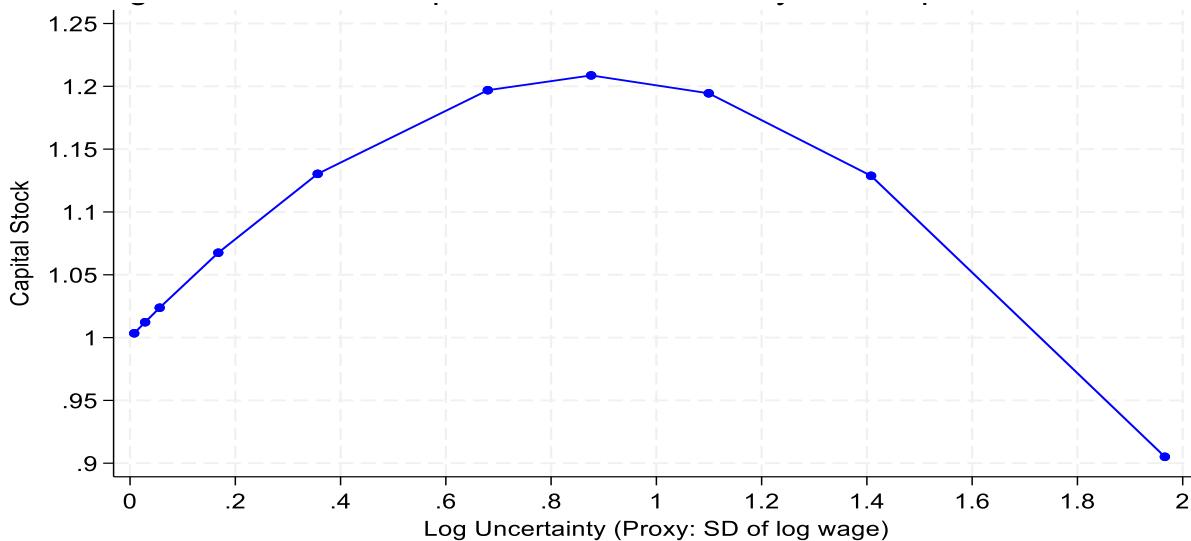
Table 4: The relationship between firm-specific uncertainty and capital stock across percentiles

Percentiles	log uncertainty	log capital	capital
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

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

Figure 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 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 2: The Relationship between Uncertainty and Capital Accumulation



5. 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 5). Second, we use another alternative: the coefficient of variation of the original measures (Table 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 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 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	0.051*** (0.013)	0.061* (0.029)	0.065* (0.032)	0.055** (0.019)	-0.009 (0.052)	0.389** (0.123)	0.055** (0.019)
Uncertainty ²	-0.002*** (0.004)	-0.003** (0.009)	-0.004** (0.001)	-0.002*** (0.006)	-0.005 (0.007)	-0.089*** (0.024)	-0.0023*** (0.006)
Log(Firm_Size)	1.135*** (0.059)	1.149*** (0.057)	1.122*** (0.049)	1.107*** (0.053)	1.149*** (0.059)	1.145*** (0.058)	1.107*** (0.053)
Log(Firm_Age)	-0.240*** (0.016)	-0.239*** (0.015)	-0.248*** (0.021)	-0.239*** (0.019)	-0.243*** (0.018)	-0.240*** (0.018)	-0.239*** (0.019)
Log(Export)	0.034 (0.021)	0.037 (0.021)	0.041 (0.024)	0.037 (0.022)	0.0367 (0.022)	0.0402* (0.021)	0.0371 (0.022)
Log(Import)	0.058*** (0.016)	0.056*** (0.015)	0.057*** (0.016)	0.064*** (0.018)	0.0561*** (0.015)	0.0556*** (0.014)	0.0636*** (0.018)
HHI_Dummy	0.074 (0.047)	0.088* (0.044)	0.075** (0.027)	0.069* (0.033)	0.095* (0.044)	0.094* (0.047)	0.069* (0.033)
Location FE	Yes						
Industry FE	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 TFP; **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 the variables as a measure of uncertainty

Table 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						
Industry FE	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: In model (1): Coefficient of variation (CV) of log sales; In model (2): CV of log output; In model (3): CV of log value added; In model (4): CV of log TFP; In model (5): CV of log wage cost; In model (6): CV of log total employees; In model (7): CV of log profit

Use of panel observations (firm-year observation >= 6)

Table 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						
Industry FE	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: In model (1): Standard deviation (SD) of log sales; In model (2): SD of log output; In model (3): SD of log value added; In model (4): SD of log TFP; In model (5): SD of log wage cost; In model (6): SD of log total employees; In model (7): SD of log profit; In model (8): SD of log of a PCA-based composite index

6. 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.

References

- Abel, A. B., & Eberly, J. C. (1999). The effects of irreversibility and uncertainty on capital accumulation. *Journal of monetary economics*, 44(3), 339-377. [https://doi.org/10.1016/S0304-3932\(99\)00029-X](https://doi.org/10.1016/S0304-3932(99)00029-X)
- Abreha, K. G. (2019). Importing and firm productivity in Ethiopian manufacturing. *The World Bank Economic Review*, 33(3), 772–792. <https://doi.org/10.1093/wber/lhx009>
- Ahmad, F., Rashid, A., & Shah, A. (2022). Monetary policy, financial development and firm investment in Pakistan: an empirical analysis. *Journal of Economic and Administrative Sciences*. <https://doi.org/10.1108/JEAS-04-2022-00981>
- Afaro, I., Bloom, N., & Lin, X. (2024). The finance uncertainty multiplier. *Journal of Political Economy*, 132(2), 577-615. <https://www.journals.uchicago.edu/doi/full/10.1086/726230>
- Amiti, M., & Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. *American Economic Review*, 97(5), 1611–1638. <https://doi.org/10.1257/aer.97.5.1611>
- Anh, D. L. T., Gan, C., Jin, S., & Anh, N. T. (2024). Uncertainty, risk aversion and corporate performance: evidence from the Asia-Pacific region. *Journal of the Asia Pacific Economy*, 29(3), 1191-1211. <https://doi.org/10.1080/13547860.2022.2154927>
- Arellano, C., Bai, Y., & Kehoe, P. J. (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy*, 127(5), 2049-2103. Retrieved from <https://www.jstor.org/stable/pdf/26846684.pdf>
- Awano, G., Bloom, N., Dolby, T., Mizen, P., Riley, R., Senga, T. & Wales, P. (2018). A firm-level perspective on micro-and macro-level uncertainty. *ESCoE Discussion Paper*, 10. Retrieved from: <https://escoe-website.s3.amazonaws.com/wp-content/uploads/2020/07/13160453/2018-10.pdf>
- Bachmann, R., Elstner, S., & Hristov, A. (2017). Surprise, surprise—Measuring firm-level investment innovations. *Journal of Economic Dynamics and Control*, 83, 107-148. <https://doi.org/10.1016/j.jedc.2017.07.009>

Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5(2), 217-249.

<https://www.aeaweb.org/articles?id=10.1257/mac.5.2.217>

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4), 1593-1636. <https://doi.org/10.1093/qje/qjw024>

Bas, M., & Strauss-Kahn, V. (2014). Does importing more inputs raise exports? Firm-level evidence from France. *Review of World Economics*, 150, 241-275.

<https://doi.org/10.1007/s10290-013-0175-0>

Baum, C. F., Caglayan, M., & Talavera, O. (2008). Uncertainty determinants of firm investment. *Economics Letters*, 98(3), 282-287. <https://doi.org/10.1016/j.econlet.2007.05.004>

Baum, C. F., Caglayan, M., & Talavera, O. (2010). On the sensitivity of firms' investment to cash flow and uncertainty. *Oxford Economic Papers*, 62(2), 286-306.

<https://doi.org/10.1093/oep/gpp015>

Beladi, H., Deng, J., & Hu, M. (2021). Cash flow uncertainty, financial constraints and R&D investment. *International Review of Financial Analysis*, 76, 101785.

<https://doi.org/10.1016/j.irfa.2021.101785>

Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2007). Firms in international trade. *Journal of Economic perspectives*, 21(3), 105-130. <https://doi.org/10.1257/jep.21.3.105>

Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., & Teal, F. (2005). Adjustment costs and irreversibility as determinants of investment: Evidence from African manufacturing. *Contributions in Economic Analysis & Policy*, 4(1), 1–27.

<https://doi.org/10.2202/1538-0645.1228>

Bigsten, A., Gebreeyesus, M., & Söderbom, M. (2016). Tariffs and firm performance in Ethiopia. *The Journal of Development Studies*, 52(7), 986–1001.

<https://doi.org/10.1080/00220388.2016.1139691>

Bloom, N., Bond, S., & Van Reenen, J. (2007). Uncertainty and investment dynamics. *The Review of Economic Studies*, 74(2), 391–415. <https://doi.org/10.1111/j.1467-937X.2007.00426.x>

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623–685. <https://doi.org/10.3982/ECTA6248>

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, 86(3), 1031–1065. <https://doi.org/10.3982/ECTA10927>

Bloom, N., Davis, S. J., Foster, L., Lucking, B., Ohlmacher, S., & Saporta-Eksten, I. (2020). *Business-level expectations and uncertainty* (NBER Working Paper No. 28259). National Bureau of Economic Research. <https://www.nber.org/papers/w28259>

Bo, H. (2002). Idiosyncratic uncertainty and firm investment. *Australian Economic Papers*, 41(1), 1–14. <https://doi.org/10.1111/1467-8454.00146>

Bo, H., & Lensink, R. (2005). Is the investment-uncertainty relationship nonlinear? An empirical analysis for the Netherlands. *Economica*, 72(286), 307–333. <https://doi.org/10.1111/j.0013-0427.2005.00416.x>

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3), 531–558.
<https://doi.org/10.1016/j.jfineco.2018.05.007>

Bond, S. R., Söderbom, M., & Wu, G. (2007). *Uncertainty and capital accumulation: empirical evidence for African and Asian firms*. Mimeo, Department of Economics, University of Oxford. Retrieved from

<https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=841ee56af948ad3b9ecaa640438626a4f85ec5ea>

Bond, S. R., Söderbom, M., & Wu, G. (2011). Pursuing the wrong options? Adjustment costs and the relationship between uncertainty and capital accumulation. *Economics Letters*, 111(3), 249–251. <https://doi.org/10.1016/j.econlet.2011.01.020>.

Bontempi, M. E., Golinelli, R., & Parigi, G. (2010). Why demand uncertainty curbs investment: Evidence from a panel of Italian manufacturing firms. *Journal of Macroeconomics*, 32(1), 218–

238. <https://doi.org/10.1016/j.jmacro.2009.03.004>

Byun, S. J. & Jo, S. (2018). Heterogeneity in the dynamic effects of uncertainty on investment. *Canadian Journal of Economics/Revue canadienne d'économique*, 51(1), 127–155.
<https://doi.org/10.1111/caje.12318>

Castro, R., Clementi, G. L, & MacDonald, G. (2009). Legal institutions, sectoral heterogeneity, and economic development. *The Review of Economic Studies*, 76(2), 529–561.
<https://doi.org/10.1111/j.1467-937X.2008.00528.x>

Chirinko, R. S. (1993). Business fixed investment spending: Modeling strategies, empirical results, and policy implications. *Journal of Economic literature*, 31(4), 1875–1911.
<https://www.jstor.org/stable/2728330>

Choi, S., Furceri, D., Huang, Y., & Loungani, P. (2018). Aggregate uncertainty and sectoral productivity growth: The role of credit constraints. *Journal of International Money and Finance*, 88, 314–330. <https://doi.org/10.1016/j.jimonfin.2017.07.016>

Chortareas, G., Noikokyris, E., & Rakeeb, F. R. (2021). Investment, firm-specific uncertainty, and market power in South Africa. *Economic Modelling*, 96, 389–395.

<https://doi.org/10.1016/j.econmod.2020.03.021>

Davis, S. J, & Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3), 819–863.

<https://doi.org/10.2307/2118365>

Diao, X., Ellis, M., McMillan, M., & Rodrik, D. (2024). Africa's manufacturing puzzle: Evidence from Tanzanian and Ethiopian firms. *The World Bank Economic Review*, 39(2), 308–340.

<https://doi.org/10.1093/wber/lhae029>

Dinh, H.T., Palmade, V., Chandra, V., & Cossar, F. (Eds.). (2012). *Light manufacturing in Africa: Targeted policies to enhance private investment and create jobs* (Africa Development Forum Series). World Bank Publications. <https://doi.org/10.1596/978-0-8213-8961-4>

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2063–2117). Elsevier.
[https://doi.org/10.1016/S1574-0080\(04\)80005-1](https://doi.org/10.1016/S1574-0080(04)80005-1)

Erena, O. T, Kalko, M. M, & Debele, S. A. (2021). Technical efficiency, technological progress and productivity growth of large and medium manufacturing industries in Ethiopia: A data envelopment analysis. *Cogent Economics & Finance*, 9(1), Article 1997160.

<https://doi.org/10.1080/23322039.2021.1997160>

Evans, D. S. (1987). Tests of alternative theories of firm growth. *Journal of political economy*, 95(4), 657-674. <https://doi.org/10.1086/261480>

Fazzari, S., Hubbard, R. G., & Petersen, B. (1988). Investment, financing decisions, and tax policy. *The American economic review*, 78(2), 200-205. <https://www.jstor.org/stable/1818123>

Ferderer, J. P. (1993). The impact of uncertainty on aggregate investment spending: An empirical analysis. *Journal of Money, Credit and Banking*, 25(1), 30–48.

<https://doi.org/10.1080/01603477.1993.11489966>

Fiorini, M., Sanfilippo, M., & Sundaram, A. (2021). Trade liberalization, roads and firm productivity. *Journal of Development Economics*, 153, Article 102712. <https://doi.org/10.1016/j.jdeveco.2021.102712>

Gebreeyesus, M., Hailu, B.K., Ohno.K., & Tekleselassie, T. (2020). *Ethiopia productivity report 2020*. Policy Studies Institute (PSI) and National Graduate Institute for Policy Studies (GRIPS). Retrieved from https://psi.gov.et/ETproductivityreport_20200212.pdf

Ghosal, V., & Loungani, P. (2000). The differential impact of uncertainty on investment in small and large businesses. *Review of Economics and Statistics*, 82(2), 338–343.

<https://doi.org/10.1162/003465300558722>

Gilchrist, S., Sim, J. W., & Zakrajšek, E. (2014). *Uncertainty, financial frictions, and investment dynamics* (Finance and Economics Discussion Series No. 2014-69). Board of Governors of the Federal Reserve System. <https://doi.org/10.17016/FEDS.2014.69>

Guiso, L., & Parigi, G. (1999). Investment and demand uncertainty. *The Quarterly Journal of Economics*, 114(1), 185-227. <https://doi.org/10.1162/003355399555981>

Gulen, H., & Ion, M. (2016). Policy uncertainty and corporate investment. *Review of Financial Studies*, 29(3), 523–564. <https://doi.org/10.1093/rfs/hhv050>

Haile, G., Srour, I., & Vivarelli, M. (2017). Imported technology and manufacturing employment in Ethiopia. *Eurasian Business Review*, 7(1), 1–23. <https://doi.org/10.1007/s40821-016-0051-7>

Handley, K., & Li, J. F. (2020). Measuring the effects of firm uncertainty on economic activity: New evidence from one million documents (NBER Working Paper No. 27896). National Bureau of Economic Research. <https://doi.org/10.3386/w27896>

Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly journal of economics*, 124(4), 1403-1448.

<https://doi.org/10.1162/qjec.2009.124.4.1403>

Huizinga, J. (1993). Inflation uncertainty, relative price uncertainty, and investment in US manufacturing. *Journal of Money, Credit and Banking*, 25(3), 521-549.

<https://www.jstor.org/stable/2077721>

Jorgenson, D. W. (1963). Capital theory and investment behavior. *The American economic review*, 53(2), 247-259. <https://www.jstor.org/stable/1823868>

Kellogg, R. (2014). The effect of uncertainty on investment: Evidence from Texas oil drilling. *American Economic Review*, 104(6), 1698-1734. <https://doi.org/10.1257/aer.104.6.1698>

Koetse, M. J., de Groot, H. L., & Florax, R. J. G. M. (2011). A Meta-Regression Analysis of the Investment-Uncertainty Relationship. *Improving Energy Efficiency Through Technology: Trends, Investment Behaviour and Policy Design*, Edward Elgar, Cheltenham, 176-204.

<https://doi.org/10.4337/9780857930606>

Lakdawala, A., & Moreland, T. (2024). Firm-level uncertainty and the transmission of monetary policy. *The Review of Economics and Statistics*, 1–28. https://doi.org/10.1162/rest_a_01440

Leahy, J. V., & Whited, T. M. (1996). The effect of uncertainty on investment: Some stylized facts. *Journal of Money, Credit and Banking*, 28(1), 64–83. <https://doi.org/10.2307/2077967>

Lensink, R. (2002). Is the uncertainty–investment link non-linear? Empirical evidence for developed economies. *Weltwirtschaftliches Archiv* (Review of World Economics), 138(1), 131–147. <https://doi.org/10.1007/BF02707327>

McMillan, M., Rodrik, D., & Verduzco-Gallo (2014). Globalization, structural change, and productivity growth, with an update on Africa. *World Development*, 63, 11–32. <https://doi.org/10.1016/j.worlddev.2013.10.012>

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6), 1695–1725. <https://doi.org/10.1111/1468-0262.00467>

Nguyen, M. H. & Trinh, V. Q. (2023). UK economic policy uncertainty and innovation activities: A firm-level analysis. *Journal of Economics and Business*, 123, Article 106093. <https://doi.org/10.1016/j.jeconbus.2022.106093>

Panousi, V., & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. *Journal of Finance*, 67(3), 1113–1148. <https://doi.org/10.1111/j.1540-6261.2012.01743.x>

Pindyck, R. S. (1990). Irreversibility, uncertainty, and investment. *Unpublished working paper, Massachusetts Institute of Technology*. <https://doi.org/10.3386/w3307>

Rajan, R. G., & Zingales, L. (1996). Financial dependence and growth. NBER Working Paper No. 5758. National Bureau of Economic Research. <https://doi.org/10.3386/w5758>

Rashid, A. (2011). How does private firms' investment respond to uncertainty? Some evidence from the United Kingdom. *Journal of Risk Finance*, 12(4), 339–347. <https://doi.org/10.1108/15265941111158514>

Rashid, A., & Saeed, M. (2017). Firms' investment decisions—explaining the role of uncertainty. *Journal of Economic Studies*, 44(5), 833–860. <https://doi.org/10.1108/JES-02-2016-0041>

Rashid, A., Nasimi, A. N., & Nasimi, R. N. (2022). The uncertainty–investment relationship: scrutinizing the role of firm size. *International Journal of Emerging Markets*, 17(10), 2605-2635.
<https://doi.org/10.1108/IJOEM-09-2019-0698>

Rodrik, D. (2013). Structural change, fundamentals, and growth: an overview. *Institute for Advanced Study*, 23, 1-12. Retrieved from

https://scholar.harvard.edu/sites/scholar.harvard.edu/files/dani-rodrik/files/structural-change-fundamentals-and-growth-an-overview_revised.pdf

Schauer, C. (2019). How asset irreversibility influences the investment-uncertainty relationship. *Bulletin of Economic Research*, 71(3), 283–306. <https://doi.org/10.1111/boer.12164>

Schmalensee, R. (1989). Inter-industry studies of structure and performance. *Handbook of industrial organization*, 2, 951-1009. [https://doi.org/10.1016/S1573-448X\(89\)02004-2](https://doi.org/10.1016/S1573-448X(89)02004-2)

Senga, T. (2015). *A new look at uncertainty shocks: Imperfect information and misallocation* (No. 763). Working paper. <https://hdl.handle.net/10419/130777>

Shiferaw, A. (2006). Entry, survival, and growth of manufacturing firms in Ethiopia. *ISS Working Paper Series/General Series*, 425, 1-36. Retrieved from <https://repub.eur.nl/pub/19185/wp425.pdf>

Shiferaw, A. (2009). *Which firms invest less under uncertainty? evidence from ethiopian manufacturing* (No. 2). Discussion Papers. <https://hdl.handle.net/10419/90464>

Shiferaw, A., & Söderbom, M. (2018). The Ethiopian manufacturing sector: productivity, export orientation, and competitiveness. *The Oxford Handbook of the Ethiopian Economy, Oxford Handbooks* (2019).

Shima, K. (2016). Negative uncertainty sensitivity of investment and market structure. *Economics Letters*, 147, 93-95. <https://doi.org/10.1016/j.econlet.2016.08.023>

Siba, E., & Gebreeyesus, M. (2016). Learning to export and learning from exporting: The case of Ethiopian manufacturing. *Journal of African Economies*, 26(1), 1–23.
<https://doi.org/10.1093/jae/ejw022>

Söderbom, M. (2012). Firm size and structural change: A case study of Ethiopia. *Journal of African Economies*, 21(suppl_2), ii126–ii151. <https://doi.org/10.1093/jae/ejr046>

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, 49(2), 326–365. <https://doi.org/10.1257/jel.49.2.326>

Tran, T. L. (2014). Uncertainty and investment: Evidence from Australian firm panel data. *Economic Record*, 90, 87–101. <https://doi.org/10.1111/1475-4932.12133>

Tsaedu, K. G. & Chen, Z. (2021). The dynamics of firm growth in Sub-Saharan Africa: Evidence from Ethiopian manufacturing sector 1996–2017. *Journal of Industry, Competition and Trade*, 21(3), 367–392. <https://doi.org/10.1007/s10842-021-00361>