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

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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.

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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.

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Abstract

This paper examines whether firm-specific uncertainty is associated with capital accumulation in a nonlinear manner among Ethiopian manufacturing firms. Using firm-level panel data covering the period 1996–2016, we construct a cross-sectional dataset by averaging observations over time. Uncertainty is measured ex ante and capital stocks are measured ex post to mitigate concerns about contemporaneous feedback. We estimate OLS models using multiple backward-looking proxies for firm-specific uncertainty and include high-dimensional fixed effects to control for sectoral and regional heterogeneity. The results reveal a nonlinear (inverted U-shaped) relationship between uncertainty and long-run capital stocks: capital stocks increase with uncertainty at lower levels but decline as uncertainty becomes more pronounced. This pattern is consistent with real options theory, which emphasizes the interaction between uncertainty and irreversibility in shaping long-run capital accumulation. The findings are robust across alternative uncertainty measures and model 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 or policy-related, shapes decision-making and resource allocation (Arellano, 2019; Alfaro et al., 2024).[3] At the macro level, heightened uncertainty is associated with reductions in investment and output growth (Baker et al., 2016; Bloom et al., 2018; Gilchrist et al., 2014). At the firm level, uncertainty is linked to distortions in capital allocation and delays in adjustment (Guiso and Parigi, 1999; Gulen and Ion, 2016; Nguyen and Trinh, 2023). While the uncertainty–investment relationship has been widely studied, with an emphasis on mechanisms such as investment irreversibility and adjustment frictions (Bloom et al., 2007; Pindyck, 1990; Rashid and Saeed, 2017), most existing evidence comes from advanced economies. Empirical work remains relatively limited in low-income contexts characterized by macroeconomic volatility and underdeveloped financial systems (Bigsten et al., 2005; Shiferaw, 2009).

This paper contributes to this literature by examining how firm-specific uncertainty is associated with long-run capital accumulation in Ethiopia's manufacturing sector. Unlike short-term investment flows, capital accumulation reflects firms' cumulative responses to persistent uncertainty and adjustment constraints, offering a more comprehensive measure of productive capacity and structural transformation (Bond et al., 2008; Chirinko, 1993; Rodrik, 2013). Ethiopian manufacturing firms operate under persistent macroeconomic instability and policy unpredictability, making them a particularly informative setting for studying uncertainty and capital accumulation (Dinh et al., 2012; Shiferaw, 2009). Their relatively high capital intensity and limited access to secondary markets make them especially exposed to capital irreversibility (Diao et al., 2024; Shiferaw, 2009). Despite this, empirical evidence on how idiosyncratic uncertainty shapes long-run capital accumulation in such environments remains scarce.

From a theoretical perspective, the long-run relationship between uncertainty and capital accumulation is ambiguous. Real options models emphasize that uncertainty interacts with capital irreversibility to shape firms' accumulation outcomes, with opposing forces that can either raise or lower long-run capital stocks depending on the level of uncertainty (Abel and Eberly, 1999). As

[3] Throughout this paper, uncertainty is taken to represent unpredictability in key economic factors that affect firm investment decisions, such as output prices, productivity, and factor costs.

a result, linear empirical specifications may obscure important nonlinearities. Building on Bo and Lensink (2005), this paper explicitly tests whether firm-level capital accumulation responds nonlinearly to firm-specific uncertainty.

Using a cross-sectional dataset constructed from firm-level panel data for Ethiopian manufacturing establishments covering the period 1996 to 2016, we estimate OLS models to assess the relationship between firm-specific uncertainty and long-run capital stocks. Uncertainty is measured using multiple backward-looking proxies that capture different sources of firm-level variability, while capital accumulation is measured over subsequent periods to reflect longer-run outcomes rather than short-term fluctuations.

This paper contributes to the literature in various ways. First, it addresses an important empirical gap by focusing on Ethiopia, where structural and institutional constraints magnify the role of uncertainty. Second, it focuses on long-run capital accumulation and explicitly tests for nonlinearities in the uncertainty–capital relationship that linear models may overlook.

Our findings reveal a nonlinear relationship between firm-specific uncertainty and long-run capital stocks. Capital stocks increase with uncertainty at lower levels but decline as uncertainty becomes more pronounced. This inverted U-shaped pattern is consistent with real options theory, which highlights the interaction between uncertainty and irreversibility in shaping long-run capital accumulation outcomes (Abel and Eberly, 1999). The results are robust across alternative uncertainty measures and model specifications, underscoring the importance of accounting for nonlinear effects when studying uncertainty in developing-country contexts.

The remainder of the paper is structured as follows. Section 2 presents the theoretical underpinnings and the empirical framework. Section 3 describes the data and variable construction. Section 4 presents and discusses the empirical results, including robustness checks. Section 5 concludes with a summary of the findings, policy implications, and directions for future research.

2. Capital Accumulation under Uncertainty and Irreversibility

Uncertainty and irreversibility are first-order features of capital accumulation in African manufacturing. Firm-level studies document that investment is infrequent and lumpy, with many episodes of zero investment despite high average returns, and that this pattern is closely linked to macroeconomic instability, policy volatility, and information problems that raise perceived risk (Gunning and Mengistae, 2001; Shiferaw, 2006). At the same time, underdeveloped second-hand markets for machinery and equipment severely limit firms' ability to resell or redeploy installed capital, so that investment outlays are largely sunk and disinvestment options are limited. These features make African manufacturing a natural setting for applying theories of irreversible investment under uncertainty, and they motivate the Abel–Eberly framework used in the next section to interpret firms' capital accumulation decisions when both high uncertainty and weak reversibility are present.

The empirical literature on how African firms adjust investment in response to changing levels of uncertainty is limited. [4] Available evidence indicates that heightened uncertainty depresses or delays capital spending, especially in settings characterized by irreversible investment and elevated policy-related risk. Even less is known about how persistent uncertainty shapes long-run capital stocks at the firm level. This gap matters because uncertainty may affect long-run capital accumulation through several distinct channels. It can alter firms' desired target capital, induce prolonged periods of under-investment or scrapping, and interact with financing constraints and adjustment costs. As a result, the long-run impact on productive capacity may be complex and theoretically ambiguous.

Abel and Eberly (1999) develop a theoretical model to study how irreversible investment and demand uncertainty shape long-run capital accumulation for firms. In this model, irreversibility

[4] Shiferaw (2006) finds that Ethiopian manufacturing firms experience persistent zero investment episodes despite high average profits, linking this to uncertainty and limited reversibility due to underdeveloped second-hand markets Bigsten et al. (1999) and Gunning et al. (1999) provide evidence from multiple African countries showing that irreversibility and adjustment costs are key factors shaping investment dynamics, with many firms facing large investment spikes separated by zero investment periods. Additional work confirms that uncertainty, proxied by profit volatility or demand variance, raises the threshold for investment and reduces investment rates more strongly when capital is irreversible (Pattillo, 1997; Shiferaw, 2009). Servén (1996) highlights macroeconomic instability as a major source of uncertainty deterring fixed investment in Sub-Saharan Africa.

raises the user cost of capital, since firms cannot freely disinvest when conditions deteriorate, which tends to reduce the desired capital stock. At the same time, a "hangover effect" arises because the irreversibility constraint occasionally binds, leaving firms stuck with excess capital when the marginal revenue product of capital is low. The hangover effect tends to increase the expected capital stock. In this framework, greater uncertainty can either increase or decrease the expected long-run capital stock, implying that the sign of the uncertainty–capital accumulation relationship is theoretically ambiguous. This ambiguity underscores the importance of empirical evidence in assessing the net effect of uncertainty on long-run capital accumulation. Interpreted through the lens of the Abel-Eberly model, it should be noted that higher uncertainty combined with irreversibility is always costly. Although the hangover effect increases the capital stock, it does so inefficiently, leading to lower profits and firm value relative to a setting without uncertainty.

Drawing on the theoretical insights of Abel and Eberly, we propose the following a simple empirical specification for analyzing the relationship between capital accumulation and uncertainty:

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

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[5]; 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.

Most empirical studies proxy for firm-specific uncertainty using volatility-based measures, often with the standard deviation of firm sales used as a proxy for firm-specific uncertainty (Bond et al.,

[5] In this specification, 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.

2008; Castro et al., 2009; Comin & Mulani, 2006; Rashid, 2011; Rashid & Saeed, 2017; Shima, 2016). 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), the coefficient of variation of output (Shiferaw, 2009), and the variance of returns (Ferderer, 1993). In this study, we construct multiple proxies of firm-specific uncertainty using 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]. We estimate our model using 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 underlying firm-level panel dataset is described in the next section.

3. Data, Measurement and Summary Statistics

3.1 Data

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). 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. The

[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.

dataset has been widely used in empirical studies on Ethiopian manufacturing, including research on firm performance[7], firm entry and survival[8], Africa's manufacturing puzzle[9] and Ethiopia's productivity performance[10]. 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.

3.2 Construction of Variables

We hypothesize that firms adjust capital accumulation in response to perceived uncertainty, which in turn is based on variability in previously experienced outcomes. We exploit the long time-series dimension of the data to construct measures of uncertainty using several years of outcome data prior (ex ante) to the period over which we study capital accumulation (ex post). Constructing measures of uncertainty using several years of firm-level time series data is essential to accurately capture variability, as longer data spans reduce noise and improve the reliability of these measures. Separating the timing of uncertainty measurement from investment outcomes is not only appropriate on theoretical grounds, but also reduces the risk that contemporaneous feedback distorts the estimated relationship between uncertainty and capital formation.

Since our focus is on long-run capital accumulation, we abstract from short-term fluctuations in capital and measure firms' average capital stocks over multiple years. This approach collapses the data into one observation per firm, making the econometric analysis essentially cross-sectional while still relying on a rich, long panel dataset underlying these averages. By smoothing out short-term volatility, the method better captures sustained investment behavior rather than temporary adjustments. This also reduces noise and measurement errors inherent in annual capital data, improving estimation precision. The underlying capital stock variable is constructed using book value data on machinery and equipment, combined with information on purchases of new equipment.

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[7] See e.g. 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 and Gebreeyesus (2016); Söderbom (2012); and Tsaedu & Chen (2021).
[8] Shiferaw (2006).
[9] Diao et al. (2024).
[10] Gebreeyesus et al. (2020).

Our regressions control for firm characteristics such as firm size, firm age, trade status, and market concentration – see appendix A for details on how these variables are defined and constructed. Firm size is expected to be positively associated with capital accumulation, as larger firms typically enjoy better access to finance, economies of scale, and stronger internal resource generation (Fazzari et al., 1988; Rajan and Zingales, 1995). Firm age may affect capital accumulation in opposing ways. Older firms may have accumulated intangible assets, gained operational efficiency, and thus rely less on physical capital. In contrast, younger firms tend to be more volatile and often exhibit higher capital intensity during early growth phases (Evans, 1987). Firms that import intermediate inputs are more likely to engage in advanced and potentially capital-intensive production processes. As part of upgrading and expanding production capabilities, such firms may therefore hold higher levels of capital stock (Amiti and Konings, 2007; Bas and Strauss-Kahn, 2014). Similarly, exporting firms tend to be more productive and larger, and often invest more in capital in order to meet international standards. Exporters are generally more productive and more capital-intensive than non-exporters (Melitz, 2003; Bernard et al., 2007). Finally, market structure may shape capital accumulation incentives. Firms operating in more concentrated industries may accumulate more capital due to higher profitability associated with market power (Schmalensee, 1989).[11]

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. Since unobservables may be correlated within each of these groups, 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. Nevertheless, the results should be interpreted with appropriate caution.

We estimate multiple model specifications, each using a different proxy for uncertainty, including

[11] A 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.

the standard deviations of sales, output, value added, total factor productivity, wage costs, material costs, employment, and profits, as well as a composite index constructed using Principal Component Analysis (PCA).[12] This approach allows for an assessment of the robustness in the relationship between capital accumulation and firm-specific uncertainty across a diverse set of idiosyncratic uncertainty measures. We further assess robustness using alternative uncertainty measures (variance and coefficient of variation), by excluding firms with short panel histories, and by employing varying thresholds to classify uncertainty measures (ex ante) and capital accumulation (ex post).[13]

3.3 Summary Statistics

Table 1 presents descriptive statistics for the variables that we use in our empirical analyiss. 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).

[12] 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.

[13] 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).

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. 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 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 from multiple regression models examining the relationship between firm-specific uncertainty and long-run capital accumulation, with a particular focus on whether this 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. Firm-specific uncertainty is proxied using the standard deviation of log-transformed sales, output, value added, total factor productivity, wage costs, employment, profits, and a composite index derived from Principal Component Analysis. This approach allows for a systematic assessment of whether the relationship between uncertainty and capital stocks is robust across different sources of firm-level variability.

The results reported in Table 3 show consistently high adjusted R-squared values across all models (approximately 0.65–0.67), indicating strong explanatory power. The F-tests are statistically significant in all specifications, confirming the joint relevance of the explanatory variables. In addition, joint hypothesis tests reject the null that the linear and squared uncertainty terms are jointly equal to zero across all models. This provides strong support for the inclusion of a nonlinear specification when examining the association between uncertainty and capital stocks.

In some specifications (notably Model 7), the squared uncertainty term is not individually statistically significant; however, the joint significance of the linear and squared terms indicates that the nonlinear specification remains informative. The inclusion of high-dimensional fixed effects for industry and location controls for persistent structural differences in capital intensity across sectors and regions. Standard errors are clustered at both the industry and location levels to account for potential correlation in unobservables within these dimensions.

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.*

Model 1 uses the standard deviation of the log of sales as the proxy for uncertainty. The linear term is positive and statistically significant (0.271), while the squared term is negative (–0.063) and marginally significant. This pattern indicates a nonlinear association between sales uncertainty and capital stocks: at lower levels of uncertainty, higher variability in sales is associated with higher observed capital stocks, whereas at higher levels of uncertainty, further increases are associated with lower capital accumulation.

Model 2 uses the standard deviation of the log of output as the uncertainty proxy. The estimated coefficients on the linear (0.315) and squared (–0.072) terms are both statistically significant, again supporting an inverted U-shaped relationship. This suggests that moderate output variability is associated with higher capital stocks, while more extreme output uncertainty is associated with reduced capital accumulation.

Model 3 employs the standard deviation of the log of value added as the measure of uncertainty. Because value added abstracts from fluctuations in input costs driven by external shocks, it provides a clearer measure of firm-specific performance variability. The linear term (0.371) is positive and the squared term (–0.089) is negative, with both statistically significant, reinforcing the presence of a nonlinear relationship between uncertainty and capital stocks.

Model 4 uses the standard deviation of the log of total factor productivity (TFP) as the uncertainty proxy. The linear term is large and positive (0.702), while the squared term is negative (–0.434); both coefficients are statistically significant. The magnitude of these estimates suggests that productivity-related uncertainty is strongly associated with higher capital stocks at moderate levels, but that this relationship reverses as uncertainty becomes more pronounced. This pattern highlights the importance of productivity fluctuations in shaping long-run capital accumulation outcomes.

Model 5 uses the standard deviation of log wage costs to capture labor cost uncertainty. The estimated coefficients on the linear (0.441) and squared (–0.251) terms are both statistically significant, continuing the pattern of a nonlinear relationship. This indicates that wage cost variability is associated with higher capital stocks at lower levels of uncertainty, but with lower capital accumulation as wage uncertainty becomes more severe.

Model 6 employs the standard deviation of the log of total employment as the uncertainty measure. The linear term is positive (0.599) and statistically significant, while the squared term is negative (–0.276) and also statistically significant. This result again supports a nonlinear association, suggesting that moderate employment variability is associated with higher capital stocks, whereas high employment uncertainty is associated with reduced capital accumulation.

Model 7 uses the standard deviation of the log of profits as the uncertainty proxy. The linear term is positive, while the squared term is negative but not individually statistically significant. However, the joint significance test indicates that the two terms are jointly significant, providing support for a nonlinear specification. Given the imprecision of the squared term, the shape of the relationship for profit-related uncertainty should be interpreted with caution.

Model 8 employs a PCA-based composite uncertainty index. The linear term is positive (0.139), while the squared term is negative (–0.024) and statistically significant, reaffirming the inverted U-shaped relationship. The smaller coefficient magnitudes likely reflect the aggregation of multiple uncertainty sources into a single index. By capturing a broader uncertainty environment, this measure further strengthens the robustness of the observed nonlinear association. Across all specifications, the control variables—particularly firm size, firm age, trade activity, market concentration, and location—exhibit signs and significance levels consistent with expectations.

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 and the negative coefficient on the squared term indicate that observed capital stocks increase with uncertainty up to a threshold, beyond which further increases in uncertainty are associated with lower capital accumulation. This pattern is most pronounced in Model 4 (TFP-based uncertainty), where both terms are larger and statistically significant, suggesting a stronger nonlinear association. Similar patterns are observed for models using wage cost, output, and PCA-based uncertainty measures. Overall, these results indicate that the relationship between uncertainty and long-run capital stocks depends not only on the level of uncertainty but also on its source and intensity.

These findings provide robust evidence of a nonlinear relationship between firm-specific uncertainty and long-run capital accumulation. Interpreted through the lens of the real options framework of Abel and Eberly (1999), this pattern reflects the interaction between uncertainty and capital irreversibility rather than an active increase in desired investment. In their framework, irreversibility raises the user cost of capital and reduces desired investment, while occasionally binding adjustment constraints generate hangover effects that leave firms temporarily over-capitalized when conditions deteriorate. At moderate levels of uncertainty, such hangover effects may dominate, leading to higher observed capital stocks, whereas at higher levels of uncertainty the option value of waiting becomes more important, reducing long-run capital accumulation. Thus, the inverted U-shaped relationship is consistent with opposing forces emphasized in the theory.

The observed nonlinear relationship is consistent with empirical findings by Bo and Lensink

(2005), who also document a nonlinear association between uncertainty and investment. These studies suggest that uncertainty can affect capital accumulation through multiple channels, including delayed adjustment, capital stickiness, and the irreversibility of investment expenditures. While moderate uncertainty may be associated with higher observed capital stocks due to limited disinvestment options, higher uncertainty tends to discourage capital accumulation as firms become more cautious and defer irreversible commitments. Related evidence from Arellano et al. (2019) and Gilchrist et al. (2014) further highlights that the effects of uncertainty on investment outcomes are context-specific, shaped by factors such as financial frictions, market structure, and firm capabilities.

Regarding the control variables, firm size is consistently positive and significant across all models, indicating that larger firms hold higher capital stocks. This pattern is consistent with larger firms having better access to finance, greater economies of scale, and stronger internal resource generation (Beck et al., 2005; Rajan and Zingales, 1995). Firm age is negatively associated with capital accumulation, suggesting that older firms may operate with lower capital intensity due to improved efficiency, slower expansion, or greater reliance on accumulated intangible assets. This interpretation is in line with Evans (1987), who shows that younger firms tend to expand more aggressively and accumulate capital more rapidly.

Trade-related variables are positively associated with capital accumulation across most specifications. Import activity, in particular, shows a strong positive association with capital stocks, consistent with importing firms operating more capital-intensive production processes and investing in infrastructure and technology to utilize imported inputs effectively. Bernard et al. (2007) emphasize importing as an important dimension of firm heterogeneity linked to production structure and investment patterns. Export activity is also positively associated with capital accumulation in some models, reflecting the higher capital requirements associated with competing in international markets and meeting quality standards. This finding aligns with evidence from Melitz (2003), Bernard et al. (2007), and Bernard and Jensen (1999), who show that exporters tend to be larger, more productive, and more capital-intensive.

Finally, the positive and significant coefficient on the market concentration measure (HHI) suggests that firms operating in more concentrated industries tend to hold higher capital stocks. This pattern is consistent with firms in concentrated markets benefiting from higher and more stable profits, which may support greater capital accumulation over the long run. Gutiérrez and Philippon (2017) document that rising industry concentration has been accompanied by increased investment among leading firms, supporting the link between market power and capital accumulation observed in our results.

4.3. Percentile Based Analysis

To further explore the nonlinear relationship between uncertainty and long-run capital stocks, we examine how capital varies across percentiles of the uncertainty distribution. Table 4 reports predicted capital stocks corresponding to uncertainty levels from the 1st to the 99th percentile. The results show that observed capital stocks increase steadily at low to moderate levels of uncertainty, reaching a maximum around the upper-middle percentiles of the distribution. Beyond this point, further increases in uncertainty are associated with declining capital stocks, with a sharp drop at the highest percentiles. This pattern provides additional evidence that the relationship between uncertainty and capital accumulation is nonlinear and varies across the distribution of firm-specific uncertainty.

The increase in capital stocks at lower and intermediate uncertainty levels is consistent with the earlier regression results, which indicate that moderate uncertainty is associated with higher long-run capital holdings. At higher levels of uncertainty, however, capital stocks decline markedly, suggesting that extreme uncertainty is associated with substantially lower capital accumulation. The pronounced drop observed at the 99th percentile highlights the particularly strong association between very high uncertainty and reduced capital stocks. These results reinforce the importance of allowing for nonlinear effects when modeling the relationship between uncertainty and capital accumulation.

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 of wage is used as a proxy to measure uncertainty

Figure 2: The Relationship between Uncertainity and Capital Accumulation

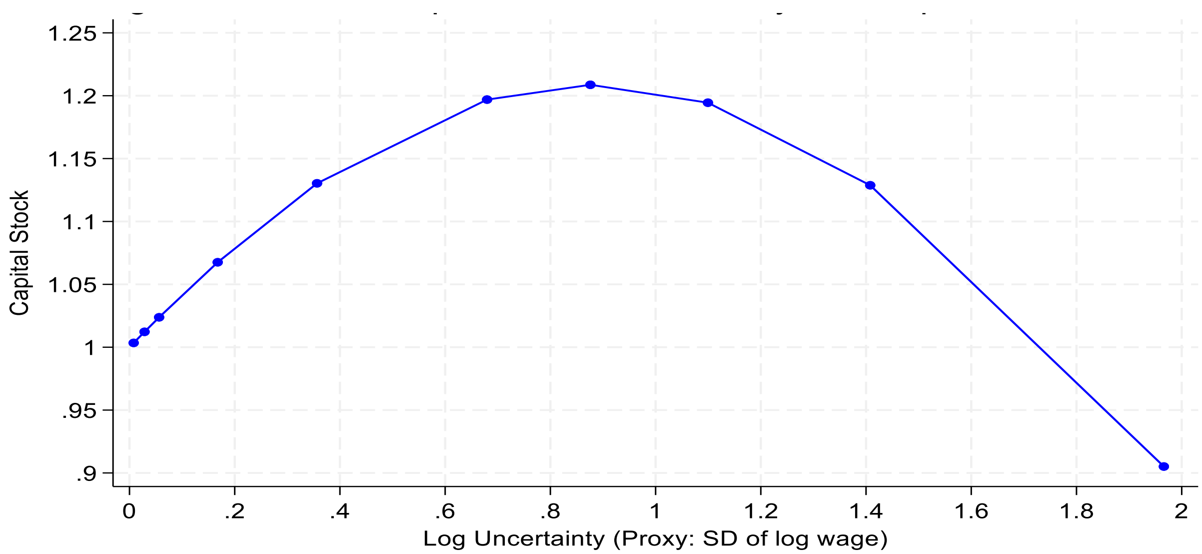

Figure 2 illustrates the relationship between uncertainty and capital stocks across the percentiles of the uncertainty distribution. Capital stocks are lowest at very low uncertainty levels, increase steadily through the lower and middle percentiles, and peak around the 75th percentile. Beyond this point, capital stocks decline sharply across the upper percentiles of the uncertainty distribution. This graphical evidence closely mirrors the regression-based findings and visually underscores the nonlinear association between uncertainty and long-run capital accumulation.

Overall, the percentile-based analysis complements the regression results by showing that the relationship between uncertainty and capital stocks differs markedly across the uncertainty distribution, providing further support for the inclusion of nonlinear terms in the empirical specification.

4.5 Robustness checks

We conduct several robustness checks to assess the stability of the relationship between firm-specific uncertainty and long-run capital stocks. Specifically, we re-estimate the baseline specification using alternative uncertainty measures, including the variance and the coefficient of variation of the original proxies, and we restrict the sample to firms with longer panel histories to address potential concerns related to data quality and firm longevity. Across these alternative specifications, the estimated nonlinear relationship between uncertainty and capital stocks remains qualitatively similar. Overall, these robustness checks suggest that the main results are not driven by specific modeling choices or sample composition (see Appendix B, Tables B1–B3).

5. Conclusions

This study provides robust evidence of a nonlinear (inverted U-shaped) relationship between firm-specific uncertainty and long-run capital stocks in Ethiopian manufacturing. 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 particularly pronounced when uncertainty is measured using TFP- and output-based proxies, indicating that the association between uncertainty and capital stocks is strongest at moderate levels of uncertainty. These findings are consistent with real options theory, which emphasizes that under uncertainty and capital irreversibility, opposing forces can shape long-run capital accumulation, leading to nonlinear outcomes.

The results carry important implications for both policymakers and firm managers. While moderate levels of uncertainty are associated with higher observed capital stocks, high and persistent uncertainty is linked to substantially lower capital accumulation. From a policy perspective, this highlights the importance of reducing extreme or unmanaged sources of uncertainty rather than attempting to eliminate uncertainty altogether. Policies that improve macroeconomic stability, strengthen market institutions, and reduce volatility in input and output markets may help support sustained capital accumulation. Expanding firms' access to finance, insurance, and risk-management instruments can further mitigate the adverse effects of high uncertainty. In addition, policies that support technological upgrading and productivity growth may help firms better withstand uncertainty, particularly when it is driven by productivity fluctuations.

Despite these contributions, the study has several limitations that suggest avenues for future research. First, the analysis 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 additional insights into firms' investment environments. Second, although the empirical strategy separates ex-ante uncertainty from ex-post capital accumulation and controls for high-dimensional fixed effects, the estimates should be interpreted as associations rather than causal effects, as reverse causality and omitted variable bias cannot be fully ruled out. Third, averaging firm-level panel data limits the ability to capture dynamic investment responses and adjustment processes over time.

In addition, the focus on manufacturing firms in Ethiopia may limit the generalizability of the findings to other sectors or institutional contexts. Finally, heterogeneity across firms—such as differences in size, ownership structure, and access to finance—is not explored explicitly, leaving open important questions about which types of firms are most sensitive to uncertainty. Addressing these issues in future research would contribute to a more comprehensive understanding of how uncertainty shapes capital accumulation in developing-country firms.

Appendix A: Control variables

Firm size is measured as the total number of employees.

Firm age denotes the number of years a firm has been in operation.

Imported inputs represent the value of imported intermediate inputs.

Exports represent the value of a firm's exports, expressed as a share in the firm's total output.

Market concentration is measured using the Herfindahl–Hirschman Index (HHI), calculated as the sum of squared market shares within an industry (Shiferaw, 2009). To capture the role of market power, we construct a dummy variable equal to one if a firm's HHI exceeds the median and zero otherwise.

Industry and location fixed effects are included to control for unobserved heterogeneity across sectors and regions, including 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 reflects within-industry and within-location variation.

Appendix B: Additional Regression Results

Table B1: 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)
Uncertainty²	-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	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 TFP;* ***Model 5****: Variance of log wage cost;* ***Model 6****: Variance of log total employees;* ***Model 7****: Variance of log profit*

Table B2: 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)
Uncertainty²	-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_Statstics	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

Table B3: 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)
Uncertainty²	-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: 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

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